Contents

Viewpoint

Mental Health in Urban Environments: Uncovering the Black Box of Person-Place Interactions Requires Interdisciplinary Approaches (e41345)
Martina Kanning, Li Yi, Chih-Hsiang Yang, Christina Niermann, Stefan Fina. ................................................................. 9

Reviews

Behavior Change Effectiveness Using Nutrition Apps in People With Chronic Diseases: Scoping Review (e41235)
Emily Salas-Groves, Shannon Galyean, Michelle Alcorn, Allison Childress. ................................................................. 16

Effectiveness of mHealth on Adherence to Antiretroviral Therapy in Patients Living With HIV: Meta-analysis of Randomized Controlled Trials (e42799)
Liang Sun, Mengbing Qu, Bing Chen, Chuancang Li, Haohao Fan, Yang Zhao. ................................................................. 45

mHealth Intervention for Improving Pain, Quality of Life, and Functional Disability in Patients With Chronic Pain: Systematic Review (e40844)
Marta Moreno-Ligero, Jose Moral-Munoz, Alejandro Salazar, Inmaculada Falide. ................................................................. 55

The Feasibility of Using Smartphone Sensors to Track Insomnia, Depression, and Anxiety in Adults and Young Adults: Narrative Review (e44123)
Doaa Alamoudi, Emma Breeze, Esther Crawley, Ian Nabney. ................................................................. 80

Effectiveness of Remote Fetal Monitoring on Maternal-Fetal Outcomes: Systematic Review and Meta-Analysis (e41508)
Suya Li, Qing Yang, Shuya Niu, Yu Liu. ................................................................. 89

Community Health Worker Use of Smart Devices for Health Promotion: Scoping Review (e42023)
Merlin Greuel, Frithjof Sy, Till Bärmighausen, Maya Adam, Alain Vandormael, Jennifer Gates, Guy Harling. ................................................................. 104

Design Features Associated With Engagement in Mobile Health Physical Activity Interventions Among Youth: Systematic Review of Qualitative and Quantitative Studies (e40898)
Ayla Schwarz, Laura Winkens, Emely de Vet, Dian Ossendrijver, Kirsten Bouwsema, Monique Simons. ................................................................. 116

Smartphone and Mobile App Use Among Physicians in Clinical Practice: Scoping Review (e44765)
Mauricette Lee, Abu Bin Mahmood, Eng Lee, Helen Smith, Lorainne Tudor Car. ................................................................. 140
Health Monitoring Using Smart Home Technologies: Scoping Review (e37347)
Plinio Morita, Kirti Sahu, Arlene Oetomo. ................................................................. 154

Mobile Health Self-management Support for Spinal Cord Injury: Systematic Literature Review (e42679)
Renaldo Bernard, Vanessa Seijas, Micheal Davis, Anel Volkova, Nicola Diviani, Janina Lüscher, Carla Sabariego. ................................................................. 169

Assessing the Pragmatic Nature of Mobile Health Interventions Promoting Physical Activity: Systematic Review and Meta-analysis (e43162)
Chad Stecher, Bjorn Pfisterer, Samantha Harden, Dana Epstein, Jakob Hirschmann, Kathrin Wunsch, Matthew Buman. ................................................................. 186

Participant Engagement in Microrandomized Trials of mHealth Interventions: Scoping Review (e44685)
Utek Leong, Bibhas Chakraborty. ................................................................................. 205

Conversational Agents and Avatars for Cardiometabolic Risk Factors and Lifestyle-Related Behaviors: Scoping Review (e39649)
Lynnette Lyzwinski, Mohamed Elgendi, Carlo Menon. ................................................. 222

Influencing Factors to mHealth Uptake With Indigenous Populations: Qualitative Systematic Review (e45162)
Andrew Goodman, Ray Mahoney, Geoffrey Spurling, Sheleigh Lawler. ..................... 257

Knowledge Discovery in Ubiquitous and Personal Sleep Tracking: Scoping Review (e42750)
Nhung Hoang, Zilu Liang. .......................................................................................... 271

Digital Technologies for Women's Pelvic Floor Muscle Training to Manage Urinary Incontinence Across Their Life Course: Scoping Review (e44929)
Stephanie Woodley, Brittany Moller, Alys Clark, Melanie Bussey, Bahram Sangelaji, Meredith Perry, Jennifer Kruger. ................................................................. 288

Parents' Perceptions of Children’s and Adolescents’ Use of Electronic Devices to Promote Physical Activity: Systematic Review of Qualitative Evidence (e44753)
María Visier-Alfonso, Mairena Sánchez-López, Beatriz Rodríguez-Martín, Abel Ruiz-Hermosa, Raquel Bartolomé-Gutiérrez, Irene Sequi-Dominguez, Vicente Martínez-Vizcaíno. ................................................................................................................................. 316

Interventions Aimed at Enhancing Health Care Providers' Behavior Toward the Prescription of Mobile Health Apps: Systematic Review (e43561)
Ohoud Alkhaldi, Brian McMillan, Noha Maddah, John Ainsworth. ......................... 480

Planting Seeds for the Future: Scoping Review of Child Health Promotion Apps for Parents (e39929)
Sarah Blakeslee, Kristin Vieler, Ingo Horak, Wiebke Stritter, Georg Seifert. ................................. 1002

Stress Management Apps: Systematic Search and Multidimensional Assessment of Quality and Characteristics (e42415)
Sarah Paganini, Evelyn Meier, Yannik Terhorst, Ramona Wurst, Vivien Hohberg, Dana Schultchen, Jana Strahler, Max Wursthorn, Harald Baumeister, Eva-Maria Messner. ................................................................. 1019

Augmented Reality in Real-time Telemedicine and Telementoring: Scoping Review (e45464)
Alana Dinl, Andrew Yin, Deborah Estrin, Peter Greenwald, Alexander Fortenko. ................................. 1190

Associations Between Social Cognitive Determinants and Movement-Related Behaviors in Studies Using Ecological Momentary Assessment Methods: Systematic Review (e44104)
Kelsey Bittel, Kate O'Briant, Rena Ragaglia, Lake Buseth, Courtney Murtha, Jessica Yu, Jennifer Stanely, Brynn Hudgins, Derek Hevel, Jaclyn Maher. ................................................................. 1284
Original Papers

Understanding Mobile Health and Youth Mental Health: Scoping Review (e44951)
Xiaoxu Ding, Kelli Wuerth, Brodie Sakakibara, Julia Schmidt, Natalie Parde, Lisa Holsti, Skye Barbic. 243

Current Status and Trends in mHealth-Based Research for Treatment and Intervention in Tinnitus: Bibliometric and Comparative Product Analysis (e47553)
Yuanjia Hu, Yang Lu, Chenghua Tian, Yunfan He, Kaiyi Rong, Siija Pan, Jianbo Lei. 333

Collecting Food and Drink Intake Data With Voice Input: Development, Usability, and Acceptability Study (e41117)
Louise Millard, Laura Johnson, Samuel Neaves, Peter Flach, Kate Tilling, Deborah Lawlor. 350

G Tolerance Prediction Model Using Mobile Device–Measured Cardiac Force Index for Military Aircrew: Observational Study (e48812)
Ming-Hao Kuo, You-Jin Lin, Wun-Wei Huang, Kwo-Tsao Chiang, Min-Yu Tu, Chi-Ming Chu, Chung-Yu Lai. 365

The Use of a Decision Support System (MyFood) to Assess Dietary Intake Among Free-Living Older Adults in Norway: Evaluation Study (e45079)
Frida Severinsen, Lene Andersen, Mari Paulsen. 377

An Overview of Chatbot-Based Mobile Mental Health Apps: Insights From App Description and User Reviews (e44838)
M Haque, Sabirat Rubya. 391

Acceptability of Personal Sensing Among People With Alcohol Use Disorder: Observational Study (e41833)
Kendra Wyant, Hannah Moshontz, Stephanie Ward, Gaylen Fronk, John Curtin. 409

The Implementation of a GPS-Based Location-Tracking Smartphone App in South Africa to Improve Engagement in HIV Care: Randomized Controlled Trial (e44945)
Kate Clouse, Sandisiwe Noholoza, Sindiswa Madwayi, Megan Mrubata, Carol Camlin, Landon Myer, Tamsin Phillips. 434

Using Chatbot Technology to Improve Brazilian Adolescents’ Body Image and Mental Health at Scale: Randomized Controlled Trial (e39934)
Emily Matheson, Harriet Smith, Ana Amaral, Juliana Meireles, Mireille Almeida, Jake Linardon, Matthew Fuller-Tyszkiewicz, Phillipa Diedrichs. 445

Recommendations for the Quality Management of Patient-Generated Health Data in Remote Patient Monitoring: Mixed Methods Study (e35917)
Robab Abdolkhani, Kathleen Gray, Ann Borda, Ruth DeSouza. 460

Effectiveness of a Mindfulness Meditation App Based on an Electroencephalography-Based Brain-Computer Interface in Radiofrequency Catheter Ablation for Patients With Atrial Fibrillation: Pilot Randomized Controlled Trial (e44855)
Ying He, Zhijie Tang, Guozhen Sun, Cheng Cai, Yao Wang, Gang Yang, ZhiPeng Bao. 498

The Treatment Outcome of Smart Device–Based Tinnitus Retraining Therapy: Prospective Cohort Study (e38986)
Myung-Whan Suh, Moo Park, Yoonjoong Kim, Young Kim. 509

Impact of an eHealth Smartphone App on Quality of Life and Clinical Outcome of Patients With Hand and Foot Eczema: Prospective Randomized Controlled Intervention Study (e38506)
Wanja Weigandt, Yannic Schardt, Aimee Bruch, Raphael Herr, Matthias Goebeler, Johannes Benecke, Astrid Schmieder. 519
Effectiveness of a Sodium-Reduction Smartphone App and Reduced-Sodium Salt to Lower Sodium Intake in Adults With Hypertension: Findings From the Salt Alternatives Randomized Controlled Trial (e43675)
Helen Eyles, Jacqueline Grey, Yannan Jiang, Elaine Umali, Rachael McLean, Lisa Te Morenga, Bruce Neal, Anthony Rodgers, Robert Doughty, ClionaNiMhurchu

The Effect of a mHealth App (KENPO-app) for Specific Health Guidance on Weight Changes in Adults With Obesity and Hypertension: Pilot Randomized Controlled Trial (e43236)
Naoki Sakane, Akiko Suginuma, Masayuki Domichi, Shin Sukino, Keiko Abe, Akiyoshi Fujisaki, Al Kanazawa, Mamiko Sugimoto

Improving Kidney Outcomes in Patients With Nondiabetic Chronic Kidney Disease Through an Artificial Intelligence-Based Health Coaching Mobile App: Retrospective Cohort Study (e45531)
Wei Liu, Xiaojuan Yu, Jianguang Wang, Tianmeng Zhou, Ting Yu, Xuyong Chen, Shasha Xie, Fuman Han, Zi Wang

mHealth Apps Targeting Obesity and Overweight in Young People: App Review and Analysis (e37716)
Elena Vlahu-Gjorgievska, Andrea Burazor, Khin Win, Vladimir Trajkovic

Loss-Framed Adaptive Microcontingency Management for Preventing Prolonged Sedentariness: Development and Feasibility Study (e41660)
Woohyeok Choi, Uichin Lee

Promoting Hand Hygiene During the COVID-19 Pandemic: Parallel Randomized Trial for the Optimization of the Soapp App (e43241)
Dario Baretta, Melanie Amrein, Carole Bäder, Gian Ruschetti, Carole Rüttimann, Maria Del Rio Carral, Carlo Fabian, Jennifer Inauen

Associations Between Product Type and Intensity of Tobacco and Cannabis Co-use on the Same Day Among Young Adult Smokers: Smartphone-Based Daily-Diary Study (e40736)
Nhung Nguyen, Johannes Thrul, Torsten Neilands, Pamela Ling

Evaluating the Effects of the Supportive Parenting App on Infant Developmental Outcomes: Longitudinal Study (e43885)
Shefaly Shorey, Yap Chong, Luming Shi, Jing Chua, Thilagamangai, Jancy Mathews, Siew Lim, Ruochen Du, Yiong Chan, Thiam Tan, Cornelia Chee, Evelyn Law

Effectiveness of a Mobile App to Increase Risk Perception of Tobacco, Alcohol, and Marijuana Use in Mexican High School Students: Quantitative Study (e37873)
Patricia Fuentes A, Alberto Jiménez Tapia, Unice Ruiz-Cortés, Fernando Bolaños-Ceballos, Julio Flores Castro, Rafael Gutiérrez, Catalina González-Fortaleza

Characterization of Self-reported Improvements in Knowledge and Health Among Users of Flo Period Tracking App: Cross-sectional Survey (e40427)
Liudmila Zhaunova, Ryan Bamford, Tara Radovic, Aidan Wickham, Kimberly Pevenski, Jazz Croft, Anna Klepchukova, Sonia Ponzo

Delivering a Postpartum Weight Loss Intervention via Facebook or In-Person Groups: Results From a Randomized Pilot Feasibility Trial (e41545)
Molly Waring, Sherry Pagoto, Tiffany Moore Simas, Loneke Blackman Carr, Madison Eamiello, Brooke Libby, Lauren Rudin, Grace Heersping

The Relationship Between How Participants Articulate Their Goals and Accomplishments and Weight Loss Outcomes: Secondary Analysis of a Pilot of a Web-Based Weight Loss Intervention (e41275)
Danielle Jake-Schoffman, Molly Waring, Joseph DiVito, Jared Goetz, Cindy Pan, Sherry Pagoto

The Effect of Periodic Email Prompts on Participant Engagement With a Behavior Change mHealth App: Longitudinal Study (e43033)
Elena Agachi, Tammo Bijnol, Koert van Ittersum, Jochen Mierau
How Notifications Affect Engagement With a Behavior Change App: Results From a Micro-Randomized Trial (e38342)
Lauren Bell, Claire Garnett, Yihan Bao, Zhaoxi Cheng, Tianchen Qian, Olga Perski, Henry Potts, Elizabeth Williamson.......................................................... 723

A Smartphone-Based Implicit Theories Intervention for Health Behavior Change: Randomized Trial (e36578)
Mike Schreiber, Simone Dohle. ............................................................................. 738

Using Smartphone Survey and GPS Data to Inform Smoking Cessation Intervention Delivery: Case Study (e43990)
Amanda Luken, Michael Desjardins, Meghan Moran, Tamar Mendelson, Vadim Zipunnikov, Thomas Kirchner, Felix Naughton, Carl Latkin, Johannes Thrul. .................................................................................................................. 752

Incorporating Consumers' Needs in Nutrition Apps to Promote and Maintain Use: Mixed Methods Study (e39515)
Sandra van der Haar, Ireen Raaijmakers, Muriel Verain, Saskia Meijboom. .................................................................................................................................................. 766

The Effectiveness of a Traditional Chinese Medicine–Based Mobile Health App for Individuals With Prediabetes: Randomized Controlled Trial (e41099)
Hsueh-Wen Chung, Chen-Jei Tai, Polon Chang, Wen-Lin Su, Li-Yin Chien. .......................................................... 780

The Effectiveness of a Mobile Phone–Based Physical Activity Program for Treating Depression, Stress, Psychological Well-Being, and Quality of Life Among Adults: Quantitative Study (e46286)
Hyungsok Kim, Kikwang Lee, Ye Lee, Yoonjung Park, Yonghyun Park, Yeonwoo Yu, Jaeyoung Park, Sihyeon Noh. .................................................................................................................................................. 795

Feasibility, Acceptability, and Potential Impact of a Novel mHealth App for Smokers Ambivalent About Quitting: Randomized Pilot Study (e46155)
Jennifer McClure, Jaimee Heffner, Chloe Krakauer, Sophia Mun, Predrag Klasnja, Sheryl Catz. .......................................................... 810

A Mental Health and Well-Being Chatbot: User Event Log Analysis (e43052)
Frederick Booth, Courtney Potts, Raymond Bond, Maurice Mulvenna, Catrine Kostenius, Indika Dhanapala, Alex Vakaloudis, Brian Cahill, Lauri Kuosmanen, Edel Ennis. .................................................................................................................................................. 825

Patterns and Predictors of Engagement With Digital Self-Monitoring During the Maintenance Phase of a Behavioral Weight Loss Program: Quantitative Study (e45057)
Nicole Crane, Charlotte Hagerman, Olivia Horgan, Meghan Butryn. .......................................................... 842

WeChat-Based HIV e-Report, a New Approach for HIV Serostatus Requests and Disclosures Among Men Who Have Sex With Men: Prospective Subgroup Analysis of a Randomized Controlled Trial (e44513)
Hai-Tong Sun, Xiao-Ru Fan, Yu-Zhou Gu, Yong-Heng Lu, Jia-Ling Qiu, Qing-Ling Yang, Jing-Hua Li, Jing Gu, Chun Hao. .................................................................................................................................................. 858

The Effectiveness of an eHealth Family-Based Intervention Program in Patients With Uncontrolled Type 2 Diabetes Mellitus (T2DM) in the Community Via WeChat: Randomized Controlled Trial (e40420)
Yuheng Feng, Yuxi Zhao, Linqi Mao, Minmin Gu, Hong Yuan, Jun Lu, Qi Zhang, Qian Zhao, Xiaohong Li. .................................................................................................................................................. 871

Testing Mechanisms of Change for Text Message–Delivered Cognitive Behavioral Therapy: Randomized Clinical Trial for Young Adult Depression (e45186)
Michael Mason, J Coatsworth, Nikola Zaharakis, Michael Russell, Aaron Brown, Sydney McKinstry. .................................................................................................................................................. 887

Virtual Digital Psychotherapist App–Based Treatment in Patients With Methamphetamine Use Disorder (Echo-APP): Single-Arm Pilot Feasibility and Efficacy Study (e40373)
Tianzhen Chen, Liyu Chen, Shuo Li, Jiang Du, Hang Su, Hafeng Jiang, Qianying Wu, Lei Zhang, Jiayi Bao, Min Zhao. .................................................................................................................................................. 903

Improving Children's Sleep Habits Using an Interactive Smartphone App: Community-Based Intervention Study (e40836)
Arika Yoshizaki, Emi Murata, Tomoka Yamamoto, Takashi Fujisawa, Ryuzo Hanaie, Ikuko Hirata, Sayuri Matsumoto, Ikuko Mohri, Masako Taniike. .................................................................................................................................................. 915
Clinic-Integrated Smartphone App (JomPrEP) to Improve Uptake of HIV Testing and Pre-exposure Prophylaxis Among Men Who Have Sex With Men in Malaysia: Mixed Methods Evaluation of Usability and Acceptability (e44468)
Roman Shrestha, Frederick Atice, Antoine Khati, Iskandar Azwa, Kamal Gautam, Sana Gupta, Patrick Sullivan, Zhao Ni, Adeeba Kamarulzaman, Panyaphon Phiphatkunarun, Jeffrey Wickersham ................................................................. 931

Acceptability and Utility of a Smartphone App to Support Adolescent Mental Health (BeMe): Program Evaluation Study (e47183)
Judith Prochaska, Yixin Wang, Molly Bowdring, Amy Chieng, Neha Chaudhary, Danielle Ramo ................................................................. 946

Critical Criteria and Countermeasures for Mobile Health Developers to Ensure Mobile Health Privacy and Security: Mixed Methods Study (e39055)
Rita Rezaee, Mahboobeh Khashayar, Saeed Saeedinezhad, Mahdi Nasiri, Sahar Zare ................................................................. 964

Mobile Health Apps for Breast Cancer: Content Analysis and Quality Assessment (e43522)
Seongwoo Yang, Cam Bui, Kyounghoon Park ................................................................. 977

Menstrual Tracking Mobile App Review by Consumers and Health Care Providers: Quality Evaluations Study (e40921)
Suyeon Ko, Jisan Lee, Doyeon An, Hyekyung Woo ................................................................. 990

Usage and Daily Attrition of a Smartphone-Based Health Behavior Intervention: Randomized Controlled Trial (e45414)
Erlandur Eglisson, Ragnar Bjarnason, Urdur Njardvik ................................................................. 1037

Trajectories of Symptoms in Digital Interventions for Depression and Anxiety Using Routine Outcome Monitoring Data: Secondary Analysis Study (e41815)
Diana Cumpanasoiu, Angel Enrique, Jorge Palacios, Daniel Duffy, Scott McNamara, Derek Richards ................................................................. 1050

Longer-Term Effects of Cardiac Telerehabilitation on Patients With Coronary Artery Disease: Systematic Review and Meta-Analysis (e46359)
Wen Zhong, Rui Liu, Hongxin Cheng, Lin Xu, Lu Wang, Chengqi He, Quan Wei ................................................................. 1064

Effects of a Mobile-Based Intervention for Parents of Children With Crying, Sleeping, and Feeding Problems: Randomized Controlled Trial (e41804)
Michaela Augustin, Maria Licata-Dandel, Linda Breeman, Mathias Harrer, Ayten Bilgin, Dieter Wolke, Volker Mall, Margret Ziegler, David Ebert, Anna Friedmann ................................................................. 1081

Clinical Study of a Wearable Remote Rehabilitation Training System for Patients With Stroke: Randomized Controlled Pilot trial (e40416)
Liquan Guo, Jiping Wang, Quqiang Wu, Xinming Li, Bochao Zhang, Linfu Zhou, Daxi Xiong ................................................................. 1098

Engagement and Utilization of a Complete Remote Digital Care Program for Musculoskeletal Pain Management in Urban and Rural Areas Across the United States: Longitudinal Cohort Study (e44316)
Justin Scheer, Anabela Areias, Maria Molinos, Dora Janela, Robert Moulder, Jorge Lains, Virgilio Bento, Vijay Yanamadala, Fernando Dias Correia, Fabiola Costa ................................................................. 1116

Smartphone-Tracked Digital Markers of Momentary Subjective Stress in College Students: Idiographic Machine Learning Analysis (e37469)
George Aalbers, Andrew Hendrickson, Mariak Vanden Abeele, Loes Keijzers ................................................................. 1131

Smartwatch-Based Maximum Oxygen Consumption Measurement for Predicting Acute Mountain Sickness: Diagnostic Accuracy Evaluation Study (e43340)
Xiaowei Ye, Mengjia Sun, Shiyong Yu, Jie Yang, Zhen Liu, Hailin Lx, Boji Wu, Jingyu He, Xuhong Wang, Lan Huang ................................................................. 1145
Development and Validation of Multivariable Prediction Algorithms to Estimate Future Walking Behavior in Adults: Retrospective Cohort Study (e44296)
Junghwan Park, Gregory Norman, Predrag Klasnja, Daniel Rivera, Eric Hekler. ................................................................. 1161

Exploring the Feasibility and Usability of Smartphones for Monitoring Physical Activity in Orthopedic Patients: Prospective Observational Study (e44442)
Arash Ghaffari, Rikke Kildahl Lauritsen, Michael Christensen, Trine Rolighed Thomsen, Harshit Mahapatra, Robert Heck, Søren Kold, Ole Rahbek. ........................................................................................................... 1174

Willingness to Use and Pay for Digital Health Care Services According to 4 Scenarios: Results from a National Survey (e40834)
Junbok Lee, Yumi Oh, Meelim Kim, Belong Cho, Jaeyong Shin. ............................................................................................... 1211

Economic Evaluation of Digital Therapeutic Care Apps for Unsupervised Treatment of Low Back Pain: Monte Carlo Simulation (e44585)
Daniel Lewkowicz, Erwin Bottinger, Martin Siegel. ............................................................................................................... 1220

The Impact of a Digital Weight Loss Intervention on Health Care Resource Utilization and Costs Compared Between Users and Nonusers With Overweight and Obesity: Retrospective Analysis Study (e47473)
Ellen Mitchell, Alexander Fabry, Annabell Ho, Christine May, Matthew Baldwin, Paige Blanco, Kyle Smith, Andreas Michaelides, Mostafa Shokoohi, Michael West, Kim Gotera, Omnya El Massad, Anna Zhou. ......................................................................................................................................................... 1234

Exploring Digital Biomarkers of Illness Activity in Mood Episodes: Hypotheses Generating and Model Development Study (e45405)

Reliability and Validity of Noncognitive Ecological Momentary Assessment Survey Response Times as an Indicator of Cognitive Processing Speed in People’s Natural Environment: Intensive Longitudinal Study (e45203)
Raymond Hernandez, Claire Hoogendoorn, Jeffrey Gonzalez, Haomiao Jin, Elizabeth Pyatak, Donna Spruijt-Metz, Doerte Junghaenel, Pey-Juan Lee, Stefan Schneider. ........................................................................................................ 1306

Corrigenda and Addendas

Correction: WeChat-Based HIV e-Report, a New Approach for HIV Serostatus Requests and Disclosures Among Men Who Have Sex With Men: Prospective Subgroup Analysis of a Randomized Controlled Trial (e48961)
Hai-Tong Sun, Xiao-Ru Fan, Yu-Zhou Gu, Yong-Heng Lu, Jia-Ling Qiu, Qing-Ling Yang, Jing-Hua Li, Jing Gu, Chun Hao. ................................................................................................................................. 1248

Correction: Evaluation Criteria for Weight Management Apps: Validation Using a Modified Delphi Process (e47584)
Noemi Robles, Elisa Puigdomènec Puig, Corpus Gómez-Calderón, Francesc Saigí-Rubió, Guillem Cuatrecasas Cambra, Alberto Zamora, Montse Moharra, Guillermo Paluzie, Mariona Balfegó, Carme Carrion. ............................................................................................................................ 1254

Correction: Assessment of the Efficacy, Safety, and Effectiveness of Weight Control and Obesity Management Mobile Health Interventions: Systematic Review (e47585)
Elisa Puigdomenech Puig, Noemi Robles, Francesc Saigí-Rubió, Alberto Zamora, Montse Moharra, Guillermo Paluzie, Mariona Balfegó, Guillem Cuatrecasas Cambra, Pilar García-Lorda, Carme Carrion. ..................................................................................................................... 1256

Correction: Predictors of Playing Augmented Reality Mobile Games While Walking Based on the Theory of Planned Behavior: Web-Based Survey (e49937)
Hyeseung Koh, Jeeyun Oh, Michael Mackert. ............................................................................................................................... 1258

JMIR mHealth and uHealth 2023 | vol. 11 | p.7
Correction: Efficacy, Effectiveness, and Quality of Resilience-Building Mobile Health Apps for Military, Veteran, and Public Safety Personnel Populations: Scoping Literature Review and App Evaluation (e51609)
Melissa Voth, Shannon Chisholm, Hannah Sollid, Chelsea Jones, Lorraine Smith-MacDonald, Suzette Brémault-Phillips ................................................................. 1260

Research Letters

The Effects of Providing a Connected Scale in an App-Based Digital Health Program: Cross-sectional Examination (e40865)
Lisa Auster-Gussman, Mohit Rikhy, Kimberly Lockwood, OraLee Branch, Sarah Graham. ................................................................................................................ 1323

Uptake of Remote Physiologic Monitoring in the US Medicare Program: A Serial Cross-sectional Analysis (e46046)
Jeffrey Curtis, James Willig. ................................................................. 1326
Mental Health in Urban Environments: Uncovering the Black Box of Person-Place Interactions Requires Interdisciplinary Approaches

Martina Kanning¹, Prof Dr; Li Yi², Phd; Chih-Hsiang Yang³, PhD; Christina Niermann⁴, PhD; Stefan Fina⁵, Prof Dr

¹Department of Sport Science, University of Konstanz, Konstanz, Germany
²Department of Nutrition, Harvard TH Chan School of Public Health, Boston, MA, United States
³Department of Exercise Science and TecHealth Center, University of South Carolina, Columbia, SC, United States
⁴Institute of Interdisciplinary Exercise Science and Sports Medicine, Medical School Hamburg, Hamburg, Germany
⁵Faculty of Architecture and Civil Engineering, University of Applied Sciences Augsburg, Augsburg, Germany

Corresponding Author:
Martina Kanning, Prof Dr
Department of Sport Science
University of Konstanz
Universitätsstraße 10
Konstanz, 78464
Germany
Phone: 49 7531 88 3154
Fax: 49 7531 88 3154
Email: martina.kanning@uni-konstanz.de

Abstract

Living in urban environments affects individuals’ mental health through different pathways. For instance, physical activity and social participation are seen as mediators. However, aiming to understand underlying mechanisms, it is necessary to consider that the individual is interacting with its environment. In this regard, this viewpoint discusses how urban health research benefits from integration of socioecological and interdisciplinary perspectives, combined with innovative ambulatory data assessments that enable researchers to integrate different data sources. It is stated that neither focusing on the objective and accurate assessment of the environment (from the perspective of spatial sciences) nor focusing on subjectively measured individual variables (from the public health as well as a psychosocial perspective) alone is suitable to further develop the field. Addressing person-place interactions requires an interdisciplinary view on the level of theory (eg, which variables should be focused on?), assessment methods (eg, combination of time-varying objective and subjective measures), as well as data analysis and interpretation. Firstly, this viewpoint gives an overview on previous findings addressing the relationship of environmental characteristics to physical activity and mental health outcomes. We emphasize the need for approaches that allow us to appropriately assess the real-time interaction between a person and a specific environment and examine within-subject associations. This requires the assessment of environmental features, the spatial-temporal behavior of the individual, and the subjective experiences of the situation together with other individual factors, such as momentary affective states. Therefore, we finally focused on triggered study designs as an innovative ambulatory data assessment approach that allows us to capture real-time data in predefined situations (eg, while walking through a specific urban area).

(Keywords: physical activity; urban health; ambulatory assessment; environment; mental health; real-time data; within-subject association)

Introduction

Globally, 76% of people live in cities, and a growing number of people are expected to move into urban surroundings within the next two decades [1]. Although urban settings are frequently associated with locational advantages (eg, proximity to job and educational opportunities, cultural diversity, as well as service and infrastructure provision), they are also shown by empirical evidence to increase risks for psychological stress and mental disorders among their residents [2]. Even though mental health has complex determinants, theoretical assumptions about urban health and empirical evidence suggest that increasing physical activity levels and social interactions improve mental health (eg, well-being, quality of life, and satisfaction with life) in...
Why Do We Need Information About Person-Place Interactions to Create Health-Promoting Urban Environments?

According to socioecological approaches, individuals interact with their physical and natural environment as well as the social neighborhood setting, which affects health-related behaviors such as physical activity [6]. According to Stokols [7], this interaction can be described as “cycles of mutual influences”—the environmental features of a local neighborhood are associated with urban residents’ behavior and health. Reciprocally, individuals live and act within these settings and engage with environmental features in a “more or less” health-enhancing way. For instance, on the one hand, design features of the built environment as well as opportunities to get active in social settings can stimulate physical activity (eg, creating attractive stairs in urban environments). On the other hand, a person who is highly motivated to improve activity levels, experiences and perceives the environment differently than a person who is less motivated, and therefore, acts differently based on these subjective experiences and perceptions (eg, using such stairs not only for stair climbing but also for a workout or to do parkour). Furthermore, according to socioecological approaches, individuals’ behavior is affected by more than just the individual level (eg, motivation, self-efficacy, habits, and personal physiological constitution) and the perceived environment (eg, attractive stairs, perceptions of urban green or blue, and noise) but also by the sociocultural factors, factors arising from the built and the social environment, as well as policy factors [8]. Therefore, learning more about person-place interactions from an interdisciplinary perspective—integrating knowledge from spatial science, psychology, sport science, transport systems, politics, and sociology—is a precondition for creating health-promoting environments. For example, an urban health policy to add cycling lanes to promote physical activity levels may be less effective, if the fit between these environmental features (eg, cycling lanes) and the target groups’ needs, preferences, social-cognitive constructs (eg, attitudes), and sociodemographic backgrounds (eg, age and proportion of bike owners) are not considered. As Stokols [9] emphasized, this fit serves as an important predictor of health and well-being.

Evidence About the Associations Between the Environment, Physical Activity, and Mental Health

Considering current studies, key findings confirm that environmental features are associated with physical activity and health. An analysis of previous systematic reviews and meta-studies [10] summarizes associations between built environmental features, dietary intake, physical activity, and obesity. More than half of the included reviews focused on physical activity (n=46) and reported consistent evidence about the positive associations between walkability and physical activity (supported by 83% of the reviews), followed by positive associations between access to recreational facilities, shops and services, and parks or trails and physical activity (supported by 63% to 70% of the reviews). Another systematic review of longitudinal studies (N=36) about the effects of the built environment on adults’ physical activity came to similar conclusions: new infrastructures for walking, cycling, and using public transport increase overall physical activity [11]. Further reviews, especially in the past few years, support such results for older adults [12] and children [13].

In terms of mental health impacts, an overview of systematic reviews assessed the association between the built environment and different mental health indicators (eg, well-being, depression, and stress) [14]. The authors included 11 reviews and reported insufficient and heterogeneous evidence for health-enhancing effects of the environment, with a critically low methodological study quality of 80% of the included reviews. Another meta-narrative review synthesizes the impacts of urban green space on different indicators of mental health from 38 intervention studies [15]. The results were discussed in an international World Health Organization expert panel workshop, concluding that urban green space interventions are often multifaceted but can generally be categorized in 4 groups: park-based, greenways and trails, urban greening (eg, street trees), and green built interventions (eg, green roofs). Most studies in that meta-narrative review were designed as natural experiments, and the findings showed strong evidence for park-based as well as greenway and trail interventions to promote health and well-being through increased park use and physical activity [15].
Limitations of the Empirical Evidence When Analyzing Person-Place Interactions

The aforementioned reviews provide evidence about the relationships between specific environmental features and mental health or physical activity. However, they fall short of increasing our knowledge of the time-varying associations within subjects regarding how urban residents react to specific environmental features and under which conditions such experiences result in more physical activity and improved mental health. One reason for this is that these reviews focused mainly on environmental characteristics, such as accessibility or the amount or quality of greenness, and how these characteristics moderate the relationship between the environment and physical activity or mental health. They do not provide evidence about individuals’ momentary perception, experience, and subsequent behavioral, cognitive, or affective states; nor do they show how these states are related to mental health.

Kwan [16] already criticized in 2009 that spatial research about associations between environmental features and physical activity or health mainly used a “place-based” instead of a “person-based” approach and operationalized environment exposure mostly by focusing on spatial units, such as census tracts, buffer zones, or postal codes. Such a “place-based” design neglects that individuals move around and do not stay in their “home spatial unit” during their daily activities (eg, workplace, school, and leisure activities) [17].

More than 10 years later, Zhang and colleagues [18] stated that there are still only a few studies investigating the association between environment and health from the perspective of the spatial-temporal behavior of the individual. According to the results of their survey with 1003 Chinese adults, there are significant differences between environmental exposures of individuals based on home buffer zones (ie, place-based) compared to time-weighted activity travel buffers (ie, person-based) [18].

A currently published scoping review [19] also stated that person-based approaches still are in their infancy. The review is about methodological approaches to measure the spatial contexts used in socioecological physical activity research, and the included studies have been mostly published within the last 7 years. In sum, person-based spatial methods have been used rarely; only 2% (10/412) of the included studies used activity spaces, and similarly, only 2% (8/412) of the studies buffered multiple points to capture the environment. Almost a third of the studies (118/412) used place-based approaches (eg, with administrative units) as an objective approach.

Furthermore, place-based approaches do not take into consideration that individuals have different lifestyles, psychosocial characteristics, and daily routines and may react differently to influences of similar environmental features. For instance, even persons living within the same building would perceive environmental exposure of their neighborhood differently [20]. That refers to the “uncertain geographic context problem” [21], and it also highlights the importance of interdisciplinary efforts by psychologists, sport scientists, geographers, and computer scientists [7,22]. Nevertheless, empirical evidence of interdisciplinary studies integrating assessment methods of spatial science and urban planning as well as social and health sciences is still lacking [23]. Further, these approaches do not allow detailed analysis; for example, to what extent social interaction could moderate the associations between the environment and mental health or for whom the quality of greenness may be relevant. They also neglect that the environmental exposure is not only directly associated with mental health but also via affecting health-related behaviors, such as physical activity. Thus, mediators or moderators of the associations between the environment and physical activity and health have hardly been examined so far [10]; a framework to explore relationships between place and mental health by combining GPS, Geographic Information System (GIS), and accelerometer data is available in a previous study [24].

Ambulatory Assessment Approaches Are Suitable to Analyze Person-Place Interactions

To advance our understanding of person-place interactions of urban residents in everyday life, we need more studies that collect intensive longitudinal data, which facilitates the estimation of time-varying associations between environmental features, individuals’ behavior, as well as their momentary experiences. Ambulatory assessments are suitable approaches for addressing such within-subject relations because they allow us to monitor physical activity (eg, via accelerometry), physiological function (eg, heart rate or electrodermal activity), and environmental parameters (eg, via geolocation tracking) in real time.

In 2018, Chaix [23] published an overview of different wearable sensors and devices to capture the environment (eg, air pollution and the number of mobile phones nearby), the behavior (eg, physical activity and GPS receivers), and individuals’ physiology (eg, heart rate and electrodermal activity). He recommended integrating different sensors to generate knowledge of healthy places and situations. Such an approach allows us to assess the duration, sequences, and accumulation of different environmental exposures; it also provides rich research possibilities to assess in situ changes in mental health according to different environments or environmental features [25].

A current example of combining different sensors is the study by Marquet and colleagues [26], which combined accelerometers to assess physical activity and GPS data that was linked to spatial data sets on walkability and greenness. They found that persons with high walkability and greenness in their activity spaces had higher levels of moderate-to-vigorous physical activity. In addition, a recent study [27] combined sensors that measure black carbon concentration with a sensor that assessed galvanic skin response (as a proxy measure of stress) and a GPS device and found that increases in black carbon are related to higher skin responses (indicating higher stress levels) during active travel. Green space and a good active travel infrastructure...
are associated with lower skin responses while walking or cycling.

To deepen our understanding of how different individuals react to specific environmental features, it is crucial to assess the above-mentioned environmental parameters and physiological functions using sensors in an objective way; however, it is also relevant to assess subjective experiences, preferably at that moment when an association between a person and a place is assumed. It is possible to schedule e-diaries throughout the day (eg, ecological momentary assessment) to assess different psychosocial constructs (eg, momentary affective states, momentary experiences of social interactions, and momentary motivation) via self-reported measures [28,29].

Ambulatory assessment approaches have already been applied in spatial research. Perchoux et al [30,31] introduce activity spaces as an individualized measure for environmental exposure. It considers individuals’ daily mobility patterns, including major spatial-temporal cluster movements between home and different daily locations, and characterizes its temporal structure (ie, frequency, regularity, and duration). Further, to match person- and place-based data, some research groups combined the assessment of activity spaces with multiple self-reports per day via e-diaries (eg, feelings, emotions, and evaluations of their environment) resulting in geographically explicit ecological momentary assessments (GEAs) [5,20]. GEMA studies implement innovative study designs that use mobile geographic location technologies to capture participants’ activity space, which can then be used to assess the dynamic environmental exposure via GIS. E-diaries allow us to capture subjective experiences in situ, and these data can be linked to participants’ current position in time and space. However, GEMA struggles with the disadvantages of “time-based” assessments because prompts to answer the web-based questionnaires were usually triggered at random time intervals. With such a sampling scheme, self-reports during rare events (eg, being physically active in the neighborhood) are likely to be missed and could therefore hardly be used for analyzing time-varying associations. For instance, a GEMA study [32] assessed how urban green space is associated with stress in adolescents living in urban surroundings. Outdoor behaviors were assessed via GPS-enabled mobile phones. To capture momentary experiences of stress, participants received randomly 3-6 text messages throughout the day, including a link to a web-based questionnaire. However, 72% of the web-based questionnaires have been filled in at home and not during outdoor behaviors. To ask participants to report retrospectively about their feelings, experiences, and thoughts in response to specific situations is likely to increase recall bias, for instance [29]. Furthermore, spatial accuracy of GEMA is an issue and should be taken into account when analyzing and interpreting the data in urban settings when the GPS device signals are likely to be interrupted, such as in streets with dense tree covers [33].

Methodological Improvements and Future Directions of Research

Answers to research questions, such as the following, are crucial to inform initiatives aiming to create health-promoting urban environments: “How does mental health and physical activity vary due to the momentary exposure to specific physical (eg, streetscape greenery and noise) or social environmental features (eg, crime or places enabling social interactions)?” and “How are these time-varying associations moderated by personal factors, which could be time-invariant, such as lifestyle, attitudes, socioeconomic status, obesity, and gender, as well as dynamic such as momentary feelings, experiences, motivations, and thoughts?”

To address these questions, we need data of within-subject relations during predefined situations in everyday life in which a contextual effect is assumed (eg, being physically active within a neighborhood). The above-mentioned GEMA approach is an appropriate design to provide first answers. However, to capture data during the “right” situations, it could be extended by (1) assessing physical activity directly via accelerometers and (2) using triggered assessments. Triggered assessments allow capturing data in predefined situations and have already been applied in other fields, such as examining time-sensitive associations between physical activity and affective states [34] or the time-sensitive assessment of contextual factors during episodes of prolonged sedentary bouts [35]. A recent example of a triggered e-diary regarding outdoor activities was presented in a study protocol with older residents of Paris [36]. The study combined GEMA with a GPS receiver and used this novel methodology to initiate e-diaries when participants were outdoors. Another study used momentary physical activity levels (assessed via accelerometry) and locations by mobile phone positioning services (eg, GPS and transmission tower) to identify outdoor activities. A trigger algorithm was used to start an e-diary whenever movement acceleration exceeds a certain threshold and participant’s locations were identified as outside the home [37]. The study included 46 middle-aged adults and showed that momentary affective states varied significantly due to different social (intensity of social interaction) and physical (amount of greenness) environments. The accuracy of the walking trigger has been examined in a previous study [38]. Furthermore, activity data could be integrated into a GIS to combine information of the physical environment of the activity spaces with movement data. Advanced GIs work with time-enabled spatial analysis functions to track movements with so-called “event-based feature classes.” The challenge is to provide data on the actual exposure for the time of measurement. In this context, live sensor networks are preferable over archived data but only starting to become available, for example, in Smart City Sensor Observation Networks [39,40]. Through combining different data (eg, subjective experiences via self-reports and physical activity levels and physiological functions via specific sensors) in outdoor situations with exposures to different environmental features, we would be able to investigate the associations between specific uses of the environment (eg, walking, social interactions, and doing sports) and momentary experiences (eg, reduced stress and better feelings) and how the characteristics of the environment, the living conditions, or psychological factors moderate these associations. Despite its promising future perspectives, these kinds of person-based spatial approaches lead to several methodological challenges concerning data processing, the linking of spatial
and contextual exposures to individuals, special analytical and statistical methods, and ethical aspects of participants’ privacy and security [41,42]. The solution to these challenges calls for the assembly of an interdisciplinary research team, which itself might also be challenging. However, this approach would enable us to take a broader perspective on this phenomenon and get closer to drawing a “bigger picture” of person-place interactions during the everyday life of urban residents.

Conclusions

Urbanization with its advantages and disadvantages concerning health is on the rise. This viewpoint paper highlights the importance of gaining knowledge regarding the effect of urban environments on people’s mental health by considering socioecological and interdisciplinary perspectives in combination with triggered ambulatory data assessments. It is crucial to assess time-varying associations to investigate person-place interactions between the individual and physical, social, and contextual features. Progress in technology and methodological advances enables researchers to study in more detail how people react to specific environmental features and which situational or personal factors may moderate these associations. Lastly, combining data and knowledge of different disciplines would deepen our understanding about the person-place interactions, which is crucial to create health-promoting urban environments.

Conflicts of Interest

None declared.

References


Abbreviations

GEMA: geographically explicit ecological momentary assessment
GIS: geographic information system
Review

Behavior Change Effectiveness Using Nutrition Apps in People With Chronic Diseases: Scoping Review

Emily Salas-Groves¹, MSc, RDN, LD; Shannon Galyean¹, PhD, RDN, LD; Michelle Alcorn², PhD; Allison Childress¹, PhD, RDN, LD

¹Department of Nutritional Sciences, Texas Tech University, Lubbock, TX, United States
²Department of Hospitality & Retail Management, Texas Tech University, Lubbock, TX, United States

Corresponding Author:
Shannon Galyean, PhD, RDN, LD
Department of Nutritional Sciences
Texas Tech University
1301 Akron Avenue
Lubbock, TX, 79409
United States
Phone: 1 8068342286
Email: shannon.galyean@ttu.edu

Abstract

Background: Cardiovascular disease, cancer, diabetes mellitus, and obesity are common chronic diseases, and their prevalence is reaching an epidemic level worldwide. As the impact of chronic diseases continues to increase, finding strategies to improve care, access to care, and patient empowerment becomes increasingly essential. Health care providers use mobile health (mHealth) to access clinical information, collaborate with care teams, communicate over long distances with patients, and facilitate real-time monitoring and interventions. However, these apps focus on improving general health care concerns, with limited apps focusing on specific chronic diseases and the nutrition involved in the disease state. Hence, available evidence on the effectiveness of mHealth apps toward behavior change to improve chronic disease outcomes is limited.

Objective: The objective of this scoping review was to provide an overview of behavior change effectiveness using mHealth nutrition interventions in people with chronic diseases (ie, cardiovascular disease, diabetes mellitus, cancer, and obesity). We further evaluated the behavior change techniques and theories or models used for behavior change, if any.

Methods: A scoping review was conducted through a systematic literature search in the MEDLINE, EBSCO, PubMed, ScienceDirect, and Scopus databases. Studies were excluded from the review if they did not involve an app or nutrition intervention, were written in a language other than English, were duplicates from other database searches, or were literature reviews. Following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 guidelines, the systematic review process included 4 steps: identification of records through the database search, screening of duplicate and excluded records, eligibility assessment of full-text records, and final analysis of included records.

Results: In total, 46 studies comprising 256,430 patients were included. There was diversity in the chronic disease state, study design, number of participants, in-app features, behavior change techniques, and behavior models used in the studies. In addition, our review found that less than half (19/46, 41%) of the studies based their nutrition apps on a behavioral theory or its constructs. Of the 46 studies, 11 (24%) measured maintenance of health behavior change, of which 7 (64%) sustained behavior change for approximately 6 to 12 months and 4 (36%) showed a decline in behavior change or discontinued app use.

Conclusions: The results suggest that mHealth apps involving nutrition can significantly improve health outcomes in people with chronic diseases. Tailoring nutrition apps to specific populations is recommended for effective behavior change and improvement of health outcomes. In addition, some studies (7/46, 15%) showed sustained health behavior change, and some (4/46, 9%) showed a decline in the use of nutrition apps. These results indicate a need for further investigation on the sustainability of the health behavior change effectiveness of disease-specific nutrition apps.

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https://mhealth.jmir.org/2023/11/e41235
Introduction

Background

Cardiovascular disease (CVD), cancer, diabetes mellitus (DM), and obesity are common chronic diseases [1], and their prevalence is reaching a substantial epidemic level internationally [2]. Chronic diseases are defined by the Centers for Disease Control and Prevention broadly as “conditions that last one year or more and require ongoing medical attention or limit activities of daily living or both” [3]. Chronic diseases affect hospitalization, mortality rates, and people’s overall health and quality of life (QOL) [1]. For example, CVD remains the most prevalent cause of morbidity and mortality in high-income countries despite significant advances in treatment over the last 5 decades. Recent epidemiological data show that CVD mortality is no longer declining and is indeed rising in some communities [4], and hospitalization rates are universally increasing [5]. Furthermore, chronic conditions such as cancer, CVD, DM, and chronic respiratory diseases caused approximately 33.2 million deaths worldwide in 2019 [6]. The prevalence of obesity has increased in all World Health Organization regions since 2000, which affects other chronic conditions as it is a risk factor for the development of CVD, DM, and several cancers [6].

As the impact of chronic diseases continues to increase, finding strategies to improve care, access to care, and patient empowerment becomes increasingly essential. Therefore, mobile health (mHealth) technology is rapidly gaining popularity among health care providers and consumers [7]. mHealth technology is defined as mobile devices (ie, mobile phones or monitoring devices) intended to be worn, carried, or accessed by patients or health care providers to monitor health status or improve health outcomes [8]. Among mobile devices, the most used are smartphones, with more than three-quarters of Americans having one, and at least one-third of smartphone owners use a health app [7,9]. Health care providers use mHealth to access clinical information, collaborate with care teams, communicate over long distances with patients, and facilitate real-time monitoring and interventions. These apps provide an opportunity to increase health care access for vulnerable populations [10]. Patients use mHealth to track their health data, access their clinical records, and communicate with their providers [11].

Furthermore, a meta-analysis [12] reported promising results for mHealth interventions in the improvement of patient outcomes such as body measurements (ie, weight and waist circumference), metabolic and physiological measurements (ie, blood pressure and glucose levels), adherence to and safe use of medication, physical activity performance, meal management, and awareness of health conditions and treatment options. Mobile apps that provide tools intended to facilitate nutrition care via smartphone technologies provide patients with more autonomy, thus empowering them and offsetting patient disengagement [13]. Moreover, mobile app–based interventions effectively improve diet and diet-related health outcomes, and effect sizes are comparable with those of traditional nondigital interventions [14]. For example, mHealth interventions can help improve lifestyle behaviors related to CVD [15,16]. A recent meta-analysis [17] found that using mHealth interventions for CVD was associated with improved blood pressure and hospitalization rates. In addition, mHealth apps have emerged as supportive tools in managing cancer as they reduce the financial burden, provide access to information, and facilitate communication [18]. Different studies and meta-analyses of patients with cancer have shown the benefits of mHealth, which include reducing fatigue or pain [19,20], providing distance physical activity programs [21,22], the use of social networks to improve QOL [23], and monitoring of symptoms [24]. mHealth offers improved and cost-effective care to people with type 2 DM (T2DM) through improved diabetes self-management [25,26]. These apps seem to increase the perception of self-care by contributing to better knowledge among people with T2DM [10]. Individuals with DM also become more confident in dealing with their illness, primarily because of decreased fear resulting from a lack of information [27,28]. For obesity, a systematic review [29] has found that technology-based interventions can provide a moderately effective way of facilitating lifestyle changes and weight loss. New technologies could help reduce economic costs, improve accessibility and adherence to treatment, and increase patient motivation and weight control [30].

The use of mobile apps for mHealth and of general health apps is increasing rapidly. However, these apps focus on improving general health care concerns, with limited apps focusing on specific chronic diseases and their nutritional intervention. The available evidence on the effectiveness of mHealth apps toward behavior change to improve chronic disease outcomes is also limited. Systematic reviews to date regarding nutrition apps have focused on healthy participants or examined the effects of dietary apps on diet improvement but not on chronic diseases [31]. Most reviews were inconclusive, with the authors recommending further research in this area to demonstrate possible benefits [32-34]. From a clinical point of view, it is essential to know if an app designed for chronic diseases produces behavior changes to improve an individual’s chronic disease outcomes. From an app creator’s point of view, it is crucial to see what needs to be done when developing an app directed toward people with chronic diseases to enhance the app’s effectiveness on behavior change and produce positive outcomes. The goal of this review was to define behavioral theories associated with mHealth use, evaluate behavior change techniques (BCTs), and describe the behavior change effectiveness using mHealth nutrition interventions in people with chronic diseases (ie, CVD, DM, cancer, and obesity).
Models and Theories of Health Behavior and Clinical Interventions

Health care and self-management of chronic conditions require effort and commitment on the part of the patient to follow treatment plans. These treatments involve many behaviors, such as dietary intake, physical activity, and prescription drug use. Theories and models are used in treatment planning to understand and explain the health behavior of individuals and can help guide clinicians to develop interventions that increase the effectiveness of health behavior change. The role of behavioral theories and models in informing digital health interventions is important to support sustainable health behavior change. A brief explanation of some of the theories and models of behavior used in these studies may help with understanding their constructs [36]: (1) the transtheoretical model shows how individuals move through 6 stages of behavior change (ie, precontemplation, contemplation, preparation, action, maintenance, and termination), which can be used to support behavior change and self-efficacy for the cessation of unhealthy behaviors and encourage a healthy lifestyle; (2) Social Cognitive Theory emphasizes self-efficacy and focuses on behavior change and outcome expectations by mastering steps to behavior change, observing others who are successful, improving mood, and ultimately increasing self-efficacy for health behavior change; (3) the Health Belief Model is based on the concept of expectancy-value and constitutes an individual’s belief that their health condition is serious, their actions will reduce their risk or illness, there is a benefit to taking action for their health condition, and they have the ability to take action for health behavior change (self-efficacy); and (4) the theory of planned behavior emphasizes that motivation that is directly influenced by ability (ie, an individual’s self-efficacy or perceived control over outside factors) is key to making a health behavior change [36]. There are other theories that can be used as well. For health behavior change, there is a general acceptance of the Health Belief Model along with a focus on self-efficacy found in many behavioral models such as the Social Cognitive Theory [35]. In addition, a commonly used theory to guide lifestyle interventions is the transtheoretical model [36]. There are several theories identified in this review that are important to chronic disease research on health behavior.

Methods

Information Sources and Search Strategies

In April 2022, a systematic literature search was conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) strategy for each of the following diseases: obesity, DM, CVD, and cancer [37]. The PRISMA method allows for the transparent selection and analysis of literature for inclusion. The databases used in the search were MEDLINE, EBSCO, PubMed, ScienceDirect, and Scopus. These databases were chosen based on their extensive health- and technology-related literature [38]. The search strategy was similar for all diseases. It included the following keywords searched among titles, keywords, and abstracts: (1) mobile applications or apps or mobile apps or mHealth or eHealth AND nutritioneduction AND obesity, (2) mobile applications or apps or mobile apps or mHealth or eHealth AND nutritioneduction AND type 2 diabetes, (3) mobile applications or apps or mobile apps or mHealth or eHealth AND nutritioneduction AND cardiovascular disease, and (4) mobile applications or apps or mobile apps or mHealth or eHealth AND nutritioneduction AND cancer.

Eligibility Criteria

To summarize the evidence available on the topic, we included primary research studies involving an app and a nutrition intervention. Studies were excluded from the review if they did not involve an app or nutrition intervention, were written in a language other than English, were duplicates from other database searches, or were literature reviews.

Procedures

Following the PRISMA 2020 method, the systematic review process included four steps: (1) identification of records through the database search, (2) screening of duplicate and excluded records, (3) eligibility assessment of full-text records, and (4) final analysis of included records. This process can be seen in Figure 1. The results of the database searches were exported to Microsoft Excel (Microsoft Corp) for further analysis. Duplicates were removed. The remaining studies were moved to the eligibility phase, in which the authors assessed the eligibility of the articles based on the inclusion and exclusion criteria of the full text. The reason for exclusion was listed for each excluded article. The citation of the article, name of the mobile app used if available, type of intervention used, year of publication, population and sample details, study design details, purpose of the research, behavioral effectiveness, behavioral techniques, theory used, outcome measures, and results were recorded for all included studies. The authors independently reviewed the articles found in each search, and a second screening was performed by a different author. The process for screening was as follows: SG initially screened articles found in the obesity search, MA initially screened articles found in the DM search, ESG initially screened articles found in the cancer search, and AC initially screened articles found in the CVD search. SG performed a second screening of articles found in the obesity search, MA performed a second screening of articles found in the DM search, MA performed a second screening of articles found in the CVD search, and ESG performed a second screening of articles found in the cancer search.
Results

CVD Results

Demographic, Participant, and Study Design Details

There were 6 studies and mHealth app nutrition interventions comprising 451 patients included for CVD. Of the 6 studies, 4 (67%) randomized controlled trials, 1 (17%) qualitative descriptive design study, and 1 (17%) intervention evaluation were analyzed. The populations analyzed had diverse ethnicities, education levels, ages, and diagnoses. Furthermore, there were different diets or treatments among the studies, with variations in targeted behavioral domains and outcomes measured in the mHealth app nutrition interventions. App features for these studies included food tracking [8,39-41], physical activity tracking [8,41,42], nutrition and exercise knowledge and recommendations [8,40-43], scheduled reminders [39,40,42,43], clinician portals [41-43], connectivity to digital health devices [42], demonstration of the desired behavior [40,43], and challenges [41]. The aim of all studies (6/6, 100%) was to evaluate the effectiveness of mHealth in the CVD population. The included studies on nutrition apps for people with CVD can be found in Table 1.
Table 1. Included studies on cardiovascular disease (CVD; n=6).

<table>
<thead>
<tr>
<th>Study</th>
<th>Country</th>
<th>Study design</th>
<th>Purpose</th>
<th>Name of mobile app and features</th>
<th>Behavior change theory or model</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eyles et al [39]</td>
<td>New Zealand</td>
<td>Randomized</td>
<td>Evaluate whether the SaltSwitch app is effective in helping people with CVD select lower-salt food purchases</td>
<td>SaltSwitch—all-smartphone app; features: food tracking and reminders</td>
<td>None</td>
<td>A significant reduction in mean household purchases of salt was observed during the 4-week intervention phase. A total of 87% of the participants reported using the SaltSwitch app, and 75% reported finding the SaltSwitch app very easy to use.</td>
</tr>
<tr>
<td>Indraratna et al [42]</td>
<td>New Zealand</td>
<td>Randomized</td>
<td>Investigate the feasibility, efficacy, and cost-effectiveness of a smartphone app–based model of care in patients discharged after ACS admission or HF admission</td>
<td>TeleClinical Care TCC—all-smartphone app; features: physical activity tracking, knowledge, reminders, connectivity to digital health devices, and clinician portal</td>
<td>None</td>
<td>The intervention was associated with a significant reduction in unplanned hospital readmissions, including cardiac readmissions, and higher rates of cardiac rehabilitation completion and medication adherence. The average usability rating for the app was 4.5/5.</td>
</tr>
<tr>
<td>Agher et al [8]</td>
<td>France</td>
<td>Survey</td>
<td>Design an mHealth app, Prevent Connect, to assess its quality for evaluating patient behavior for 4 cardiovascular risk factors (unhealthy eating, sedentary lifestyle, and alcohol and tobacco consumption) and suggest personalized recommendations and mHealth interventions for risky behaviors</td>
<td>Prevent Connect—all-smartphone app; features: food and physical activity tracking and knowledge</td>
<td>None</td>
<td>The app was deemed of good quality, with a mean uMARS quality score of 4 on a 5-point Likert scale. The functionality and information content of the app were particularly appreciated, with a mean uMARS score of &gt;4. The esthetics and engagement of the app were appreciated (uMARS score of 3.7). A total of 80% (42/52) of the participants declared that the app helped them become aware of the importance of addressing health behavior, and 65% (34/52) said that the app helped motivate them to change lifestyle habits.</td>
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<tr>
<td>Schmaderer et al [43]</td>
<td>United States</td>
<td>Qualitative</td>
<td>Explore the experience of using a self-management mHealth intervention in individuals with HF to inform a future mHealth intervention study</td>
<td>Play-It Health—all-smartphone app; features: knowledge, reminders, clinician portal, and demonstration of behavior</td>
<td>None</td>
<td>Participants reported an overall positive experience. The education provided during the study increased self-awareness and promoted self-management of their HF. The mHealth app supported patient empowerment, resulting in better HF management and improved quality of life.</td>
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<tr>
<td>Steinberg et al [40]</td>
<td>United States</td>
<td>Randomized</td>
<td>Improve adherence to the DASH diet among women with HTN or pre-HTN</td>
<td>Nutritionix—all-smartphone app; features: food tracking, knowledge, reminders, and demonstration of behavior</td>
<td>Behavior change principles</td>
<td>Intervention participants had lower systolic and diastolic BP compared with active comparator participants. Most intervention participants (23/29, 79%) said that they would recommend the DASH Cloud intervention to a friend or family member. However, only 34% (10/59) indicated that the feedback SMS text messages helped them reach their diet goals.</td>
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<tr>
<td>Study</td>
<td>Country</td>
<td>Study design</td>
<td>Purpose</td>
<td>Name of mobile app and features</td>
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<tr>
<td>Choi et al [41]</td>
<td>United States</td>
<td>Randomized controlled trial</td>
<td>Discover whether dietary counseling supplied through a custom smartphone app results in better adherence to a Mediterranean diet in a non-Mediterranean population than the traditional standard-of-care counseling</td>
<td>Unknown name—all-smartphone app; features: food and physical activity tracking, knowledge, clinician portal, and challenges</td>
<td>None</td>
<td>There were no significant differences between EXP^h and SOC^i regarding BP, lipid parameters, HbA_{1c}, or C-reactive protein. EXP achieved a significantly greater weight loss on average of 3.3 lbs versus 3.1 lbs for SOC. Adherence to the Mediterranean diet increased significantly over time for both groups, but there was no significant difference between the groups. Similarly, there was no significant difference in diet satisfaction between EXP and SOC, although diet satisfaction increased significantly over time for both groups. The proportion of participants with high Mediterranean diet compliance increased significantly over time—from 18.4% to 57.1% for SOC and from 27.5% to 64.7% for EXP; however, there was no significant difference between the groups.</td>
</tr>
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</table>

### Targeted Behavior and Outcome Measures

The most commonly measured outcome in the CVD studies was usability or engagement in 83% (5/6) of the studies, followed by diet intake or quality and metabolic and physiological measurements (ie, blood pressure and urinary sodium) in 67% (4/6) of the studies. In addition, treatment adherence (ie, diet, cardiac rehabilitation, and medication) was measured in 50% (3/6) of the studies. Other measured outcomes included physical activity, weight loss, dietary knowledge, sustainability, tobacco or alcohol consumption, hospital readmissions, cost-effectiveness, food purchases, and self-management in 17% (1/6) of the studies.

### BCTs Used

The most commonly used BCT was motivation or encouragement, which was used in all reviewed studies (6/6, 100%). Knowledge or education and self-monitoring were used in 83% (5/6) of the studies. Both prompts or cues and feedback were used in 50% (3/6) and 33% (2/6) of the studies, respectively. The least common BCTs included graded tasks or challenges, demonstration of behavior, self-efficacy, and goal setting in 17% (1/6) of the studies reviewed.

### Behavioral Theory or Model

In total, 17% (1/6) of the analyzed studies were based on behavioral theories or models. The others (5/6, 83%) did not mention a theory. The transtheoretical model, Social Cognitive Theory, the theory of planned behavior, the Health Belief Model, the precaution adoption model, and goal-setting theories were used as the basis for 17% (1/6) of the interventions in this review section. Evidence for informing digital technology interventions reveals that the Health Belief Model has been widely used for goal setting and lifestyle changes for reducing cardiovascular risk as it focuses on confidence in one's ability to take action [36].

### Behavior Change Effectiveness

CVD-specific mHealth apps significantly improved the completion of cardiac rehabilitation, were significantly cost-effective, and resulted in substantial weight loss and less salt purchases in 17% (1/6) of the studies. Furthermore, significant engagement was observed in 67% (4/6) of the studies.

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^aACS: acute coronary syndrome.  
bHF: heart failure.  
cmHealth: mobile health.  
eDASH: Dietary Approaches to Stop Hypertension.  
fHTN: hypertension.  
gBP: blood pressure.  
hEXP: experimental.  
iSOC: standard of care.
In addition, some studies (1/6, 17%) showed improvement in blood pressure and self-management and rated the app quality as good. However, linking BCTs and theoretical frameworks to behavior change and CVD health measures is challenging. Therefore, this area of study should be investigated further.

Cancer Results

Demographic, Participant, and Study Design Details

In total, 9 cancer-related studies comprising 645 patients were included. Of the 9 studies, 3 (33%) focused on survivors of breast cancer, 2 (22%) focused on breast cancer, 2 (22%) focused on esophageal cancer, 1 (11%) focused on patients with either gastric or colon cancer, and 1 (11%) focused on pancreatic cancer. Various study designs were used: 22% (2/9) prospective quasi-experimental studies, 22% (2/9) prospective pilot studies, 11% (1/9) interventional observation studies, 11% (1/9) nonrandomized 2-group controlled design studies, 11% (1/9) randomized controlled trials, 11% (1/9) randomized pretest-posttest design studies, and 11% (1/9) clinical trials were analyzed. These studies can be found in Table 2. Each app had different features, including digital diaries [7,44-49], coach feedback [7,44-47,49-51], personalized physical exercise programs and nutrition plans [49,50], general nutrition and physical exercise guidelines [45,51], psychological support courses [45,51], a secure message portal to their health care teams [7,48], health knowledge education [46,48,51], and daily tasks [48,51].
Table 2. Included studies on cancer (n=9).

<table>
<thead>
<tr>
<th>Study</th>
<th>Country</th>
<th>Study design</th>
<th>Purpose</th>
<th>Name of mobile app and features</th>
<th>Behavior change theory or model</th>
<th>Results</th>
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</thead>
<tbody>
<tr>
<td>Stubbins et al [7]</td>
<td>United States</td>
<td>Prospective, single-arm, open-label clinical trial</td>
<td>To evaluate the feasibility and usability of MOCHA to improve daily accounting of PA and food intake in survivors of breast cancer and improve engagement with health practitioners and peers</td>
<td>MOCHA—Apple-and Android-based app; features: food and PA tracking, coach feedback, and clinician portal</td>
<td>None</td>
<td>The average number of daily uses was approximately 3.5 times per day; participants lost an average of 2 lbs. The average usability score was 77.4, which was greater than the acceptable level. More than 90% of patients found MOCHA easy to navigate, and 84% were motivated to use MOCHA daily.</td>
</tr>
<tr>
<td>Lozano-Lozano et al [49]</td>
<td>Spain</td>
<td>Prospective test-retest quasi-experimental study</td>
<td>To investigate the feasibility of BENECA mHealth in an ecological clinical setting with survivors of breast cancer by studying (1) its feasibility and (2) pretest-posttest differences regarding the lifestyles, QOL, and PA motivation of survivors of breast cancer</td>
<td>BENECA mHealth—all-smartphone app; features: food and PA tracking, coach feedback, and personalized programming</td>
<td>Theories of learning, Goal-Setting Theory, and Social Cognitve Theory</td>
<td>BENECA was considered feasible by survivors of breast cancer in terms of use (76%, 58/76), adoption (69%, 80/116), and satisfaction (positive NPS3). BENECA mHealth improved the QOL, EAT5 score, and daily moderate to vigorous PA of the participants and reduced their body weight.</td>
</tr>
<tr>
<td>Lozano-Lozano et al [50]</td>
<td>Spain</td>
<td>Prospective quasi-experimental pre-post study</td>
<td>(1) Check whether it is feasible to find changes in inflammation biomarkers through an mHealth strategy app as a delivery mechanism of an intervention to monitor energy balance and (2) discover potential predictors of change in these markers in survivors of breast cancer</td>
<td>BENECA mHealth—all-smartphone app; features: food and PA tracking, coach feedback, and personalized programming</td>
<td>Theory of learning, Goal-Setting Theory, and Social Cognitve Theory</td>
<td>Differences between pre- and postassessment CRP and IL-6 showed a significant decrease in both markers. Stepwise regression analyses revealed that changes in global QOL, as well as uMARS score and hormonal therapy, were possible predictors of change in CRP concentration after using the mHealth app. Participants showed moderate satisfaction with the mHealth app; high app use (mean 47.9; maximum 56 days); and moderate to low scores in general QOL, fatigue, and pain.</td>
</tr>
<tr>
<td>Cheng et al [45]</td>
<td>China</td>
<td>Prospective, single-arm, nonrandomized pilot study</td>
<td>To evaluate the feasibility, safety, and efficacy of a comprehensive intervention model using an mHealth system (CIMmH) in patients with esophageal cancer after esophagectomy</td>
<td>CIMmH—web-based program; features: food and PA tracking, knowledge, and psychological support courses</td>
<td>Comprehenssive intervention model</td>
<td>At the 3-month follow-up, except for pain, eating difficulty, dry mouth, and trouble with talking, all other QOL dimensions returned to the preoperative level. There were significant reductions in weight and BMI throughout the study, and no significant changes were observed for physical fitness measured by change in the 6-minute Walk Test distance between baseline and the 1-month follow-up or between baseline and the 3-month follow-up. Depressive symptoms significantly increased 1 month after surgery, whereas other psychological measures did not show relevant changes. Although there were declines in many measures 1 month after surgery, these were much improved at the 3-month follow-up, and the recovery was more profound and faster than with traditional rehabilitation programs. Participants viewed, on average, 84% (3.38/4) of the web-based video intervention content and completed, on average, 14% (3.20/23) and 34% (9.44/28) of the web-based audio and article content, respectively. Participants completed, on average, 63% (5.01/8), 100% (1/1), and 24% (10.89/46) of the web-based nutrition, physical exercise, and psychological intervention content, respectively.</td>
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<tr>
<td>Soh et al [48]</td>
<td>Korea</td>
<td>Prospective  study</td>
<td>To develop and validate a multidisciplinary mobile care system that can provide health education and self-management features to improve multiple clinical measures for patients with advanced gastrointestinal cancer</td>
<td>Life Manager—all-smartphone app; features: food and PA tracking, clinician portal, knowledge, and daily tasks</td>
<td>None</td>
<td>For the gastric cancer group, the “general gastric cancer education” was the most frequently viewed (322 times), and for the colon cancer group, the “warming-up exercise” was the most viewed (340 times). Of 13 measurements taken from participants, 9 were taken offline (response rate: 52%-90.1%), and 3 were taken on the web (response rate: 17.6%-57.4%). The overall satisfaction rate among participants was favorable and ranged from 3.93 to 4.01 on a 5-point Likert scale.</td>
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<tr>
<td>Cairo et al [44]</td>
<td>United States</td>
<td>Nonrandomized 2-group controlled study design with pre-post repeated measures</td>
<td>To evaluate if a readily available mHealth intervention (ie, Vida) can lead to healthier lifestyle habits for survivors of breast cancer</td>
<td>Vida—all-smartphone app; features: food and PA tracking and coach feedback</td>
<td>Behavior change theory</td>
<td>At 6 months, more patients in the app group experienced weight loss and had a significantly greater reduction in overall BMI. The app group also demonstrated statistically significant improvements in “strenuous” PA and had significant improvements in their dietary patterns as compared with the self-guided group. The app group had greater reduction in fatigue and improvement in depression, but these changes were not statistically significant. At 12 months, none of the app users were still using the app, but many were still following their wellness plan and had maintained their weight loss.</td>
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<tr>
<td>Yang et al [47]</td>
<td>Korea</td>
<td>Prospective pilot study</td>
<td>To evaluate the usefulness of a health care mobile app in preventing malnutrition and excessive muscle loss in patients with esophageal cancer receiving NACRT$^1$</td>
<td>Noom—Android- and Apple-based app; features: food and PA tracking, coach feedback, and knowledge</td>
<td>None</td>
<td>The use (or activation) of the app was noted in approximately 70% (25/36) of the patients until the end of the trial. Compared with the 1:2-matched usual care group by propensity scores balanced with their age, primary tumor location, tumor stage, pre-RT BMI, and pre-RT SMI level, 30 operable patients showed less aggravation of the prognostic nutritional index. However, there was no significant difference in the SMI change or the number of patients with excessive muscle loss. In patients with excessive muscle loss, the walk steps significantly decreased in the last 4 weeks compared with those in the first 4 weeks. Age affected the absolute number of walk steps, whereas pre-RT sarcopenia was related to the recovery of the reduced walk steps.</td>
</tr>
<tr>
<td>Keum et al [46]</td>
<td>Korea</td>
<td>Randomized controlled study</td>
<td>To evaluate the efficacy of a mobile app-based program, Noom, in patients receiving chemotherapy for PDAC$^0$</td>
<td>Noom—Android- and Apple-based app; features: food and PA tracking, coach feedback, and knowledge</td>
<td>None</td>
<td>All the study participants showed a significant improvement in nutritional status according to the PG-SGA$^5$ score regardless of Noom app use. Noom users showed statistically significant improvements on the global health status and QOL scales compared with non–Noom users based on the EORTC QLQ$^6$. The SMI decreased in both groups during chemotherapy. The decrement was higher in the non–Noom user group than in the Noom user group, but it was not statistically significant.</td>
</tr>
</tbody>
</table>
**Target Behavior and Outcome Measures**

The most targeted behaviors were physical activity, observed in 56% (5/9) of the included studies, and dietary behavior, observed in 78% (7/9) of the studies. The questionnaires measured both behaviors. Furthermore, QOL was measured in 67% (6/9) of the studies, followed by app use and satisfaction in 56% (5/9) of the studies. Less frequently measured outcomes included app adherence in 44% (4/9) of the studies, depression in 33% (3/9) of the studies, and fatigue in 22% (2/9) of the studies.

**BCTs Used**

Self-monitoring and feedback were the most frequently used in mHealth apps for cancer (8/9, 89% of the studies), followed by goal setting and motivation in 44% (4/9) of the studies each. However, only 22% (2/9) of the studies used knowledge.

**Behavioral Theory or Model**

Most of the analyzed studies (6/9, 67%) seemed not to be based on common theories. Only 33% (3/9) of the studies reported at least one theory. The only reported theories were Social Cognitive Theory, Goal-Setting Theory, and the comprehensive intervention model. This result is surprising given that most apps used feedback, goal setting, and motivation to conduct behavior change. Therefore, further research could use behavioral theory or models to enhance their apps for this chronic disease. However, in physical interventions (no digital technology involved), some evidence showed that the transtheoretical model combined with other models was successful in breast cancer screening behavior as it is based on the stages of behavior change and interventions can be tailored to each individual, which increases their empowerment to make change [52].

**Behavior Change Effectiveness**

Cancer-specific mHealth apps helped significantly improve QOL in 44% (4/9) of the studies, followed by changes in anthropometrics in 33% (3/9) of the studies. A total of 11% (1/9) of the studies reported an increase in QOL and a decrease in distress level. In contrast, physical activity and nutritional status were only significantly improved in 22% (2/9) of the studies. Similar to the CVD section, linking BCTs and theoretical frameworks to behavior change and cancer health measures is challenging. Therefore, this area of study should be investigated further.

**DM Results**

**Demographic, Participant, and Study Design Details**

In total, 13 studies comprising 1559 patients were included. Of the 13 studies, we analyzed 10 (77%) randomized controlled trials, 1 (8%) single-arm feasibility study, 1 (8%) case report, and 1 (8%) uncontrolled study. The studies included in this review involving nutrition apps for diabetes can be found in Table 3. Overall, there was a diverse population of patients diagnosed with prediabetes (glucose: 5.55-6.94 mmol/L or 100-125 mg/dL; HbA1c: 39-46 mmol/mol or 5.7%-6.4%), type

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**Table**

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<tr>
<td>Çınar et al [51]</td>
<td>Turkey</td>
<td>Single-blind, single-centered, and randomized design</td>
<td>Mobile app–based training given to cope with the side effects of EHT and how managing the symptoms and the disease process will affect the QOL of women with breast cancer</td>
<td>Name not provided—all-smartphone app; features: coach feedback, knowledge, psychological support courses, and daily tasks</td>
<td>None</td>
<td>QOL of the treatment group after the intervention increased, and distress level was lower compared with the control group; these results were statistically significant. Most of the patients reported that the mobile app was “informative and useful.”</td>
</tr>
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*a* MOCHA: Methodist Hospital Cancer Health Application.  
*b* PA: physical activity.  
*c* BENECA: the Energy Balance on Cancer mobile health system.  
*d* mHealth: mobile health.  
*e* QOL: quality of life.  
*f* NPS: Net Promoter Score.  
*g* EAF: Spanish self-efficacy scale for physical activity.  
*h* CRP: C-reactive protein.  
*i* IL-6: interleukin-6.  
*k* CIMmH: Comprehensive Intervention Model Using a Mobile Health System.  
*l* NACRT: neoadjuvant chemoradiotherapy.  
*m* RT: radiotherapy.  
*n* SMI: skeletal muscle index.  
*o* PDAC: pancreatic ductal adenocarcinoma.  
*p* PG-SGA: Patient-Generated Subjective Global Assessment.  
*q* EORTC QLQ: European Organisation for Research and Treatment of Cancer Quality of Life Questionnaire.  
*r* EHT: adjuvant endocrine hormonal therapy.
1 DM, T2DM, and gestational DM (2-hour oral glucose tolerance test level of ≥9 mmol/L). The features of each app included food tracking [53-62], education, knowledge, or recommendations [54-56,59-65], physical activity tracking [54-56,59-62], weight monitoring [56,59-62], glucose monitoring [55,57,60,61,64], blood pressure monitoring [60], community support [54,59,60], feedback [54-56,59,61,62,64], health coaches [55], clinician portals [60-62], connectivity to digital health devices [56,57], scheduled reminders [56,58,59,62], gamification [59,63], and goal setting [59]. In addition, several targeted behavioral domains and outcomes were measured as a result of the mHealth app nutrition intervention. This factor revealed some interesting insights for future investigations into digital health interventions among people with DM.
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<tr>
<td>Hong et al [53]</td>
<td>Korea</td>
<td>Case study</td>
<td>Examine the effect of a mobile app program (“Diabetes &amp; Nutrition”) developed between 2011 and 2012 for self-management in patients with T2DM and recommend important considerations when the mobile app program is developed</td>
<td>Diabetes &amp; Nutrition—all-smartphone app; features: food tracking</td>
<td>None</td>
<td>At 3 months, body weight had decreased by 4.4 kg, waist circumference had decreased by 5 cm, and HbA1c level had decreased from 7.9% to 6.1%. The medication was reduced from the dose of 850 mg to 500 mg of metformin twice a day. Since then, the patient did not continue to use the “Diabetes &amp; Nutrition” app as their level of blood glucose had stabilized and the patient felt that it was inconvenient and annoying to use the program. At 6 months, no significant change in body weight and body composition was observed in comparison with those at 3 months.</td>
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<tr>
<td>Xu et al [54]</td>
<td>China</td>
<td>2-arm RCTb with TTM-based social media intervention</td>
<td>Examine the effectiveness of a 6-month mobile-based intervention (DHealthBar, a WeChat applet) combined with behavioral theory compared with a printed intervention in improving dietary behaviors, physical activity, and intention to change these behaviors among populations at high risk of T2DM</td>
<td>DHealthBar—all-smartphone app; features: food and physical activity tracking, knowledge, community support, and coach feedback</td>
<td>TTM</td>
<td>Participants in both groups reported a statistically significant decrease in energy intake at the 2 follow-up assessments compared with baseline. At 6 months, a significantly larger decrease was observed in the intervention group in energy, fat, and carbohydrate intake accompanied by a significantly larger increase in moderate-intensity physical activity compared with the control group. After 6 months of the intervention, participants were more likely to be at higher stages of dietary behaviors and physical activity than the control group.</td>
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<tr>
<td>Koot et al [55]</td>
<td>Singapore</td>
<td>6-month (24-week), single-arm, preintervention baseline and follow-up evaluation</td>
<td>Using the RE-AIM5 evaluation framework, this study assessed the potential effectiveness and feasibility of GlycoLeap, a mobile lifestyle management program for people with T2DM, as an add-on to standard care.</td>
<td>GlycoLeap—all-smartphone app; features: food and physical activity tracking, knowledge, glucose monitoring, and coach feedback</td>
<td>Several theoretical frameworks, including the TTM and Health Belief Model</td>
<td>Program engagement (implementation) started out high but decreased with time for all evaluated components. Self-reported survey data suggest that participants monitored their blood glucose on more days in the previous week at follow-up compared with baseline and reported positive changes to their diet because of app engagement. Statistically significant improvements were observed for HbA1c, with greater improvements for those who logged their weight more often. Participants had a 2.3% reduction in baseline weight. User satisfaction was high, with 74% (59/80) and 79% (63/80) of participants rating the app as good or very good and claiming that they would probably or definitely recommend it to others.</td>
</tr>
<tr>
<td>Griauzde et al [56]</td>
<td>United States</td>
<td>12-week, parallel, 3-arm, mixed methods pilot RCT</td>
<td>Examine the feasibility and acceptability of an mHealth4 intervention designed to increase autonomous motivation and healthy behaviors among adults with prediabetes who had previously declined participation in a diabetes prevention program; in addition, the study aimed to examine changes in autonomous motivation among adults who were offered 2 versions of the mHealth program compared with an information-only control group</td>
<td>mHealth—all-smartphone app; features: food and physical activity tracking, knowledge, weight monitoring, coach feedback, connectivity to digital health devices, and reminders</td>
<td>Self-determination theory</td>
<td>No significant differences were observed in adherence rates between app-only and app-plus participants. Among all participants, mean autonomous motivation measures were relatively high at baseline (6.0 out of a 7.0 scale), with no statistically significant within- or between-group differences in follow-up scores.</td>
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<td>Torb-jørnsen et al</td>
<td>Norway</td>
<td>3-armed RCT with 2 intervention groups and 1 control group</td>
<td>This study aimed to explore associations between the level of acceptability of a mobile diabetes app and the initial ability to self-manage in patients with T2DM.</td>
<td>Diabetes diary app (no name)—all-smartphone app; features: food tracking, glucose monitoring, and connectivity to digital health devices</td>
<td>None</td>
<td>The study found statistically significant associations between 5 of the 8 self-management domains and “perceived benefit,” being one of the acceptability factors. However, when adjusting for age, gender, and frequency of use, only 1 domain, “skill and technique acquisition,” remained independently associated with “perceived benefit.” Frequency of use of the app was the factor that revealed the strongest association with the acceptability domain “perceived benefit.” Moreover, an association was revealed between gender and frequency of use where 69% (25/36) of the high-frequency users were men.</td>
</tr>
<tr>
<td>Alfonsi et al</td>
<td>Canada</td>
<td>Iterative usability testing (3 cycles)</td>
<td>Test the app’s usability and potential impact on carbohydrate counting accuracy</td>
<td>iSpy—all-smartphone app; features: food tracking and reminders</td>
<td>None</td>
<td>Use of iSpy was associated with improved carbohydrate counting accuracy (total grams per meal), reduced frequency of individual counting errors of &gt;10 g, and lower HbA1c levels. Qualitative interviews and acceptability scale scores were positive. Moreover, 43% (9/21) of iSpy participants were still engaged, with use at least once every 2 weeks at the end of the study.</td>
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<tr>
<td>Block et al</td>
<td>United States</td>
<td>Clinical trial</td>
<td>The aim was to evaluate the effectiveness of a fully automated, algorithm-driven behavioral intervention for diabetes prevention, Alive-PD, delivered via the internet, mobile phone, and automated phone calls.</td>
<td>Alive-PD—web-based application; features: food and physical activity tracking, knowledge, weight monitoring, community support, coach feedback, reminders, gamification, and goal setting</td>
<td>Learning, Social Cognitive Theory, and theory of planned behavior</td>
<td>Alive-PD participants achieved significantly greater reductions than controls in fasting glucose, HbA1c, and body weight. Reductions in BMI, waist circumference, and TG/HDL ratio were also significantly greater in Alive-PD participants than in the control group. At 6 months, the Alive-PD group reduced their Framingham 8-year diabetes risk from 16% to 11%, significantly more than the control group. Participation and retention were good; intervention participants interacted with the program a median of 17 out of 24 weeks, and 71.1% (116/163) were still interacting with the program in month 6.</td>
</tr>
<tr>
<td>Kelmuh et al</td>
<td>Iran</td>
<td>Interventional study</td>
<td>The aim of this study was to evaluate the effect of mobile game-based learning apps on improving dietary information in patients with T2DM.</td>
<td>Amoo—mobile phone game for all smartphones; features: knowledge and gamification</td>
<td>None</td>
<td>The results indicated a statistically significant difference between the pre- and posttest scores in the intervention group. However, there was no significant difference in fasting blood sugar.</td>
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<tr>
<td>Yu et al</td>
<td>China</td>
<td>24-week, 4-arm, parallel group, nonblinded randomized trial</td>
<td>The aim of this study was to evaluate the effects of an MPA combined with or without SMBG on glycemic control in patients with diabetes.</td>
<td>Diabetes-Carer—all-smartphone app; features: food and physical activity tracking; knowledge; weight, blood pressure, and glucose monitoring; community support; and clinician portal</td>
<td>None</td>
<td>The HbA1c levels in patients of all groups decreased significantly from baseline. There were significant differences in the proportions of patients that achieved HbA1c &lt;7% between groups, especially in group C and group D compared with group A at week 24. 1.5-anhydroglucitol changes were obvious in group A and group C at week 24 from baseline. Factorial ANOVA showed that the MPA intervention was the main effective factor for HbA1c change, and there was no effect on HbA1c change for the SMBG intervention.</td>
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<tr>
<td>Garnweider-Holme et al [64]</td>
<td>Norway</td>
<td>2-arm, multicenter, non-blinded RCT</td>
<td>The study analyzed secondary data from a 2-arm, multicenter, and nonblinded RCT to determine whether a smartphone app with targeted dietary information and blood glucose monitoring had an effect on the dietary behavior of women with GDM.</td>
<td>Pregnant—all-smartphone app; features: knowledge, glucose monitoring, and coach feedback</td>
<td>None</td>
<td>All the participants showed improvements in their HDS-P+ from baseline. However, the Pregnant+ app did not have a significant effect on their HDS-P+. The control group reported a higher weekly frequency of choosing fish meals. No other significant differences were found between the intervention and control groups.</td>
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<tr>
<td>Agarwal et al [61]</td>
<td>Canada</td>
<td>Multicenter pragmatic RCT</td>
<td>The primary objective of this study was to conduct a pragmatic RCT of the Bluestar mobile app to determine if app use led to improved HbA1c levels among diverse participants in real-life clinical contexts. The authors hypothesized that this mobile app would improve self-management and HbA1c levels compared with controls.</td>
<td>BlueStar—all-smartphone app; features: food and physical activity tracking, knowledge, weight and glucose monitoring, coach feedback, and clinician portal</td>
<td>TTM</td>
<td>The results of an analysis of covariance controlling for baseline HbA1c levels did not show evidence of intervention impact on HbA1c levels at 3 months. Similarly, there was no intervention effect on secondary outcomes measuring diabetes self-efficacy, quality of life, and health care use behaviors. An exploratory analysis of 57 ITG participants investigating the impact of app use on HbA1c levels showed that each additional day of app use corresponded with a 0.016-point decrease in participants’ 3-month HbA1c levels. App use varied significantly by site as participants from one site logged in to the app a median of 36 days over 14 weeks; those at another site used the app significantly less.</td>
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<tr>
<td>Lim et al [62]</td>
<td>Singapore</td>
<td>Randomized clinical trial conducted at multiple primary care centers</td>
<td>Compare the effects of a culturally contextualized smartphone-based intervention with usual care on weight and metabolic outcomes</td>
<td>Nutritionist Buddy Diabetes—all-smartphone app; features: food and physical activity tracking, knowledge, weight monitoring, coach feedback, clinician portal, and reminders</td>
<td>Several theoretical models combined that included accountability, communication, and motivation to help adherence</td>
<td>Compared with the control group, intervention participants achieved significantly greater reductions in weight and HbA1c levels, with a greater proportion experiencing a reduction in diabetes medications at 6 months. The intervention led to a greater HbA1c reduction among participants with HbA1c levels of ≥8%. Intergroup differences favoring the intervention were also noted for fasting blood glucose, diastolic blood pressure, and dietary changes.</td>
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<tr>
<td>Juan et al [65]</td>
<td>Spain</td>
<td>Uncontrolled study</td>
<td>Users would have a statistically significant increase in knowledge about the carbohydrate choices of real packaged foods after using the app.</td>
<td>Augmented Reality—all-smartphone app; features: knowledge</td>
<td>None</td>
<td>The results reported that their initial knowledge about carbohydrate choices was very low. This indicates that education about nutritional information in packaged foods is needed. An analysis of the pre- and postknowledge questionnaires showed that users had a statistically significant increase in knowledge of carbohydrate choices after using the app. Gender and age did not influence the knowledge acquired. The participants were highly satisfied with the app.</td>
</tr>
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</table>

aT2DM: type 2 diabetes mellitus.  
bRCT: randomized controlled trial.  
cTTM: transtheoretical model.  
dRE-AIM: Reach, Effectiveness, Adoption, Implementation, and Maintenance.  
eTG: triglyceride.  
fHDL: high-density lipoprotein.  
gMPA: mobile phone app.  
hSMBG: self-monitoring of blood glucose.  
iGDM: gestational diabetes mellitus.  
jHDS-P+: healthy dietary score for Pregnant+.  
kITG: immediate treatment group.

**Targeted Behavior and Outcome Measures**

The most frequently targeted behaviors were glycemic control measured using HbA1c and DM self-efficacy or self-management in 46% (6/13) of the reviewed studies. In addition, dietary behavior, levels of engagement, user acceptability, or motivation, and weight or BMI were measured in 46% (6/13) of the studies, followed by waist circumference in 23% (3/13) of the studies. Less frequently measured outcomes included physical activity, stages of change, carbohydrate counting accuracy, QOL, health care use behavior, and lipids in 23% (3/13) of the studies.

**BCTs Used**

Numerous BCTs can be used to induce behavior change. All the DM studies reviewed (13/13, 100%) used knowledge and education, followed by self-monitoring in 77% (10/13) of the studies. Both social support or encouragement and autonomous personalized feedback were used in 54% (7/13) of the studies. Prompts or cues were used in 31% (4/13) of the studies, followed by graded tasks and gamification in 15% (2/13) of the studies. Real-time feedback and goal setting were used in 15% (2/13) of the studies reviewed. Unfortunately, no standard definition of techniques is included in the BCTs, making it challenging to identify the techniques used in the interventions [66].

**Behavioral Theory or Model**

Some of the analyzed studies (7/13, 54%) seemed not to be based on behavioral theories or models. In total, 46% (6/13) of the studies reported at least one theory. The transtheoretical model was most frequently used in 23% (3/13) of the studies, followed by Social Cognitive Theory, self-determination theory, models centering on cues and triggers, theory of planned behavior, behavioral economics, positive psychology, and motivational interviewing as other reported theories. Some research has shown that Social Cognitive Theory has been used in feasibility studies among populations with diabetes as it can increase confidence and promote greater sustained effort to change, making it a guide for digital technology interventions. This theory also includes skill training, which can benefit diabetes management and education programs [67,68].

**Behavior Change Effectiveness**

DM-specific mHealth apps improved glycemic control by significantly reducing HbA1c values in 46% (6/13) of the studies. In addition, 15% (2/13) of the interventions [53,62] resulted in a decrease in the medications used for glycemic control. Some studies (6/13, 46%) showed significant engagement; however, 17% (1/6) of these studies showed a decline in engagement over time, and 17% (1/6) did not have follow-up data for engagement. Sustainability needs to be considered for the effectiveness of these types of interventions. There were also significant changes in anthropometrics in 31% (4/13) of the reviewed studies. DM self-efficacy and self-management, decrease in energy intake, and increase in physical activity were observed in 8% (1/13) of the studies. Not all studies analyzed the same outcomes for each intervention, making it difficult to link BCTs and theoretical frameworks to behavior change and health measures.

**Obesity Results**

**Demographic, Participant, and Study Design Details**

A total of 18 studies comprising 253,775 patients were included. Among these 18 studies, we analyzed 5 (28%) randomized controlled trials, 5 (28%) experimental studies, 3 (17%) feasibility studies, 2 (11%) observations, and 1 (6%) prospective...
cohort study. The studies involving nutrition apps among people with obesity can be found in Table 4. The studies focused on obesity prevention and treatment in many diverse populations that ranged in age, socioeconomic background, and physical status (ie, pregnancy and post partum). App features included physical activity tracking [69-78], food tracking [70,72-83], knowledge, education, or recommendations [70,72-76,78,79,82-86], push notifications or scheduled reminders [74-76,78,79,81-84,86], weight monitoring [75,76,78,81,85,86], behavior demonstration [69,75,83], motivational challenges [69,75-78,83], goal setting [69,73-75,78,81,84,85], feedback [69,70,73,75,76,81-83,86], community support [70,75,78,85], connectivity to digital health devices [70,72,81,86], clinician portals [72,73,82], and access to a health coach [76-78,81]. Furthermore, numerous behaviors were targeted, and the outcomes were analyzed to determine the effectiveness of a mobile nutrition intervention in promoting healthy weight. This information will help develop approaches and techniques for digital health behavior change interventions to prevent and treat obesity.
## Table 4. Included studies on obesity (n=18).

<table>
<thead>
<tr>
<th>Study</th>
<th>Country</th>
<th>Study design</th>
<th>Purpose</th>
<th>Name of mobile app and features</th>
<th>Behavior change theory or model</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lubans et al [69]</td>
<td>Australia</td>
<td>Cluster RCTa</td>
<td>Focused on the promotion of lifetime (eg, resistance training) and lifestyle (eg, active transport) physical activities and was aligned with current physical activity guidelines, which include a recommendation to engage in muscle- and bone-strengthening physical activities at least 3 days per week</td>
<td>ATLASb—all-smartphone app; features: physical activity tracking, behavior demonstration, challenges, goal setting, and coach feedback</td>
<td>Self-determination theory and Social Cognitive Theory</td>
<td>Focus group participants reported enjoyment of the program and felt that it had provided them with new skills, techniques, and routines for the future. However, their engagement with the smartphone app was limited. Barriers to the implementation and evaluation of the app included limited access to smartphone devices, technical problems with the push notifications, lack of access to use data, and the challenges of maintaining participants’ interest in using the app.</td>
</tr>
<tr>
<td>Griffin et al [84]</td>
<td>United States</td>
<td>1-group, pre-to posttest study design</td>
<td>To evaluate changes in dietary and physical activity behaviors and weight after implementation of a 12-week SMS text messaging initiative (My Quest)</td>
<td>SMS text messaging initiative (My Quest)—all smartphones; features: knowledge, reminders, and goal setting</td>
<td>Social Cognitive Theory</td>
<td>Participants significantly improved dietary and physical activity behaviors and food environment, increased their dietary and physical activity goal setting, and reduced their body weight. A total of 56 posttest assessments were completed (84% response rate).</td>
</tr>
<tr>
<td>Van der Pligt et al [71]</td>
<td>Australia</td>
<td>Pilot intervention study nested within a cluster RCT</td>
<td>Effectiveness of the Mums OnLiNE® intervention with respect to reducing PPWR and improving diet, physical activity, and sedentary behavior</td>
<td>Mums OnLiNE Combined and FANT Extend—a web-based application or smartphone app with telephone-based support; features: physical activity tracking</td>
<td>Social Cognitive Theory</td>
<td>Mean PPWR decreased in the intervention group and the comparison group 2 although the changes were not significant. Mean waist circumference for all groups exceeded recommendations at baseline but decreased to below recommendations for women in the intervention group and significantly for the intervention group compared with comparison groups 1 and 2. Changes in diet, physical activity, or sedentary behaviors were not significant.</td>
</tr>
<tr>
<td>Hull et al [79]</td>
<td>United States</td>
<td>Observational design based on data collected after the testing period</td>
<td>This paper describes the development and beta testing of the CHEW smartphone app. The objective of beta testing was to test the CHEW app prototype with target users focusing on use, usability, and perceived barriers and benefits of the app.</td>
<td>CHEW smartphone app—Android-based app; features: food tracking and knowledge</td>
<td>Socioecological model</td>
<td>Study participants used the app on average once a week for approximately 4.5 minutes per session. Use of specific features averaged at 1-2 times per month for shopping-related activities and 2-4 times per month for the snack gallery. Mothers classified as users rated the app’s WIC® Shopping Tools relatively high on usability and benefits. The Yummy Snack Gallery and Healthy Snacking Tips scored higher on usability than on benefits, suggesting that the nutrition education components may have been appealing.</td>
</tr>
<tr>
<td>Bughin et al [72]</td>
<td>France</td>
<td>Randomized controlled study</td>
<td>The aim of this study was to compare the changes in body composition, anthropometric parameters, exercise capacity, and QOL within 12 weeks of patients in the TRG program with those of usual care patients with obesity.</td>
<td>TR Program—Android-based or web-based; features: food and physical activity tracking, knowledge, connectivity to digital health devices, and clinician portal</td>
<td>None</td>
<td>No significant group × time interaction was found for fat mass. Compared with the UCG, TRG patients tended to significantly improve their waist-to-hip ratios and improved their QOL physical impact. Significant time effects were observed for body composition, 6-minute Walk Test distance, exercise metabolism, sedentary time, and QOL. Adherence (95%) and satisfaction in the TRG were good.</td>
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JMIR Mhealth Uhealth 2023 | vol. 11 | e41235 | p.32 (page number not for citation purposes)
<table>
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<tr>
<td>Toro-Ramos et al</td>
<td>Korea</td>
<td>Intervention</td>
<td>This study investigated the efficacy of a smartphone intervention using a designated app with a lifestyle intervention-focused approach, including a human coaching element, toward weight loss in Korean adults who were overweight or obese.</td>
<td>Noom—Android and Apple-based app; features: food and physical activity tracking, knowledge, reminders, weight monitoring, challenges, goal setting, community support, and coach feedback</td>
<td>None</td>
<td>Participants showed a clinically significant weight loss effect of –7.5% at the end of the 15-week program, and a 52-week follow-up, a weight loss effect of –5.2% was maintained. At 15 weeks, percentage of body fat and visceral fat decreased by –6.0% to –5.4% and –3.4 kg to –2.7 kg, respectively. Fasting blood glucose level also decreased significantly by –5.7 to –14.6 mg/dL at 15 weeks. Lipid parameters showed significant improvements except for high-density lipoprotein cholesterol. The frequency of logging meals and exercise was associated with body fat loss.</td>
</tr>
<tr>
<td>Pellegrini et al</td>
<td>United States</td>
<td>6-month technology-supported weight loss trial</td>
<td>Examine within-person variation in dietary self-monitoring during a 6-month technology-supported weight loss trial as a function of time-varying factors, including time in the study, day of the week, and month of the year</td>
<td>ENGAGED—smartphone provided with the app; features: food and physical activity tracking, knowledge, feedback, community support, and connectivity to digital health devices</td>
<td>None</td>
<td>Participants recorded less as time in the study progressed. Fewer foods were reported on the weekends compared with on weekdays. More food was self-monitored in January compared with in October; however, a seasonal effect was not observed.</td>
</tr>
<tr>
<td>Dodd et al [74]</td>
<td>Australia</td>
<td>Multicenter, nested randomized trial</td>
<td>The objective was to evaluate the impact of a smartphone app as an adjunct to face-to-face consultations in facilitating dietary and physical activity change among pregnant women.</td>
<td>Name not provided—smartphone was provided with the app; features: food and physical activity tracking, knowledge, reminders, and goal setting</td>
<td>None</td>
<td>Mean difference in HEIM score was 0.01 at 28 weeks of pregnancy and –1.16 at 36 weeks of pregnancy. There was no significant additional benefit from the provision of the smartphone app in improving HEI score. Although all women improved dietary quality throughout their pregnancy, use of the smartphone app was poor.</td>
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<tr>
<td>Stasina-Salas et al [77]</td>
<td>Switzerland</td>
<td>Unblinded RCT</td>
<td>The objective of the study was to assess novel obesity management that moved the focus from on-site consultations in a specialized childhood obesity center to an appealing, youth-friendly, low-threshold mobile intervention (PathMate2) under the supervision of pediatric obesity experts.</td>
<td>PathMate2—smartphone provided with the app; features: food and physical activity tracking, challenges, and coach feedback</td>
<td>None</td>
<td>At intervention start, median BMI SDS of all patients was 2.61. BMI-SDS decreased significantly in the control group at time 1 but not at time 2 and did not decrease in the intervention group during the study. Muscle mass, strength, and agility improved significantly in both groups at time 2; only the intervention group significantly reduced their body fat at time 1 and time 2. Average daily PathMate2 app use rate was 71.5%. Cortisol serum levels decreased significantly after biofeedback but with no association between stress parameters and BMI-SDS.</td>
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<tr>
<td>Ali et al [73]</td>
<td>UAE</td>
<td>Nonrandomized, 2-arm feasibility study</td>
<td>Develop and test a nutrition education intervention delivered via a website and mobile apps to university students in the UAE who were overweight and obese</td>
<td>Rashakaty-Basic and Rashakaty-Enhanced—web-based application and all-smartphone app; features: food and physical activity tracking, knowledge, goal setting, feedback, and clinician portal</td>
<td>Social Cognitive Theory</td>
<td>There was no significant difference in weight loss between the 2 arms. However, waist circumference decreased more in the Rashakaty-Enhanced group. Changes in knowledge related to sources of nutrients and diet-disease relationships were significantly higher among the Rashakaty-Enhanced group. Rashakaty-Enhanced participants reported increased number of days spent on moderate physical activity and minutes walked. They also reported higher scores in social support from friends to reduce fat intake and from family and friends to increase physical activity.</td>
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<tr>
<td>Study</td>
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<tr>
<td>Senecal et al [86]</td>
<td>China</td>
<td>Retrospective observational analysis</td>
<td>To evaluate whether individuals following a weight loss program based on a mobile app, wireless scale, and nutritional program but no face-to-face care could achieve clinically significant weight loss in a large cohort</td>
<td>MetaWell—Android- and Apple-based app; features: knowledge, reminders, weight monitoring, feedback, and connectivity to digital health</td>
<td>None</td>
<td>251,718 individuals (79% female) were included with a mean weight loss of 4.3 kg and a mean follow-up of 120 days. Mean weight loss at 42, 60, 90, and 120 days was 4.1 kg, 4.9 kg, 5.6 kg, and 5.4 kg, respectively. At 120 days, 62.7% of participants had lost at least 5% of their initial weight. Both genders and all use frequencies showed statistically significant weight loss from baseline at each interval, and this loss was greater in men than in women. The frequency of recording was associated with greater weight loss when comparing high-, medium-, and low-use groups at all time intervals investigated.</td>
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<tr>
<td>Delisle Nys-tröm et al [82]</td>
<td>Sweden</td>
<td>2-arm parallel RCT</td>
<td>Investigate the 12-month after-baseline measurements of the MINISTOP intervention</td>
<td>MINISTOP—both web-based application and all-smartphone app; features: food tracking, knowledge, reminders, feedback, and clinician portal</td>
<td>Social Cognitive Theory</td>
<td>At the 12-month follow-up, no statistically significant difference was observed between the intervention and control groups for FMI, and no maintained effect for the change in composite score was observed.</td>
</tr>
<tr>
<td>Stein and Brooks [81]</td>
<td>United States</td>
<td>Longitudinal observational study</td>
<td>Evaluate weight loss, changes in meal quality, and app acceptability among users of the HCAI® with the overarching goal of increasing access to compassionate health care via mHealth®</td>
<td>Lark Weight Loss HCAI—Android- and Apple-based app; features: food tracking, reminders, weight monitoring, goal setting, coach feedback, and connectivity to digital health devices</td>
<td>None</td>
<td>Weight loss was 2.38% of baseline weight. The average duration of app use was 15 weeks, and users averaged 103 sessions each. The percentage of healthy meals increased by 31%. The in-app user trust survey had a 100% response rate and positive results, with a satisfaction score of 87 out of 100 and Net Promoter Score of 47.</td>
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<tr>
<td>Prasad et al [80]</td>
<td>United States</td>
<td>Open-label, nonrandomized, prospective 90-day TRE® intervention</td>
<td>The primary aim was to test the feasibility of a TRE intervention administered via a smartphone app aimed at reducing the eating window by 4 hours in individuals with a habitually prolonged eating window and determine the efficacy of a 90-day TRE intervention in reducing body weight and blood pressure in adults who were overweight and obese. A secondary aim was to monitor the adherence to the intervention over time.</td>
<td>MyCircadian-Clock—all-smartphone app; features: food tracking</td>
<td>None</td>
<td>The mean duration of the baseline eating window was 14 hours and 32 minutes (SD 2 hours and 36 minutes), with 56% of participants with a duration of ≥14 hours. TRE participants successfully decreased their eating window from 16 hours and 4 minutes (SD 1 hour and 24 minutes) to 11 hours and 54 minutes (SD 2 hours and 6 minutes) and reduced the number of daily eating occasions by half. Adherence to logging and to the reduced eating window was 64% (SD 22%) and 47% (SD 19%). TRE resulted in decreases in body weight, waist circumference, and systolic blood pressure.</td>
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<tr>
<td>Simpson et al [85]</td>
<td>Scotland</td>
<td>Feasibility RCT</td>
<td>To develop and assess the feasibility and acceptability of an app-, web-, and social support–based intervention in supporting adults with obesity to achieve weight loss goals</td>
<td>HelpMeDoIt!—all-smartphone app and web-based application; features: knowledge, reminders, weight monitoring, goal setting, and community support</td>
<td>Social Cognitive Theory and control theory</td>
<td>Of the 54 (74%) participants who downloaded the app, 48 (89%) used it. Objective physical activity measures perhaps showed the most potential (daily step count [1187 steps] and sedentary time [−60.8 min]). However, these outcomes were poorly completed.</td>
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<tr>
<td>Study</td>
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<tr>
<td>Lin et al [75]</td>
<td>United States</td>
<td>RCT</td>
<td>To compare an mHealth intervention delivered via a CP app with usual care controls and compare with an in-person and phone-supplemented personal coaching intervention enhanced by CP self-monitoring with usual care</td>
<td>CITY—all-smartphone app; features: food and physical activity tracking, knowledge, reminders, weight monitoring, behavior demonstration, challenges, goal setting, feedback, and community support</td>
<td>Rooted in theoretical models and behavioral framework</td>
<td>Use of the app was highest during month 1 for both arms; thereafter, use dropped substantially and continuously until the study end. During the first 6 months, the mean percentage of days that any app component was used was higher for the CP arm (74.2%) than for the personal coaching arm (48.9%). The CP arm used the apps an average of 5.3 times per day, whereas the personal coaching participants used them 1.7 times per day. The former self-weighed more than the latter (57.1% of days vs 32.9% of days). Furthermore, the percentage of days that any app component was used, number of app uses per day, and percentage of days self-weighed all showed significant differences across the 4 weight categories for both arms. Pearson correlation showed a negative association between weight change and the percentage of days that any app component was used, number of app uses per day, and percentage of days self-weighed.</td>
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<tr>
<td>Chew et al [76]</td>
<td>Singapore</td>
<td>Prospective single-cohort study</td>
<td>Assess the effectiveness of a mobile app–based lifestyle intervention program as an early intervention before enrollment in a clinic-based multidisciplinary weight management program</td>
<td>Kurbo—all-smartphone app; features: food and physical activity tracking, knowledge, reminders, weight monitoring, challenges, and coach feedback</td>
<td>None</td>
<td>Kurbo engagement was high, with 83% (33/40) of participants completing at least 7 coaching sessions. In total, 78% (18/23) of participants rated the app as good to excellent, and 70% (16/23) stated that they would recommend it to others. There were no statistically significant changes in BMI z scores at 3 or 6 months. Participants showed statistically significant improvements in measured body fat percentage, self-reported QOL, and self-reported caloric intake from the 3-day food diaries at 3 and 6 months.</td>
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</tbody>
</table>
Results

Behavior change theory or model

<table>
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<tr>
<th>Study</th>
<th>Country</th>
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</tr>
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<tbody>
<tr>
<td>Kay et al [83]</td>
<td>United States</td>
<td>Randomized controlled feasibility trial</td>
<td>Comparing app-based diet tracking (active comparator) with app-based diet tracking plus feedback on DASH adherence via SMS text message (intervention)</td>
<td>DASH Cloud—all-smartphone app; features: food tracking, knowledge, reminders, behavior demonstration, challenges, and feedback</td>
<td>None</td>
<td>DASH Cloud did not enhance DASH adherence over diet tracking alone but resulted in greater reductions in blood pressure.</td>
</tr>
</tbody>
</table>

aRCT: randomized controlled trial.
bATLAS: Active Teen Leaders Avoiding Screen-Time.
cOnLiNE: Online, Lifestyle, Nutrition, and Exercise.
dPPWR: postpartum weight retention.
eInFANT Extend: Extended Melbourne Infant Feeding Activity and Nutrition Trial.
fCHEW: Children Eating Well.
gWIC: Women, Infants, and Children.
hQOL: quality of life.
iTR: telerehabilitation.
jUCG: usual care group.
kTRG: TR group.
lENGAGED: e-Networks Guiding Adherence to Goals in Exercise and Diet.
mHEI: healthy eating index.
nSDS: SD score.
oUAE: United Arab Emirates.
pMINISTOP: Mobile-Based Intervention Intended to Stop Obesity in Preschoolers.
qFMI: fat mass index.
rHCAI: Health Coach AI.
smHealth: mobile health.
tTRE: time-restricted eating.
uCP: cell phone.
vCITY: Cell Phone Intervention For You.
wDASH: Dietary Approaches to Stop Hypertension.

Targeted Behavior and Outcome Measures

Anthropometric measurements (ie, weight, BMI, and waist-to-hip ratio) were the most targeted health outcomes, with behavior change in 78% (14/18) of the reviewed studies, followed by diet quality and physical activity in 61% (11/18) of the studies. In addition, engagement, user acceptability, or motivation levels and body composition were measured in 39% (7/18) and 28% (5/18) of the studies, respectively. QOL, behaviors (ie, goal setting and self-efficacy), and CVD measures (ie, blood pressure, heart rate, glucose, and lipids) were included as outcomes in 22% (4/18) of the studies. Less frequent measures included stress parameters (ie, chronic stress and cortisol levels), diet knowledge, reduced screen time, and behavior and health maintenance, observed in 6% (1/18) of the studies.

BCTs Used

BCTs were incorporated into each intervention. Self-monitoring was the most commonly used BCT (14/18, 78% of the reviewed studies), followed by knowledge or education (12/18, 67% of the studies). Goal setting was used in 56% (10/18) of the studies, feedback and encouragement were used in 56% (10/18) of the studies, and prompts or cues and intention formation were used in 50% (9/18) of the studies. Feedback through private messages was used in 39% (7/18) of the studies, followed by community or social support and demonstration of behavior in 33% (6/18) of the studies each. Graded tasks and gamification or incentives were used in 17% (3/18) of the studies. Finally, information about health benefits and consequences was included in 6% (1/18) of the studies in this section. Clinician portals were used in 17% (3/18) of the interventions to improve patient care. Although it is not a BCT, it is worth mentioning as a vital intervention component.

Behavioral Theory or Model

Some interventions (10/18, 56%) did not mention the basis of behavioral theories or models. A total of 6% (1/18) of the studies mentioned that they were rooted in theoretical models but did not specify which ones. Social Cognitive Theory was the most frequently used behavior model in 33% (6/18) of the studies. Self-determination theory was used in 17% (3/18) of the studies. Furthermore, Social Cognitive Theory has been used in feasibility studies on mHealth technology lifestyle interventions for obesity, for example, by using the principle of verbal persuasion through methods such as personalized encouragement that help
individuals realize that they have the capability to make the necessary healthy lifestyle changes to lose weight [87].

**Behavior Change Effectiveness**

Obesity-specific mHealth apps improved weight through significant reductions in 39% (7/18) of the studies. Some studies (4/18, 22%) showed a substantial decrease in body fat percentage and waist circumference. There were also significant changes in cardiovascular measurements (ie, blood pressure and lipids) and QOL in 11% (2/18) of the reviewed studies. Changes in self-efficacy, decreases in energy intake and screen time, and increases in knowledge of nutrients and physical capabilities were observed in 6% (1/18) of the studies. In total, 11% (2/18) of the studies analyzed and reported significance in the maintenance of weight loss, whereas 11% (2/18) of the studies reported a decline in changes over time. The sustainability of these interventions is an area for future research to determine the effectiveness of these types of interventions.

**Discussion**

**Principal Findings**

Overall, mHealth apps used for various chronic disease populations did improve health. These studies showed significant improvements in QOL, cardiac rehabilitation completion, glycemic control (ie, HbA1c), weight reduction, and reduction in physiological measures (ie, blood pressure and lipids). In addition, some studies (3/46, 7%) showed improved self-efficacy and self-management of chronic diseases. Although many studies (35/46, 76%) did not measure long-term effectiveness, some (3/46, 7%) showed significance in maintaining weight loss, whereas others (3/46, 7%) showed a decline in changes or engagement in app use over time. A total of 24% (11/46) of the studies measured maintenance of health behavior change. Of these 11 studies, 7 (64%) sustained behavior change for approximately 6 to 12 months, and 4 (36%) showed a decline in behavior change or discontinued app use.

The main difference between the sustainability of health behavior change was the inclusion of a clinician portal or access to a health coach. Griaudze et al [56] measured postintervention qualitative data that provided reasons for app satisfaction, dissatisfaction, and ways to improve. Reasons for satisfaction included “encouraged self-reflection,” reasons for app dissatisfaction included “did not consider personal circumstances,” and strategies to improve the intervention included “increased interpersonal contact.” Of the 46 studies, 9 (20%) included a clinician portal as a feature to enhance the app intervention, allowing for additional communication between clinicians and patients. Of the 9 studies, 7 (78%) had an effective health behavior change. Silk et al [88] reported acceptability and easy-to-use features regarding the integration of the clinician portal into their mHealth intervention. This component should be considered for health behavior change interventions and investigated further.

Of the 46 nutrition apps in this review, 37 (80%) included some type of self-monitoring feature. Of those 37 apps, 35 (95%) had at least one significant improvement or good usability rating to promote engagement with mobile apps for chronic disease self-management. This is in alignment with other research that shows that the most common self-management application for mHealth is a tracking feature [89]. In addition, when surveying clinicians working in diabetes and weight management patient care settings, the most adoptable apps included self-monitoring features [90]. However, the apps that did not include self-monitoring or tracking features showed significant improvements as well. In addition, there was variability in other features combined with tracking features (ie, knowledge, goal setting, coach feedback, and clinician portals), making it difficult to attribute behavior change to self-monitoring features alone. More research is needed to correlate specific features with health behavior change.

Except for cancer populations, a key finding in this review was that 41% (19/46) of the nutrition app interventions targeted weight management, and 58% (11/19) of those studies were effective in health behavior change. This finding is similar to that of Fakih El Khoury et al [91], who reported that dietary mobile apps positively affected measured nutritional outcomes in chronic diseases, especially weight loss. The key finding for cancer populations was that mHealth nutrition apps can significantly improve QOL. A similar result was found in a review analyzing the use of mHealth involving nutrition in a chronic kidney disease population [92]. A total of 28% (13/46) of the studies examined changes in glycemic control, HbA1c, and other biometric measurements (ie, blood pressure and lipids). In total, 69% (9/13) of those studies showed a significant reduction in their measurements when using a nutrition app in their intervention. In addition, 15% (2/13) of those studies showed a decrease in medication treatment for glycemic control [53,62]. Eberle et al [93] concluded that mHealth apps with a nutrition intervention effectively enhanced diabetes management, which is comparable with our review results.

There was diversity in the chronic disease state; study design; number of participants; and variety of in-app features, BCTs, and behavior models used in the studies. However, linking these factors to a particular behavior change and health outcome posed to be difficult, which is not different from Taj et al [94] in their review of digital health behavior change technology. This review provides insight into the theories and theoretical frameworks or models used in nutrition-focused mHealth interventions to increase understanding and translate them into practice, which is essential for developing behavior change for the sustainability of health improvement. For example, this scoping review found that most apps used BCTs, such as self-monitoring in 80% (37/46) of the interventions, knowledge in 72% (33/46) of the interventions, feedback in 54% (25/46) of the interventions, and goal setting in 20% (9/46) of the interventions, for effective health behavior change, as another review [31] demonstrated.

In addition, our review found that less than half (19/46, 41%) of the studies based their nutrition apps on a behavioral theory or its constructs. Some studies (14/46, 30%) that based their interventions on theories had improved engagement, satisfaction, or app use among participants and suggested that incorporating a behavioral theory in mHealth interventions is an effective strategy, which is a comparable finding with that of another review [91]. However, other factors play a role in usability,
acceptability, and overall user satisfaction. The app features, BCTs, and theory-based interventions will all affect the effectiveness of mHealth nutrition apps in health behavior change toward chronic diseases.

Another significant development in the sector of health technology is that smartphones can also be embedded with sensors or coupled with wearable sensors for health monitoring, which could enhance a nutrition app’s effectiveness in health behavior change. Examples of these devices that could be coupled with nutrition apps include motion sensors such as accelerometers, gyroscopes, and magnetometers that measure motion and physical activity [95]; wearable devices such as glasses (analyzing the intake pattern with smart glasses) and rings (ring-type tactile sensors to detect food mass) for food intake measurement [96]; portable and handheld single-lead electrocardiogram devices in addition to fitness trackers to measure heart rate and heart rate variability [95]; wristwatches to measure glucose levels extracted from skin interstitial fluid through reverse ionophoresis or through saliva-, sweat-, or tear-based wearable biosensors [97]; a wrist-wearable watch with the function of a pulsiometer without a cuff to measure blood pressure [97]; and ingestible capsules that can be used for medical health monitoring [98]. These enhance personal health care and performance monitoring with the potential to complement nutrition apps and have a broad impact on our society.

Limitations

Although the results of this study showed health improvements achieved when using mHealth nutrition apps for behavior change in chronic diseases, some limitations need to be addressed. An important limitation is the lack of research on mobile apps’ long-term effects (>1 year) on disease state populations. Therefore, there is no conclusive result on their long-term behavior change to determine whether the behavior continues to improve or reverses compared with the baseline. Consequently, there need to be more long-term studies conducted. Second, many studies (24/46, 52%) did not include a control group for comparison, and their sample size was small, limiting the interpretation of the results of the studies. Third, many apps are at risk of becoming rapidly obsolete owing to the fast pace at which technologies progress and, therefore, new technological innovations must be considered [8]. For example, the latest mobile technologies can connect and interact with each other, update and track personal health data in real time, and send alerts to users [8]. Similarly, most health apps have encountered serious usability problems or have not undergone usability assessment [99]. Usability affects the efficiency and efficacy of the app (ie, time to complete tasks and errors) [8]. Usability must be considered to increase the chance of the app being successfully adopted by patients [8]. Barriers to using mHealth apps include the patient’s lack of integration of technology into everyday life [12] and difficulties using mobile apps [11]. In the older adult population, health problems such as cognitive changes related to aging, disability, and lack of confidence are reasons for not using digital technology [18,19]. Further research is needed to evaluate patients’ experiences with apps and the benefits gained as a result. There could be a slight bias from the user perspective as there were 2% (1/46) of apps that were Android-only or web-based applications. The others (45/46, 98%) were web-based applications or all-smartphone apps. There were a few apps (4/46, 9%) that were provided through the smartphone that participants were given as part of the study, and the smartphone was not specified. A few studies (4/46, 9%) did not report the data privacy rules or the effects of users and funders on the app interventions. In addition, there are important confidentiality and funding issues that must be considered when designing interventions [100]. Finally, proficient health care providers should be involved in the app development stage to address safety during self-management and health education [101]. There is a need for comprehensive, efficient, and flexible mobile apps for the self-management of disease states with more features to increase the number of long-term users and induce better self-management and patient empowerment [101,102]. We did not conduct a systematic review or meta-analysis and, thus, did not weigh the quality of evidence or study design against the reported results. Some studies (6/46, 13%) included few participants, and the diversity of study objectives, designs, and outcomes made it difficult to compare them. We reviewed the current evidence to expand the knowledge base regarding the impact of nutrition apps on chronic disease management and assess the effectiveness of health behavior change.

Conclusions

In this scoping review, the use of mHealth nutrition apps and their effects on health behavior change were analyzed for 4 diseases (ie, cancer, CVD, DM, and obesity). The results suggest that mHealth apps involving nutrition can significantly improve health outcomes for people with chronic diseases. The study design, demographics, targeted behavior, health outcomes, BCTs, behavioral theories, and behavior change effectiveness were profoundly diverse among these studies, indicating that a one-size-fits-all approach for designing and implementing nutrition apps as part of chronic disease treatment is not possible. Tailoring nutrition apps to specific populations is recommended for effective behavior change and improvement of health outcomes. In addition, some studies (7/46, 15%) showed sustained health behavior change, and some (4/46, 9%) showed a decline in the use of the nutrition apps. These results indicate a need for further investigation on the sustainability of the health behavior change effectiveness of disease-specific nutrition apps.

Conflicts of Interest

None declared.

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78. Salas-Groves et alJMIR MHEALTH AND UHEALTH


Abbreviations

BCT: behavior change technique
CVD: cardiovascular disease
DM: diabetes mellitus
HbA1c: glycated hemoglobin
mHealth: mobile health
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QOL: quality of life
T2DM: type 2 diabetes mellitus
Effectiveness of mHealth on Adherence to Antiretroviral Therapy in Patients Living With HIV: Meta-analysis of Randomized Controlled Trials

Liang Sun¹, DPH; Mengbing Qu¹, MPH; Bing Chen², MPH; Chuancang Li¹, MPH; Haohao Fan¹, MPH; Yang Zhao¹, DPH

¹College of Public Health, Zhengzhou University, Zhengzhou, China
²Sanmenxia Center for Disease Control and Prevention, Sanmenxia, China

Corresponding Author:
Yang Zhao, DPH
College of Public Health
Zhengzhou University
New campus of Zhengzhou University
100 Science Avenue
Zhengzhou, 450001
China
Phone: 86 13803845359
Email: zhaomiemie@126.com

Abstract

Background: The World Health Organization recommends that all adults with HIV adhere to antiretroviral therapy (ART). Good adherence to ART is beneficial to patients and the public. Furthermore, mHealth has shown promise in improving HIV medication adherence globally.

Objective: The aim of this meta-analysis is to analyze the effectiveness of mHealth on adherence to antiretroviral therapy in patients living with HIV.

Methods: Randomized controlled trials (RCTs) of the association between mHealth and adherence to ART published until December 2021 were searched in electronic databases. Odds ratios (ORs), weighted mean differences, and 95% CIs were calculated. This meta-analysis was performed using the Mantel-Haenszel method or the inverse variance test. We evaluated heterogeneity with the $I^2$ statistic. If $I^2$ was ≤50%, heterogeneity was absent, and a fixed effect model was used. If $I^2$ was >50%, heterogeneity was present, and a random effects model was used.

Results: A total of 2163 participants in 8 studies were included in this meta-analysis. All included studies were RCTs. The random effects model was used for a meta-analysis of the effects of various intervention measures compared to routine nursing; the outcome was not statistically significant (OR 1.54, 95% CI 0.99-2.38; $P$=.05). In the subgroups, only short messaging service (SMS)-based interventions significantly increased adherence to ART (OR 1.76, 95% CI 1.07-2.89; $P$=.03). Further analysis showed that only interactive or bidirectional SMS could significantly increase ART adherence (OR 1.69, 95% CI 1.22-2.34; $P$=.001). After combining the difference in CD4 cell count before and after the interventions, we concluded that there was no statistical heterogeneity among the studies ($I^2$=0%; $\tau^2$=0.37; $P$=.95).

Conclusions: Interactive or bidirectional SMS can enhance intervention effects. However, whether mHealth can improve adherence to ART in patients with HIV needs further study. Owing to a lack of the required significant staff time, training, and ongoing supervision, there is still much more to do to apply mHealth to the clinical use of ART for patients living with HIV.

Trial Registration: PROSPERO CRD42022358774; https://www.crd.york.ac.uk/prospero/display_record.php?RecordID=358774

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KEYWORDS
HIV; mHealth; antiretroviral therapy; meta-analysis
**Introduction**

HIV is a public health issue that every country needs to address. There were an estimated 37.7 million people living with HIV at the end of 2020 [1]. The World Health Organization (WHO) recommends that all adults with HIV should adhere to antiretroviral therapy (ART) [2]. ART does not cure HIV infection but strongly suppresses viral replication within a person’s body and modifies HIV from a terminal illness to a manageable chronic disease [3]. One of the most significant factors in the effectiveness of ART is adherence [4]. Good adherence to ART is beneficial to patients and public health [5,6]. In contrast, lack of adherence increases the risk of progression to AIDS and the creation of drug-resistant strains of HIV [7]. Therefore, it is important to promote ART adherence through special techniques [8,9]. However, traditional ART adherence interventions are limited in their ability to maintain behavior modification [10]. Mobile health (mHealth) technology, which refers to the use of mobile and wireless technologies to improve health, has shown promise in improving HIV medication adherence, both globally and domestically [6,11,12]. Therefore, we performed a meta-analysis of the effectiveness of mHealth for improving adherence to ART in patients living with HIV.

**Methods**

**Ethical Considerations**

This paper contains no primary data obtained directly from research participants. Data obtained from previously published resources have been acknowledged with references. Ethical approval was not required.

**Protocol Registration**

The review protocol was prospectively registered with PROSPERO (International Prospective Register of Systematic Reviews; CRD42022358774).

**Search Strategy**

This meta-analysis was performed according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement guidelines [13]. Searching was conducted using the electronic databases PubMed, EMBase, CINAHL, ScienceDirect, the Cochrane Library, Web of Science, and ClinicalTrials.gov to identify original articles meeting the evaluation criteria for inclusion and exclusion published until December 2021. Searching was conducted and evaluated by 2 independent reviewers. The search strategy for identifying studies included the key terms mobile health, human immunodeficiency virus, medication adherence, randomized controlled trial, and other related terms. These keywords were also combined using the OR and AND operators (Multimedia Appendix 1).

**Inclusion and Exclusion Criteria**

The screening process was divided into 2 phases: a preliminary selection by title and abstract and a second phase that screened the full text of the remaining articles. Articles were included based on the following criteria: (1) they reported the results of a randomized controlled trial (RCT); (2) they included HIV-positive persons receiving antiretroviral treatment regardless of age, sex, or nationality; (3) the intervention measures included, but were not limited to, short message service (SMS) texts and voice calls; (4) an mHealth intervention was used in the experimental group with no limits on intervention frequency, time, content, or period and the control group received routine nursing at the same time to help patients improve their treatment compliance; and (5) the primary outcome was adherence to ART. This was measured directly (eg, by pill count) or indirectly (eg, by self-reporting). If the article reported the use of a variety of measurement methods, priority was given to measurement results obtained with the self-report method. The secondary outcome was CD4 cell count.

The exclusion criteria included the following: (1) the study was a duplicate, (2) the study was a systematic review or meta-analysis, (3) the study was missing outcome measures, (4) the experimental group used a variety of interventions, and (5) the control group did not receive routine nursing.

**Data Extraction**

A predesigned Excel sheet was used to extract and organize the data into categories by 2 independent researchers. These data included (1) authors, (2) location, (3) publication date, (4) intervention details (ie, intervention mode and duration), (5) outcome measures, including ART adherence and CD4 cell counts, and (6) risk of bias.

**Risk of Bias and Quality Assessment**

Two of the authors assessed the risk of bias using RevMan (version 5.4; Cochrane Collaboration); the results are summarized in Figure 1. The Cochrane Collaboration’s Risk of Bias tool was also used to assess quality and risk of bias. This tool assesses bias in 7 domains: random sequence generation (for selection bias), concealment of the allocation sequence (for selection bias), blinding of participants and personnel (for performance bias), blinding of outcome assessment (for detection bias), incomplete outcome data (for attrition bias), selective outcome reporting (for reporting bias), and other biases. Studies are assigned a low risk of bias, an unclear risk of bias, or a high risk of bias.

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JMIR Mhealth Uhealth 2023 | vol. 11 | e42799 | p.46

(page number not for citation purposes)
Figure 1. Risk of bias of the studies included in the meta-analysis. Green indicates a low risk of bias, yellow indicates an unclear risk of bias, and red indicates a high risk of bias.

Data Analysis
The meta-analysis was conducted using RevMan. Measures of effect are presented as odds ratios (ORs) with the 95% CI. For continuous data, we calculated the sample-size weighted mean difference (WMD). This meta-analysis was performed using the Mantel-Haenszel method or the inverse variance test. We evaluated heterogeneity with the $I^2$ statistic. If $I^2$ was ≤50%, heterogeneity was absent, and a fixed effect model was used. If $I^2$ was >50%, heterogeneity was present, and a random effects model was used.
Results

Study Selection Process
The search strategy identified 2783 articles from the electronic databases. In total, 423 articles were excluded because of duplication. We screened the titles and abstracts of the remaining articles and included 26 for full-text review based on the inclusion and exclusion criteria. Of these 26 studies, 8 met the inclusion criteria, and 18 studies were excluded: 15 because they were missing outcome measures, 1 because a variety of interventions were used in the experimental group, and 2 because they did not use routine nursing in the control group. Therefore, 8 studies were selected for the current meta-analysis [4,9,14-19] (Figure 2).

Study Characteristics
The characteristics of the studies are summarized in Table 1. All included studies were RCTs. A total of 2163 participants in 8 studies were included in this meta-analysis. Except for the study by Mbuagbaw et al [19], all participants in the studies were aged 18 years or older. Study duration ranged between 1 and 12 months. SMS was used as the basis for the intervention in 6 studies. One of these studies used an mHealth intervention program that included text messages and WeChat. The remaining studies used voice calls.
Table 1. Characteristics of the included studies. All studies used routine nursing in the control group.

<table>
<thead>
<tr>
<th>First author, year</th>
<th>Location</th>
<th>Participants, n (age, years)</th>
<th>Recruitment period (duration)</th>
<th>Intervention</th>
<th>Outcome measures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Guo, 2018 [14]</td>
<td>South China</td>
<td>53 (≥18)</td>
<td>Oct 2016-Mar 2017 (3 months)</td>
<td>SMS and WeChat</td>
<td>CD4 cell count</td>
</tr>
</tbody>
</table>

[^a^]SMS: short message service.
[^b^]ART: antiretroviral therapy.
[^c^]VAS: visual analog scale.

**Meta-analysis**

**Medication Adherence**

Adherence to ART was measured as a primary outcome in 7 studies. The method and frequency of measuring adherence varied across the studies. The details are listed in Table 1. A random effects model was used for a meta-analysis of the effects of various intervention measures and routine nursing; the outcome was not statistically significant (OR 1.54, 95% CI 0.99-2.38; P=.05). There was also evidence of heterogeneity among the studies (I^2=74%; tau^2=0.23; P<.001; Figure 3). In the subgroups, only SMS interventions significantly increased adherence to ART (OR 1.76, 95% CI 1.07-2.89; P=.03).
Medication Adherence With SMS Intervention

Six studies were included in a meta-analysis of the effect of SMS on adherence to ART; this showed that SMS could improve adherence (OR 1.76, 95% CI 1.07–2.89; \(P=0.03\)) but also revealed considerable heterogeneity among the included studies (\(I^2=69\%; \tau^2=0.25; P=0.007; \) Figure 4). In the subgroups, only interactive or bidirectional SMS interventions could significantly increase ART adherence (OR 1.69, 95% CI 1.22–2.34; \(P=0.001\)). However, these studies did not show statistical heterogeneity (\(I^2=0\%; \tau^2=0.00; P=0.41\). A subgroup analysis of studies with unidirectional SMS interventions showed no statistical heterogeneity, but the analysis also showed a lack of effect in improving adherence (Figure 4).

CD4 Cell Count

Four studies reported CD4 cell count as a secondary outcome of medication adherence. Combining the differences in CD4 cell count before and after the interventions revealed no statistical heterogeneity among the studies (\(I^2=0\%; \tau^2=0.37; P=0.95; \) Figure 5). Meta-analysis showed that CD4 cell count measures after mHealth interventions revealed no significant difference in medication adherence among HIV patients compared with routine nursing (WMD=20.85, 95% CI 1.60–43.29; \(P=0.07\); Figure 5). Only 2 studies reported viral load as an outcome to evaluate the intervention effect, so we did not perform a meta-analysis.
Discussion

Principal Findings

A total of 2163 participants in 8 studies were included in this meta-analysis. The main result of the meta-analysis was that the pooled OR was 1.54. However, the outcome was not statistically significant, and there was considerable heterogeneity among the studies ($I^2=74\%$). Within-study heterogeneity reduces study robustness and relevance [20]. Our current results are different from those of a 2015 study [21]. That study found that mHealth interventions did seem to have been beneficial. We speculate that one of the possible reasons for this difference is that the number of articles included in our study was limited. Also, the different studies used a variety of methods to measure results. However, compared with the 2015 study, this meta-analysis combined the outcomes (separately for primary and secondary outcomes) to increase the reliability of the results.

A subgroup analysis showed that SMS interventions improved adherence to ART. Further analysis suggested that interactive or bidirectional SMS interventions could enhance intervention effects. This result matches that of a 2014 study [22]. Interactive or bidirectional SMS could increase medication adherence by enhancing engagement and the patient-provider relationship. Follow-up research could further study the content, time, and frequency of text messages. In this study, due to limitations arising from incomplete reporting of the relevant content, these aspects of the intervention were not analyzed.

CD4 cell count and viral load are good indicators of treatment success [23]. Several previous reviews did not obtain the same results as this study for CD4 cell count. One study [22] showed that compared to a control group, a group receiving text message–based support was more likely to maintain an adherence threshold at follow-up and meet the clinical goal of a higher CD4 cell count. However, another study [24], like ours, did not obtain this result. Our meta-analysis of the 4 studies that reported CD4 cell count showed considerable heterogeneity and no significant pooled mean difference. This may be attributable to the heterogeneity of the studies. We did not perform a meta-analysis of studies that measured viral load, as there was an insufficient number of these studies.

The WHO recommends mHealth strategies for improving ART adherence [25]. At the same time, against the background of the coronavirus epidemic, telemedicine has gradually continued to develop [26]. Currently, 95% of people use mobile phones and 77% of people use smartphones in different parts of the world [27]; mHealth has shown promise in increasing the accessibility of self-management interventions [28] and improving HIV health outcomes [6]. At the same time, research has indicated that patients living with HIV are interested in mobile apps to support HIV self-management [29]. However, most current mHealth interventions lack functionality, offering only medication reminders [28] or voice calls. Therefore, more comprehensive mHealth interventions that address multiple self-management needs of patients living with HIV are needed [30]. At the same time, the implementation of ART interventions in real-world clinical settings has been severely limited by a lack of the resources required to initiate and maintain the interventions [31], such as staff time, training, and ongoing supervision. Future research should focus on how to apply personalized mHealth interventions to the management of patients living with HIV.

Limitations

There are several limitations of the current review. The interventions used in the included studies differed in form and frequency. At the same time, these studies used diverse methods for measuring their primary outcomes. This may have produced bias. The robustness and relevance of results increase with the number of distinct outcome measures that show the same result [20]. However, few of the included studies reported CD4 cell count or viral load, and our analysis of these outcomes is thus insufficient.

Conclusion

Interactive or bidirectional SMS interventions can enhance intervention effects. However, whether mHealth can improve adherence to ART in patients with HIV is a question that needs further study. Owing to a lack of staff time, training, and ongoing supervision, there is still much work to be done to use mHealth in the clinic for ART adherence among patients living with HIV.

Acknowledgments

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Keywords.

References


Abbreviations
ART: antiretroviral therapy
mHealth: mobile health
OR: odds ratio
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RCT: randomized controlled trial
SMS: short message service
VAS: visual analog scale
WMD: weighted mean difference
mHealth Intervention for Improving Pain, Quality of Life, and Functional Disability in Patients With Chronic Pain: Systematic Review

Marta Moreno-Ligero1,2, MSc; Jose A Moral-Munoz2,3,4, PhD; Alejandro Salazar2,4,5, PhD; Inmaculada Failde1,2,4, PhD

1Preventive Medicine and Public Health Area, Department of Biomedicine, Biotechnology and Public Health, University of Cádiz, Cádiz, Spain
2Observatory of Pain, University of Cádiz, Cádiz, Spain
3Department of Nursing and Physiotherapy, University of Cádiz, Cádiz, Spain
4Institute of Research and Innovation in Biomedical Sciences of the Province of Cadiz (INiBICA), Cádiz, Spain
5Department of Statistics and Operational Research, University of Cádiz, Cádiz, Spain

Corresponding Author:
Jose A Moral-Munoz, PhD
Department of Nursing and Physiotherapy
University of Cádiz
Avda. Ana de Viya, 52
Cádiz, 11009
Spain
Phone: 34 956015699
Email: joseantonio.moral@uca.es

Abstract

Background: Chronic pain (CP) is 1 of the leading causes of disability worldwide and represents a significant burden on individual, social, and economic aspects. Potential tools, such as mobile health (mHealth) systems, are emerging for the self-management of patients with CP.

Objective: A systematic review was conducted to analyze the effects of mHealth interventions on CP management, based on pain intensity, quality of life (QoL), and functional disability assessment, compared to conventional treatment or nonintervention.

Methods: PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) guidelines were followed to conduct a systematic review of randomized controlled trials (RCTs) published in PubMed, Web of Science, Scopus, and Physiotherapy Evidence Database (PEDro) databases from February to March 2022. No filters were used. The eligibility criteria were RCTs of adults (≥18 years old) with CP, intervened with mHealth systems based on mobile apps for monitoring pain and health-related outcomes, for pain and behavioral self-management, and for performing therapeutic approaches, compared to conventional treatments (physical, occupational, and psychological therapies; usual medical care; and education) or nonintervention, reporting pain intensity, QoL, and functional disability. The methodological quality and risk of bias (RoB) were assessed using the Checklist for Measuring Quality, the Oxford Centre for Evidence-Based Medicine Levels of Evidence, and the Cochrane RoB 2.0 tool.

Results: In total, 22 RCTs, involving 2641 patients with different CP conditions listed in the International Classification of Diseases 11th Revision (ICD-11), including chronic low back pain (CLBP), chronic musculoskeletal pain (CMSP), chronic neck pain (CNP), unspecified CP, chronic pelvic pain (CPP), fibromyalgia (FM), interstitial cystitis/bladder pain syndrome (IC/BPS), irritable bowel syndrome (IBS), and osteoarthritis (OA). A total of 23 mHealth systems were used to conduct a variety of CP self-management strategies, among which monitoring pain and symptoms and home-based exercise programs were the most used. Beneficial effects of the use of mHealth systems in reducing pain intensity (CNP, FM, IC/BPS, and OA), QoL (CLBP, CNP, IBS, and OA), and functional disability (CLBP, CMSP, CNP, and OA) were found. Most of the included studies (18/22, 82%) reported medium methodological quality and were considered as highly recommendable; in addition, 7/22 (32%) studies had a low RoB, 10/22 (45%) had some concerns, and 5/22 (23%) had a high RoB.

Conclusions: The use of mHealth systems indicated positive effects for pain intensity in CNP, FM, IC/BPS, and OA; for QoL in CLBP, CNP, IBS, and OA; and for functional disability in CLBP, CMSP, CNP, and OA. Thus, mHealth seems to be an alternative to improving pain-related outcomes and QoL and could be part of multimodal strategies for CP self-management. High-quality studies are needed to merge the evidence and recommendations of the use of mHealth systems for CP management.
Introduction

Chronic pain (CP) is a leading cause of disability worldwide [1], affecting approximately 20% of the global population [2]. Moreover, in developed countries, up to 1 of 5 adults suffers from CP of any type [3]. This condition implies a substantial burden for people, and it also has a social and economic impact on health care systems and employment activity [2]. In fact, although the direct health care costs of managing CP conditions are important, the indirect costs, such as disability compensation and work absenteeism, are higher [4].

CP is defined as pain that persists or recurs for longer than 3 months, including a broad range of pain conditions listed in the International Classification of Diseases 11th Revision (ICD-11) [5]. It is a new and pragmatic classification system to apply in primary care and clinical settings for specialized pain management [6]. Current pain management interventions are based on multimodal and biopsychosocial models, which include pain education programs, exercise programs, cognitive and behavioral strategies, relaxation techniques, goal setting strategies, self-monitoring symptoms, and self-tailoring strategies [7-9]. Moreover, emotional distress, functional disability, and sleep disturbances are closely linked to the perception of pain and the pain-related outcomes in patients with CP [10,11]. Therefore, strategies for CP management should address all biopsychosocial aspects of this health condition.

Recently, innovative and potential alternatives to support the self-management of patients with CP have emerged, such as mobile device–based health care, or mobile health (mHealth) [12]. mHealth involves the practice of medicine and public health based on mobile devices to improve and promote health status [13]. According to the target of mHealth systems in CP, they can be grouped into 3 categories [12,14]: (1) education, including general information about pain, symptom identification, and treatment planning; (2) monitoring, tracking daily pain episodes and severity, symptoms, mood, activity, and medication use; and (3) treatment, involving several management strategies. These systems empower patients to become more engaged and encourage self-management [15], improving some pain-related outcomes. In line with this, several pain-related apps have been identified from scientific databases and app stores for the management of a wide range of pain (chronic and acute) conditions [16,17]. Nevertheless, there is a lack of scientific and health professional support in many of the mHealth systems, highlighting the need for developing appropriate apps based on the patient’s requirements, also in the management of CP [18].

The available evidence points out promising effects of internet-delivered interventions on different biopsychosocial aspects of CP. Gandy et al [19] studied the use of these interventions using any type of device and technology for CP, showing small effects on pain intensity and disability outcomes in patients with mixed CP conditions, chronic low back pain (CLBP), fibromyalgia (FM), arthritic conditions, peripheral neuropathy, spinal cord injury, migraine, and chronic pancreatitis. In a similar vein, Moman et al [14] discussed the effects of both electronic health (eHealth), based on web apps, and mHealth technologies in patients with CP (general CP, CLBP, FM, and osteoarthritis [OA]), showing significant improvements in pain intensity outcomes at short-term follow-up. Nevertheless, the study was mainly based on eHealth systems, and few findings were obtained from mobile apps. Du et al [20] analyzed the use of web-health-based interventions and mHealth interventions in patients with CLBP, showing better effects on both pain and disability outcomes in favor of mHealth systems. According to the effects of mHealth, a recent review [21] evaluated the effectiveness of app-based interventions on several CP conditions (general CP, CLBP, chronic neck pain [CNP], rheumatoid arthritis, OA, menstrual pain, frozen shoulder pain, and migraine), stating that these apps are significantly more effective, with a small effect size in reducing pain in comparison to control groups. Thurnheer et al [22] analyzed the efficacy of app usage in the management of patients with cancer and noncancer pain (chronic cancer pain, general CP, CLBP, CNP, menstrual pain, and acute pain), reporting beneficial effects on pain, particularly in an out-clinic setting. The evidence of the use of mHealth systems is still emerging and focusing mainly on its effects on pain intensity. Moreover, commonly studied pain conditions (cancer and noncancer pain) and different types of pain (acute and chronic) are mixed, leading to heterogeneity in their findings.

In view of this background and to the best of our knowledge, none of the published reviews has examined the effects of the use of mHealth systems on pain intensity along with the effects on the functional disability and quality of life (QoL) of patients with CP. Therefore, the main purpose of this systematic review is to determine the effects of the use of mHealth systems on different CP conditions listed in the ICD-11, based on the improvement of pain intensity, QoL, and functional disability, according to the findings reported with randomized controlled trials (RCTs). Furthermore, we provide an overview of the available mHealth systems for CP management, their purposes, and their features.
Methods

Study Design
The protocol of this systematic review was registered on the International Prospective Register of Systematic Reviews (PROSPERO) database (CRD42022315808) [23]. It was conducted following the 2020 PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines for systematic reviews of RCTs [24].

Search Strategy
The search strategy was based on CP diseases according to the ICD-11 [25]. The search was conducted from February to March 2022 in the following databases: PubMed, Web of Science, Scopus, and Physiotherapy Evidence Database (PEDro). The search strategy was first developed for the PubMed database using Medical Subject Headings, and it was adapted for other databases. The search was not filtered either by language or by date of publication. The search strategy for each database is provided in Multimedia Appendix 1.

Eligibility Criteria
The eligibility criteria were defined according to the PICOS (Population, Intervention, Comparison, Outcomes, Study type) framework [26]. The population included adults (≥18 years old) with any CP condition listed in the ICD-11 [25]. Interventions were mHealth systems based on mobile apps (smartphone or tablet) used for monitoring pain and health-related outcomes, for pain and behavioral self-management, and for performing therapeutic approaches. The rationale for including monitoring apps as an intervention was their effects on modifying the user’s behavior, expectation, and performance for disease management or health promotion [27]. Some of the apps’ features for promoting behavior changes are reminders and notifications, tracking activity, goal planning, and tailored information [28]. For comparison, the control group included conventional treatments (physical, occupational, and psychological therapies; care medical; and education) or nonintervention. Primary outcomes were based on pain intensity, QoL, and functional disability, and only RCTs were included as study designs.

Studies with a sample of children or adolescents; including a pain condition with a duration less than 3 months; based on the management of cancer-related pain or pre- and postsurgery trauma interventions (eg, knee arthroplasty, carpal tunnel syndrome); including websites, text messages, or other devices (eg, smartwatches, laptops); and those in which all studied tools. Furthermore, data of the main findings related to pain intensity, QoL, and functional disability were collected. Finally, specific information about the purpose and main features of the mHealth systems used as interventions was identified.

Study Selection Process
After retrieving the documents from different databases, duplicated documents were removed using Rayyan QCRI (Qatar Computing Research Institute) [29] and manual screening. Studies were first screened by title and abstract by 2 researchers (authors MML and JAMM) according to the eligibility criteria. Next, the full text of potentially relevant papers was reviewed by MML and JAMM to decide whether they should be included in the analysis. Disagreements were discussed and resolved by consensus with a third researcher (author IF).

Data Extraction
The following data were extracted from the included studies: author, year of publication, and country; CP conditions; total number of participants; demographic information, including age and gender, for each study group; intervention details (type, follow-up assessments, and total study duration); and primary and secondary outcomes, as well as outcome measurements or tools. Furthermore, data of the main findings related to pain intensity, QoL, and functional disability were collected. Finally, specific information about the purpose and main features of the mHealth systems used as interventions was identified.

Risk of Bias, Methodological Quality, and Level of Evidence Assessment
First, the risk of bias (RoB) was assessed using the Cochrane RoB 2.0 tool [30], including 5 domains and an overall judgment. The 5 domains are (1) bias arising from the randomization process, (2) bias due to deviations from intended interventions, (3) bias due to missing outcome data, (4) bias in measurement of the outcome, and (5) bias in selection of the reported result. Each domain was categorized as “low risk,” “high risk,” or “unclear risk” based on the answers to signaling questions. An overall RoB assessment of the RCTs was performed following the recommendations in the guidance document.

Second, the Checklist for Measuring Quality [31] was used. It includes 26 items categorized by 5 subscales: reporting (9 items), external validity (3 items), bias (7 items), confounding (6 items), and power (1 item). Each item is scored 0 or 1, except for 1 item in the reporting subscale whose score ranges from 0 to 2 and the single item in the power subscale whose score ranges from 0 to 5, with a maximum overall score of 31. A score less than 50% indicates low methodological quality, 50%-65% indicates medium methodological quality, and >65% indicates high methodological quality.

Finally, the levels of evidence were reported according to the 2011 Oxford Centre for Evidence-Based Medicine (OCEBM), concerning the subject area or clinical setting and the study design involving the clinical question [32]. The level of evidence ranged from 1 (strong evidence) to 5 (weak evidence).

These assessments were performed by 2 authors (MML and JAMM), and the discrepancies were solved by agreement with a third researcher (author AS). These discrepancies appeared mainly in the RoB assessment, specifically in some questions related to deviations from intended interventions and measurement of outcomes. We also discussed some items of the Checklist for Measuring Quality corresponding to external (source population) and internal (blinding and concealment) validity and the power effect.

Results

Study Selection
A total of 885 studies were retrieved from the systematic literature review, of which 490 (55.4%) were duplicates and so deleted automatically. After the first screening by title and
abstract, 62/395 (15.7%) studies were selected for full-text reviewing. According to the pre-established selection criteria, a total of 22 (35.5%) studies were finally included in the qualitative analysis. The full screening process and the main reasons for exclusion are shown in Figure 1.

Figure 1. Information flow diagram of the selection process of the systematic review. CP: chronic pain; mHealth: mobile health; PEDro: Physiotherapy Evidence Database.

Risk of Bias, Methodological Quality, and Level of Evidence

Regarding the results of RoB assessment by domain, 18/22 (82%) studies had a low RoB for the random allocation domain and 16/22 (73%) studies had a RoB for the missing outcome data domain. For the second (bias due to deviations from intended interventions) and fourth (measurement of outcomes) domains, 11 (50%) and 14 (64%) studies had some concerns, respectively. Last, in the selection of the reported results domain, 16 (73%) studies had a low RoB but 3 (14%) studies had a high RoB. For overall judgment, 7/22 (32%) studies had a low RoB for their outcomes, 10/22 (45%) studies had some concerns, and 5/22 (23%) studies had a high RoB.

Regarding the Checklist for Measuring Quality, 18 (82%) studies [33-50] reported medium methodological quality (between 50% and 65%), and the rest [51-54] scored high on methodological quality (>65%). Based on the clinical settings of the included studies, which concern therapy or treatment, the OCEBM level of evidence was based on systematic reviews of RCTs or, failing that, individual RCTs with narrow 95% CIs. Thus, all included papers yielded an OCEBM level of 2 for a clinical question of treatment benefits, considering them as highly recommendable.

Detailed results of the RoB assessment are shown in Figures 2 and 3. The methodological quality and the level of evidence and degrees of recommendation of the included studies are detailed in Multimedia Appendix 2 [33-54].
Study Characteristics

The main characteristics of the studies included are shown in Table 1. Publication dates ranged from 2015 to 2022. A total of 2641 patients with CP were involved in this present systematic review, 70.6% (1793/2539) being female. The average age was 38.93 (SD 59.29) years, excluding 1 (5%) study [47] in which this information was not available. According to CP conditions listed in the ICD-11, OA is the condition most studied in the literature, followed by CLBP [41,47,52,53] and CNP [40,49,51,54]. The lowest studies were chronic pelvic pain (CPP) [44] and interstitial cystitis/bladder pain syndrome (IC/BPS) [50].

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**Figure 2.** RoB assessment: traffic light plot. RoB: risk of bias.

<table>
<thead>
<tr>
<th>Study</th>
<th>D1</th>
<th>D2</th>
<th>D3</th>
<th>D4</th>
<th>D5</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abadiyan et al [51]</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Alatour and Almarwani [33]</td>
<td>+</td>
<td>–</td>
<td>+</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Amorim et al [50]</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Chikhar et al [34]</td>
<td>–</td>
<td>–</td>
<td>+</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Chhabra et al [53]</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>–</td>
<td>+</td>
</tr>
<tr>
<td>Faming et al [43]</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Forbes et al [44]</td>
<td>+</td>
<td>–</td>
<td>+</td>
<td>–</td>
<td>–</td>
<td>×</td>
</tr>
<tr>
<td>Gohir et al [45]</td>
<td>+</td>
<td>–</td>
<td>+</td>
<td>–</td>
<td>–</td>
<td>×</td>
</tr>
<tr>
<td>Hunt et al [46]</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
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<td>Irvine et al [47]</td>
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<td>–</td>
<td>+</td>
<td>–</td>
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<td>+</td>
</tr>
<tr>
<td>Lee et al [48]</td>
<td>+</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>×</td>
</tr>
<tr>
<td>Lee et al [49]</td>
<td>+</td>
<td>+</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>×</td>
</tr>
<tr>
<td>Lee et al [50]</td>
<td>×</td>
<td>–</td>
<td>–</td>
<td>×</td>
<td>+</td>
<td>×</td>
</tr>
<tr>
<td>Pach et al [54]</td>
<td>+</td>
<td>+</td>
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<td>+</td>
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<td>Pelle et al [35]</td>
<td>+</td>
<td>+</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Rafferty et al [36]</td>
<td>+</td>
<td>–</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Siprpnik et al [37]</td>
<td>+</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>×</td>
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<tr>
<td>Susu–Ribera et al [38]</td>
<td>+</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Thongratanaporn et al [30]</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Thongtirak et al [40]</td>
<td>+</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Yang et al [41]</td>
<td>+</td>
<td>×</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>+</td>
</tr>
<tr>
<td>Yuan et al [42]</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
</tbody>
</table>

**Figure 3.** RoB assessment: summary plot. RoB: risk of bias.
Table 1. Study characteristics.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Year of publication (N=22), n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>2015-2018</td>
<td>6 (27.3)</td>
</tr>
<tr>
<td>2019-2022</td>
<td>16 (72.7)</td>
</tr>
<tr>
<td><strong>Region where the study took place (N=22), n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>11 (50.0)</td>
</tr>
<tr>
<td>Europe</td>
<td>4 (18.2)</td>
</tr>
<tr>
<td>North America</td>
<td>5 (22.7)</td>
</tr>
<tr>
<td>South America</td>
<td>1 (4.5)</td>
</tr>
<tr>
<td>Oceania</td>
<td>1 (4.5)</td>
</tr>
<tr>
<td><strong>Age (years)(^a), mean (SD)</strong></td>
<td>38.93 (59.29)</td>
</tr>
<tr>
<td><strong>Gender (N=2539)(^b), n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>1793 (70.6)</td>
</tr>
<tr>
<td>Male</td>
<td>746 (29.4)</td>
</tr>
<tr>
<td><strong>CP(^c) conditions (N=22), n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>CLBP(^d) [41,47,52,53]</td>
<td>4 (18.2)</td>
</tr>
<tr>
<td>CMSP(^e) [38]</td>
<td>1 (4.5)</td>
</tr>
<tr>
<td>CNP(^f) [40,49,51,54]</td>
<td>4 (18.2)</td>
</tr>
<tr>
<td>CP (unspecified) [43]</td>
<td>1 (4.5)</td>
</tr>
<tr>
<td>CPP(^g) [44]</td>
<td>1 (4.5)</td>
</tr>
<tr>
<td>FM(^h) [42,48]</td>
<td>2 (9.1)</td>
</tr>
<tr>
<td>IC/BPS(^i) [50]</td>
<td>1 (4.5)</td>
</tr>
<tr>
<td>IBS(^j) [36,46]</td>
<td>2 (9.1)</td>
</tr>
<tr>
<td>OA(^k) [33-35,37,39,45]</td>
<td>6 (27.3)</td>
</tr>
<tr>
<td><strong>Interventions based on mHealth(^l) systems (N=22), n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Home-based PA(^m) program</td>
<td>9 (40.9)</td>
</tr>
<tr>
<td>Education</td>
<td>8 (36.4)</td>
</tr>
<tr>
<td>CBT(^n)</td>
<td>4 (18.2)</td>
</tr>
<tr>
<td>Monitoring pain-related outcomes and symptoms</td>
<td>10 (45.5)</td>
</tr>
<tr>
<td>Monitoring PA parameters</td>
<td>11 (50.0)</td>
</tr>
<tr>
<td>Mind relaxation techniques</td>
<td>5 (22.7)</td>
</tr>
<tr>
<td><strong>Intervention period (N=22), n (%)</strong></td>
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<tr>
<td>&lt;3 months</td>
<td>15 (68.2)</td>
</tr>
<tr>
<td>3-6 months</td>
<td>7 (31.8)</td>
</tr>
<tr>
<td><strong>Outcomes assessed (N=22), n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Pain intensity</td>
<td>17 (77.3)</td>
</tr>
<tr>
<td>QoL(^o)</td>
<td>15 (68.2)</td>
</tr>
<tr>
<td>Functional disability</td>
<td>17 (77.3)</td>
</tr>
</tbody>
</table>

\(^a\)Average age of available data except for 1 study.
\(^b\)Gender proportion of available data except for 1 study.
were the 36-item Short Form Health Survey (SF-36) [34,41,43,49-51], followed by the EuroQoL-5D [35,48].

In the case of functional disability [33-35,38,39,41-45,47-53], 17 (77%) studies (N=1928) assessed it. Although there are different tools for assessing this outcome, they usually focus on a specific condition (Multimedia Appendix 3). For example, for patients with CNP [49,51], the Neck Disability Index (NDI) was used; for patients with FM, the Fibromyalgia Impact Questionnaire (FIQ) [42,48] was used; and for patients with OA, WOMAC [33,34,45], KOOK [35,39] and HOOS [35] were used.

Effects of mHealth Interventions vs Control Groups
To provide an overview of the differences found between mHealth interventions and control groups in the included studies, a visual representation is shown in Tables 2-5. The “∗” sign indicates significance in favor of the mHealth intervention group, and the “∘” sign indicates no significant differences between groups. No significant differences in favor of the control groups were reported.

Results of home-based PA programs delivered by mHealth systems led to a significant improvement in pain intensity in patients with CNP [49,51] and OA [35,45] when compared to usual care. Likewise, this type of intervention had significant effects on functional disability [35,45,49,51,53], but only Abadiyan et al [51] showed significant differences in the QoL between groups. In addition, when home-based PA programs delivered by mHealth systems were compared with similar traditional methods, a significant improvement in favor of mHealth for pain intensity [33], QoL, and functional disability outcomes [39] was observed in patients with OA and CNP. Nevertheless, no significant differences were obtained for any of the outcomes measured in patients with FM [42].

In relation to educational interventions based on mHealth, improvements in the QoL in OA [34], IBS [36], and IC/BPS [50] conditions were observed when compared either to usual care or to similar intervention by traditional methods. This intervention also showed improvements in functionality and pain intensity in patients with OA [34] but not for pain intensity in patients with IC/BPS [50].

CBT based on mHealth systems showed some significant improvements in QoL [46,47] and functional disability [47] in favor of the mHealth group when compared to usual care or no

Types of mHealth and Comparison Interventions
Several approaches for the self-management of patients with CP involved mHealth systems. On the one hand, we found the monitoring of pain-related variables and symptoms as part of the interventions, either isolated [37,38,41,48] or in combination with other management strategies [39,40,42,47,49,50]. Similarly, the tracking of physical activity (PA) parameters (daily PA and mobility, PA-related goals achieved, and adherence) was also used in 11 (50%) studies [33,35,37,40,41,43,45,49,51-53] aiming to record PA-related goals and to enhance PA performance and behaviors. On the other hand, self-management of CP focused on home-based PA programs as the most common intervention [33,35,39,40,45,49,51,53,55], including a wide variety of exercises, both general and specific for this population. Other common self-management approaches were educational sessions and materials [34-36,45-47,50,55]. Less frequent strategies were cognitive behavioral therapy (CBT) [43,46,47,54] and relaxation and mind-body techniques [43,44,46,54,55]. A total of 23 mHealth systems were used for monitoring [37,38,41,48,52], treatment strategies [34,36,44,46,54], and a combination of both [33,35,39,40,42,43,45,47,49,51,53]. Detailed information about the mHealth systems, their purpose of use, and the principal features are summarized in Multimedia Appendix 3.

In the control groups, interventions were based on usual health care (medical and physical therapies), being the most common comparison intervention [35,37,38,41,44,45,47-54]. Other papers performed the same intervention in both groups, one using mHealth and the other using traditional methods [33,34,36,39,42]. Finally, only 3 (14%) studies [40,43,46] did not involve any intervention.

Study Outcomes and Measurement Tools Used
Pain intensity was assessed in a total of 17 (77%) studies (N=1780). The numeric rating scale (NRS) [33,37,38,45,52-54] and the visual analogue scale (VAS) [40-42,48-51] were the most used. Regarding the OA condition, the Knee injury and Osteoarthritis Outcome Score (KOOS), the Hip injury and Osteoarthritis Outcome Score (HOOS), and the Western Ontario and McMaster (WOMAC) questionnaires were specific tools also used to assess pain intensity [34,35,39].

There was a wide range of tools used in 15 (68%) studies (N=1744) for assessing the QoL. The most repeated instruments

©CP: chronic pain.
©CLBP: chronic low back pain.
©CMSP: chronic musculoskeletal pain.
©CNP: chronic neck pain.
©CPP: chronic pelvic pain.
©FM: fibromyalgia.
©IC/BPS: interstitial cystitis/bladder pain syndrome.
©IBS: irritable bowel syndrome.
©OA: osteoarthritis.
©mHealth: mobile health.
©PA: physical activity.
©CBT: cognitive behavioral therapy.
©QoL: quality of life.
intervention. Nevertheless, this intervention neither reduced pain intensity in CNP [54] nor improved the QoL and functional disability in CP significantly [43].

Finally, the results of mHealth interventions focused on monitoring pain and symptoms, compared to usual care, were inconclusive. Thus, significant improvements in reducing pain were reported for patients with OA [37] and FM [48] but not for those with CMSP [38] and CLBP [41]. In patients with CMSP and CLBP, functional disability outcomes significantly improved in favor of mHealth groups [38,41], while those diagnosed with FM did not achieve significant improvements in this outcome [48]. No significant changes in the overall QoL were observed between groups with this type of intervention [41,48].

Other interventions, such as isolated monitoring of PA parameters [52] and mindfulness meditation alone [44], did not show significant differences between the mHealth and control groups for any of the studied outcomes.

With regard to the reporting of adverse events or treatment reactions of the studied interventions, only 6 (27%) of the 22 studies [37,38,45,50,51,54] provided this information, of which only 1 (17%) [54] recorded serious adverse events (cancer, sudden hearing loss, nerve injury and spinal tap, tonsillectomy, and accident causing a fracture), but none of them was considered related to the trial intervention.
<table>
<thead>
<tr>
<th>Study</th>
<th>CP condition</th>
<th>Participants, N, intervention group (IG), n (%), control group (CG), n (%); age (years), mean (SD); gender (% female)</th>
<th>Intervention</th>
<th>Control</th>
<th>Total study duration (weeks); follow-up period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alasfour and Almarwani [33]</td>
<td>Knee OA</td>
<td>N=40; 54.40 (4.33); 100% IG: n=20; 53.65 (3.96); 100% CG: n=20; 55.15 (4.64); 100%</td>
<td>Home-based PA program (lower-limb strengthening exercises) with the My Dear Knee app; also, exercise adherence and completed sessions recorded by the app</td>
<td>Home-based PA program through paper handouts</td>
<td>6; 3rd and 6th weeks</td>
</tr>
<tr>
<td>Arfaei et al [34]</td>
<td>Knee OA</td>
<td>N=60; 58.17 (7.55); 100% IG: n=31; 57.84 (6.83); 100% CG: n=29; 58.52 (6.33); 100%</td>
<td>Educational content through the mobile app; usual medical care</td>
<td>Educational content without the app; usual medical care</td>
<td>8; 2nd month</td>
</tr>
<tr>
<td>Pelle [35]</td>
<td>Knee or hip OA</td>
<td>N=427 IG: n=214; 62.1 (7.7); 68.7% CG: n=213; 62.1 (7.0); 74.7%</td>
<td>Home-based PA program and education content provided by the Dr. Bart app, with also PA-related goals, self-monitoring, and motivational reminders</td>
<td>Usual care with no active treatment</td>
<td>24; 3rd and 6th months</td>
</tr>
<tr>
<td>Rafferty et al [36]</td>
<td>IBS</td>
<td>N=25 IG: n=14; 27.2 (9.5); 86% CG: n=11; 25.7 (11.9); 91%</td>
<td>Nutrition information and recommendations based on patient-specific and individualized diet plans through the Heali app; standard dietary education materials (online)</td>
<td>Standard dietary education materials (online)</td>
<td>4; 1st month</td>
</tr>
<tr>
<td>Skrepnik et al [37]</td>
<td>Knee OA</td>
<td>N=211; 62.6 (9.4); 50.2% IG: n=107; 61.6 (9.5); 55.1% CG: n=104; 63.6 (9.3); 45.2%</td>
<td>Monitoring pain, PA parameters, and mood data with feedback and motivational messages from the OA GO app; standard-of-care instructions and education; unblinded wearable device</td>
<td>Standard-of-care instructions and education; blinded wearable device</td>
<td>12; 1 week, 1st and 3rd months</td>
</tr>
<tr>
<td>Suso-Ribera et al [38]</td>
<td>CMS</td>
<td>N=165; 52.1 (11.2); 73.8% IG-1: 53 CG-2: 56</td>
<td>IG-1: monitoring pain-related outcomes using the Pain Monitor app with alarms and usual care; IG-2: monitoring pain-related outcomes with the Pain Monitor app without alarms and usual care</td>
<td>Usual care</td>
<td>4; 1st month</td>
</tr>
<tr>
<td>Thiengwit-tayaporn et al [39]</td>
<td>Knee OA</td>
<td>N=82 IG: n=42; 62.2 (6.8); 85.7% CG: n=40; 63.0 (9.7); 92.5%</td>
<td>Home-based PA program and education, and disease monitoring (symptoms and stages) with the Rak Kao app</td>
<td>Standard education and exercise instructions through handouts</td>
<td>4; 1st month</td>
</tr>
<tr>
<td>Thongtip-mak et al [40]</td>
<td>CNP</td>
<td>N=100 IG: n=50; 22.86 (1.99); 82% CG: n=50; 22.68 (2.23); 76%</td>
<td>Home-based PA program and monitoring pain level before and after exercises with the NeckProtector app</td>
<td>Rest</td>
<td>Same day</td>
</tr>
<tr>
<td>Yang et al [41]</td>
<td>CLBP</td>
<td>N=8 IG: n=5; 35 (10.93); 20% CG: n=3; 50.33 (9.29); 100%</td>
<td>Monitoring pain intensity and activity levels using the Pain Care app; self-management program based on individualized exercises and physiotherapy treatment</td>
<td>Online physiotherapy treatment</td>
<td>4; 2nd and 4th weeks</td>
</tr>
<tr>
<td>Yuan et al [42]</td>
<td>FM</td>
<td>N=40 IG: n=20; 43.3 (8.4); 95% CG: n=20; 42.1 (11.8); 100%</td>
<td>Self-care management based on education, home-based PA, and sleep hygiene and relaxation techniques using the ProFibro app, with also self-monitoring disease impact according to FQI domains; usual medical care</td>
<td>Traditional paper book of similar content; usual medical care</td>
<td>6; 6th week</td>
</tr>
<tr>
<td>Fanning et al [43]</td>
<td>CP</td>
<td>N=28; 70.21 (5.22); 78.6% IG: n=15; 70.12 (5.43); 86.7% CG: n=13; 70.32 (5.20); 69.2%</td>
<td>Monitoring PA-related goals, CBT, and mindfulness-based relapse prevention using the Mobile Health Intervention to Reduce Pain and Improve Health [MORPH] Companion and Fitbit apps</td>
<td>Waitlist</td>
<td>12; 3rd month</td>
</tr>
</tbody>
</table>
aCP: chronic pain.
bmHealth: mobile health.
cOA: osteoarthritis.
dPA: physical activity.
eIBS: irritable bowel syndrome.
fCMSP: chronic musculoskeletal pain.
gCNP: chronic neck pain.
hCLBP: chronic low back pain.
iFM: fibromyalgia.
jCBT: cognitive behavioral therapy.
Table 3. Characteristics of participants and study interventions (studies 12-22).

<table>
<thead>
<tr>
<th>Study</th>
<th>CPa condition</th>
<th>Participants, N, intervention group (IG), n (%), control group (CG), n (%); age (years), mean (SD); gender (% female)</th>
<th>Intervention</th>
<th>Total study duration (weeks); follow-up period</th>
</tr>
</thead>
</table>
| Forbes et al [44] | CPPc | N=90  
IG-1: n=31; 34.8 (9.9); 100%  
IG-2: n=30; 35.7 (5.7); 100%  
CG: n=29; 35.0 (8.6); 100% | IG-1: mindfulness meditation course delivered by the Headspace app and usual care; IG-2: muscle relaxation techniques in the app and usual care | Usual care | 8; 2nd, 3rd, and 6th months |
| Gohir et al [45] | Knee OAd | N=105  
IG: n=48; 65.2 (9.7); 70.8%  
CG: n=57; 68.0 (8.6); 64.9% | Home-based PA program, including strengthening, core stability and balance exercises, and educational sessions, provided by the Hereafter app | Usual care | 6; 6th week |
| Hunt et al [46] | IBSf | N=121; 32 (10.2); 75.2%  
IG: n=62  
CG: n=59 | Psychoeducation, CBT, relaxation techniques, and information about diet, provided by the Zemedy app | Waitlist | 8; 2nd month |
| Irvine et al [47] | CLBPb | N=597  
IG-1: n=199; 58.3%  
IG-2: n=199; 58.8%  
CG: n=199; 62.8% | CG: n=199; 62.8% | CG: n=199; 62.8% | CG: n=199; 62.8% | Usual care; only contacted for assessments | 8; 2nd and 4th months |
| Lee et al [48] | FMd | N=25  
IG: n=14; 42.8 (7.2); 100%  
CG: n=11; 41.7 (11.2); 100% | Monitoring pain-related outcomes (intensity, frequency, and environmental factors) with the Pain Assessment and Analysis System [PAAS] Clinic app | Usual care | 12; 1st and 3rd months |
| Lee et al [49] | CNPj | N=20  
IG: n=11; 27.09 (4.83); 55%  
CG: n=9; 27.56 (4.67); 45% | McKenzie neck exercise program with a smartphone app in the workplace environment, with also a self-feedback function and monitoring pain | Written instructions about postural hygiene | 8; 2nd month |
| Lee et al [50] | IC/BPSk | N=56  
IG: n=29; 42.9 (10.4); 100%  
CG: n=27; 46.3 (14.2); 100% | Health education and symptom self-management with the Taiwan Interstitial Cystitis Association [TICA] app; patients could continue using usual care | Usual care | 8; 2nd month |
| Abadiyan et al [51] | CNP | N=60; 38.5 (9.1)  
IG-1: n=20; 41.3 (8.1); 50%  
IG-2: n=20; 40.3 (7.9); 50%  
CG: n=20; 37.4 (9.8); 35% | IG-1: home-based PA program, global posture re-education (GPR), and self-managed work time with the Seeb app, with also recording of PA parameters; IG-2: GPR alone | Traditional neck education and exercise therapy | 8; 8th week |
| Amorim et al [52] | CLBP | N=68  
IG: n=34; 59.5 (11.9); 44%  
CG: n=34; 57.1 (14.9); 56% | Monitoring PA-related goals with the IMPACT app, with motivational messages; telephonenumber coaching sessions; PA and sedentary behavior information booklet | PA information booklet and advice to stay active | 24; weekly and 6th month |
| Chhabra et al [53] | CLBP | N=93  
IG: n=45; 41.4 (14.2)  
CG: n=48; 41.0 (14.2) | Home-based PA program, including specific back exercises and aerobic PA; monitoring daily PA parameters with the Snapcare app; written prescription and usual medical care | Written prescription, including PA advice; usual medical care | 12; 3rd month |
| Pach et al [54] | CNP | N=220  
IG: n=110; 37.9 (11); 67.3%  
CG: n=110; 39.8 (11.6); 71.8% | Relaxation exercises (autogenic training, mindfulness meditation, and guided imagery) and CBT strategies with the Relax-Neck app; follow-up data collected using app-based questionnaires | Usual care; app for data entry only | 24; 3rd and 12th months |

aCP: chronic pain.  
bmHealth: mobile health.  
cCPP: chronic pelvic pain.
dOA: osteoarthritis.
ePA: physical activity.
fIBS: irritable bowel syndrome.
gCBT: cognitive behavioral therapy.
hCLBP: chronic low back pain.
iFM: fibromyalgia.
jCNP: chronic neck pain.
kIC/BPS: interstitial cystitis/bladder pain syndrome.
Table 4. Overall RoB assessment, study outcomes, and main results (studies 1-11).

<table>
<thead>
<tr>
<th>Study</th>
<th>CP condition</th>
<th>Study outcomes (measurement tools)</th>
<th>RoB</th>
<th>Outcome results&lt;sup&gt;c&lt;/sup&gt;</th>
<th>Functional disability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Primary</td>
<td>Secondary</td>
<td></td>
<td>Pain intensity</td>
<td>QoL&lt;sup&gt;d&lt;/sup&gt;</td>
</tr>
<tr>
<td>Alasfour and Almarwani [33]</td>
<td>Knee OA&lt;sup&gt;e&lt;/sup&gt;</td>
<td>• Self-reported exercise adherence (percentage of completed exercises)</td>
<td>–</td>
<td>*</td>
<td>N/A&lt;sup&gt;f&lt;/sup&gt;</td>
</tr>
<tr>
<td>Arfaei Chitkar et al [34]</td>
<td>Knee OA</td>
<td>• Physical functioning (WOMAC&lt;sup&gt;h&lt;/sup&gt;)</td>
<td>–</td>
<td>*</td>
<td>*</td>
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<tr>
<td>Pelle [35]</td>
<td>Knee/hip OA</td>
<td>• Number of self-reported consultations in health care</td>
<td>–</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>Rafferty et al [36]</td>
<td>IBS&lt;sup&gt;m&lt;/sup&gt;</td>
<td>• IBS symptoms (5-item IBS Symptom Severity Scale [IBSS-SSS]; Rome IV)</td>
<td>N/A</td>
<td>X</td>
<td>N/A</td>
</tr>
<tr>
<td>Skrepnik et al [37]</td>
<td>Knee OA</td>
<td>Mobility (6-minute walking test [6MWT]; steps/day)</td>
<td>• Pain intensity (NRS&lt;sup&gt;9&lt;/sup&gt;)</td>
<td>–</td>
<td>*</td>
</tr>
<tr>
<td>Suso-Riera et al [38]</td>
<td>CMSP&lt;sup&gt;o&lt;/sup&gt;</td>
<td>• Pain intensity (NRS)</td>
<td>–</td>
<td>=</td>
<td>N/A</td>
</tr>
</tbody>
</table>

<sup>a</sup>RoB: Risk of Bias
<sup>b</sup>CP: Context Property
<sup>c</sup>Outcome results: Indicates whether the outcome was measured.
<sup>d</sup>QoL: Quality of Life
<sup>e</sup>Knee OA: Knee Osteoarthritis
<sup>f</sup>N/A: Not applicable
<sup>g</sup>*: Indicates presence
<sup>h</sup>WOMAC: Western Ontario and McMaster Universities Osteoarthritis Index
<sup>i</sup>SF-36: Medical Outcomes Survey Short Form 36 Item Health Survey
<sup>j</sup>KOOS: Knee Injury and Osteoarthritis Outcome Score
<sup>k</sup>HOOS: Hip and Osteoarthritis Outcome Score
<sup>l</sup>PAL: Physical Activity Level
<sup>m</sup>IBS: Irritable Bowel Syndrome
<sup>n</sup>IBS Symptom Severity Scale (IBSS-SSS)
<sup>o</sup>CMSP: Computerized Medical Support Program
<sup>p</sup>NRS: Numeric Rating Scale
<sup>q</sup>PAM-13: Physical Activity Measure-13
<sup>r</sup>LFD: Low FODMAP Diet
<sup>s</sup>LFDK Quest: Low FODMAP Knowledge Questionnaire
<sup>t</sup>VAMS: Visual Analogue Mood Scale
<sup>u</sup>TEAEs: Treatment-emergent adverse events
<sup>v</sup>NRS: Numeric Rating Scale

https://mhealth.jmir.org/2023/1/e40844
<table>
<thead>
<tr>
<th>Study</th>
<th>CP&lt;sup&gt;b&lt;/sup&gt; condition</th>
<th>Study outcomes (measurement tools)</th>
<th>RoB</th>
<th>Outcome results&lt;sup&gt;c&lt;/sup&gt;</th>
<th>Functional disability</th>
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<tbody>
<tr>
<td></td>
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<td>Primary</td>
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<td>Pain intensity</td>
<td>QoL&lt;sup&gt;d&lt;/sup&gt;</td>
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<td>Secondary</td>
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<tr>
<td>Thiengwit- &lt;br/&gt;tayaporn et al [39]</td>
<td>Knee OA</td>
<td>• Patient’s ability to correctly perform the exercises (80% completed exercise repetitions)</td>
<td>+</td>
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<td></td>
<td></td>
<td>• Range of motion (goniometer)</td>
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<td>• Pain intensity, symptoms, daily life activities, PA and sports performed, and QoL (KOOS)</td>
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<td></td>
<td></td>
<td>• Satisfaction/expectation with functional ability (Knee Society Score [KSS])</td>
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<td></td>
<td>CNP&lt;sup&gt;e&lt;/sup&gt;</td>
<td>• Pain intensity (VAS&lt;sup&gt;f&lt;/sup&gt;)</td>
<td>N/A</td>
<td>X</td>
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<td></td>
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<td>• Muscle tension (VAS)</td>
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<td>• Pressure pain threshold (pressure algometry)</td>
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<td>• Cervical range of motion (CROM; device)</td>
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<td></td>
<td>• Acceptability assessment (System Usability Scale [SUS])</td>
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<tr>
<td>Yang et al [41]</td>
<td>CLBP&lt;sup&gt;f&lt;/sup&gt;</td>
<td>• Pain intensity (VAS)</td>
<td>N/A</td>
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<td></td>
<td></td>
<td>• Disability (Roland-Morris Disability Questionnaire [RMDQ])</td>
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<td>• QoL. (SF-36)</td>
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<td>• Self-efficacy (Pain Self-Efficacy Questionnaire [PSEQ])</td>
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<tr>
<td>Yuan et al [42]</td>
<td>FM&lt;sup&gt;g&lt;/sup&gt;</td>
<td>• QoL. (FIQ&lt;sup&gt;h&lt;/sup&gt;)</td>
<td>+</td>
<td>=</td>
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<td></td>
<td></td>
<td>• Pain intensity (VAS)</td>
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<td>• Function (FIQ-Function)</td>
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<td>• Painful body regions (Widespread Pain Index [WPI])</td>
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<td>• Symptom Severity (SS) scale</td>
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<td></td>
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<td>• Self-care (Appraisal of Self-Care Agency Scaled-Revised [ASAS-R])</td>
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<tr>
<td>Fanning et al [43]</td>
<td>CP</td>
<td>• QoL. (SF-36)</td>
<td>N/A</td>
<td>+</td>
<td>N/A</td>
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<tr>
<td></td>
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<td>• Physical functioning (SF-36: physical functioning subscale)</td>
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<td></td>
<td>• Self-efficacy for walking (8-item scale)</td>
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<td>• Satisfaction with physical functioning (7-item scale)</td>
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</tbody>
</table>

<sup>a</sup>RoB: risk of bias; interpretation of RoB: +, low RoB; –, some concerns; X, high RoB.

<sup>b</sup>CP: chronic pain.

<sup>c</sup>Interpretation of outcome results: *, significant differences ($P<.05$) in favor of the mHealth group; =, nonsignificant differences between groups.

<sup>d</sup>QoL: quality of life.

<sup>e</sup>OA: osteoarthritis.

<sup>f</sup>ArWOMAC: Arabic version of Western Ontario and McMaster.

<sup>g</sup>N/A: not applicable.

<sup>h</sup>WOMAC: Western Ontario and McMaster.

<sup>i</sup>SF-36: 36-item Short-Form Health Survey.

<sup>j</sup>KOOS: Knee injury and Osteoarthritis Outcome Score.

<sup>k</sup>HOOS: Hip injury and Osteoarthritis Outcome Score.

<sup>l</sup>PA: physical activity.

<sup>m</sup>IBS: irritable bowel syndrome.
nNRS: numeric rating scale.
oCMSP: chronic musculoskeletal pain.
pCNP: chronic neck pain.
qVAS: visual analogue scale.
rCLBP: chronic low back pain.
sFM: fibromyalgia.
tFIQ: Fibromyalgia Impact Questionnaire.
<table>
<thead>
<tr>
<th>Study</th>
<th>CPb condition</th>
<th>Study outcomes (measurement tools)</th>
<th>RoB</th>
<th>Outcome resultsc</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Primary</td>
<td>Secondary</td>
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<tr>
<td>Forbes et al [44]</td>
<td>CPPc</td>
<td>Pain-related disability (Chronic Pain Grade-Disability subscale)</td>
<td>Study feasibility (CPAQ)</td>
<td></td>
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<td>App usability (System Usability Scale [SUS])</td>
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<td>Adherence to the app (frequency of app use)</td>
<td></td>
</tr>
<tr>
<td>Gohir et al [45]</td>
<td>Knee OA}</td>
<td>Pain intensity (NRSb)</td>
<td>Physical functioning (WOMAC, Timed Up &amp; Go [TUG], and 30-second sit-to-stand test)</td>
<td></td>
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<td></td>
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<td>QoL. (Musculoskeletal Health Questionnaire [MSK-HQ])</td>
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<td>Symptoms sensory (pressure pain threshold [PPT])</td>
<td></td>
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<tr>
<td>Hunt et al [46]</td>
<td>IBSd</td>
<td>QoL. (Irritable Bowel Syndrome Quality of Life [IBS-QOL])</td>
<td>Diagnostic criteria for IBS (Rome IV)</td>
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<td>Fear of food (Fear of Food Questionnaire [FFQ])</td>
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<td>Gastrointestinal (GI) symptom-specific anxiety (Visceral Sensitivity Index [VSI])</td>
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<td>Cognitions-related impact (Gastrointestinal Cognition Questionnaire [GI-COG])</td>
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<td>Depression and anxiety (Depression Anxiety Stress Scale [DASS])</td>
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<td>Diagnosis and depressive symptom severity (Patient Health Questionnaire [PHQ])</td>
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<td>Dose (number of app modules completed)</td>
<td></td>
</tr>
</tbody>
</table>

a Overall RoB assessment, study outcomes, and main results (studies 12-22). 

b Pain intensity 
c QoLd 
d Functional disability 

e CPP is a condition specific measure. 

f Pain acceptance (chronic pain acceptance questionnaire [CPAQ]) 

g Gohir et al [45] 

h Pain intensity (NRS) 
i WOMAC 
j Hunt et al [46] 
k IBS 
l Diagnostic criteria for IBS (Rome IV) 
m Fear of food (Fear of Food Questionnaire [FFQ]) 

n <ref> More references and terms are available in the full publication. </ref>
<table>
<thead>
<tr>
<th>Study</th>
<th>CP&lt;sup&gt;b&lt;/sup&gt; condition</th>
<th>Study outcomes (measurement tools)</th>
<th>RoB</th>
<th>Outcome results&lt;sup&gt;c&lt;/sup&gt;</th>
<th>Pain intensity</th>
<th>QoL&lt;sup&gt;d&lt;/sup&gt;</th>
<th>Functional disability</th>
</tr>
</thead>
</table>
| Irvine et al | CLBP<sup>k</sup>         | Physical outcomes:  
- Pain intensity, episodes, and duration (back pain scales)  
- Daily pain management activities  
- Functionality (10-item scale based on Multidimensional Pain Inventory Interference Scale [MPI] and Brief Pain Inventory [BPI])  
- QoL (Dartmouth Primary Care Cooperative Information Project [Dartmouth CO-OP] scale)  
Prevention-helping behaviors  
Worksite outcomes:  
- Worker productivity (4-item Work Limitations Questionnaire [WLQ])  
- Presenteeism (Stanford Presenteeism Scale)  
Other outcomes:  
- Responsibility of own health (Patient Activation Measure [PAM])  
- Behavior constructs (knowledge, behavioral intentions, and self-efficacy)  
- Attitudes toward pain (10-item Survey of Pain Attitudes [SOPA])  
- Catastrophizing of pain (Tampa scale) | – | N/A | * | * |
| Lee et al    | FM<sup>l</sup>            | Pain intensity (VAS)<sup>g</sup>  
QoL (EuroQoL-5D)  
Disease impact (FIQ)<sup>n</sup>  
Depression index (Beck’s Depression Index [BDI])  
Patient global assessment (patient global assessment [PtGA]) | X | * | = | = |
| Lee et al    | CNP<sup>o</sup>           | Pain intensity (VAS)  
Functional disability (NDI)<sup>p</sup>  
QoL (SF-36)<sup>g</sup>  
Maximal voluntary strength (digital handheld dynamometer)  
Fear avoidance belief (Fear-Avoidance Belief Questionnaire [FABQ])  
Exercise adherence (app) | – | * | = | * |
| Lee et al    | IC/BPS<sup>r</sup>         | QoL (SF-36)  
Symptoms (O’Leary-Sant symptom)  
Physical function, role physical, bodily pain, vitality, social function, role emotional and mental health (SF-36 subscales) | X | * | = | = |
| Abadiyan et  | CNP                      | Pain intensity (VAS)  
Disability (NDI)  
QoL (SF-36)  
Endurance (progressive isoinertial lifting evaluation [PILE] test)  
Forward head posture (craniovertebral angle) | + | * | * | * |
| Amorim et    | CLBP                     | Pain intensity (NRS)  
Disability (Roland-Morris Disability Questionnaire [RMDQ])  
Care seeking (health care consultations)  
Self-reported PA<sup>s</sup> level (International Physical Activity Questionnaire [IPAQ])  
PA data (accelerometer) | + | = | N/A | = |
| Chhabra et   | CLBP                     | Only for GI:  
Daily PA (activity tracker built within the app)  
Progress in symptoms (Current Symptom Score [CSS]) | + | = | N/A | * |
Outcome results

<table>
<thead>
<tr>
<th>Study</th>
<th>CPb condition</th>
<th>Study outcomes (measurement tools)</th>
<th>RoB</th>
<th>Outcome results(^c)</th>
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<td>Functional disability</td>
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<td>Pach et al [^{[54]}]</td>
<td>CNP</td>
<td>• Pain intensity (numeric pain rating scales [NPRS])</td>
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<td>• Disability (Modified Oswestry Disability Index [MODI])</td>
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<td>• Pain intensity during first 3 months (NRS)</td>
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<td>• Pain intensity, weekly and during the 6 months (NRS)</td>
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<td>• Adherence</td>
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</table>

\(^a\)RoB: risk of bias; interpretation of RoB: +, low RoB; –, some concerns; X, high RoB.

\(^b\)CP: chronic pain.

\(^c\)Interpretation of outcome results: *, significant differences (\(P<.05\)) in favor of the mHealth group; =, nonsignificant differences between groups.

\(^d\)QoL: quality of life.

\(^e\)CPP: chronic pelvic pain.

\(^f\)N/A: not applicable.

\(^g\)OA: osteoarthritis.

\(^h\)NRS: numeric rating scale.

\(^i\)WOMAC: Western Ontario and McMaster.

\(^j\)IBS: irritable bowel syndrome.

\(^k\)CLBP: chronic low back pain.

\(^l\)FM: fibromyalgia.

\(^m\)VAS: visual analogue scale.

\(^n\)FIQ: Fibromyalgia Impact Questionnaire.

\(^o\)CNP: chronic neck pain.

\(^p\)NDI: Neck Disability Index.

\(^q\)SF-36: 36-item Short-Form Health Survey.

\(^r\)IC/BPS: interstitial cystitis/bladder pain syndrome.

\(^s\)PA: physical activity.

**Discussion**

**Principal Findings**

This study provided an overview of the use of mHealth systems for the self-management of patients with different CP conditions. To the best of our knowledge, this is the first systematic review that identifies the available mHealth interventions and their effects on pain intensity, QoL, and functional disability in patients with CP. Results showed that some interventions based on mHealth systems have beneficial effects on reducing pain and functional disability and improving the QoL. Thus, the scientific evidence suggests that these systems could be a promising alternative in CP self-management through multimodal approaches.

Regarding the analyzed outcomes, 9 of the 17 studies assessing pain intensity [33-35,37,40,45,48,49,51] showed significant effects in reducing pain in favor of the mHealth groups. There are several systematic reviews and meta-analyses that support these findings. Pfeifer et al [21] showed that mHealth apps are more effective in reducing pain when compared to control interventions in patients with different CP conditions, such as general CP, CLBP, CNP, arthritis (rheumatoid and OA), menstrual pain, frozen shoulder pain, and migraine. Nevertheless, the authors stated that most of the included studies used co-interventions (eg, physiotherapy, self-management booklets, pharmacological approach, and wearable activity monitors), in addition to using mHealth systems. Likewise, Moman et al [14] observed significant short- and intermediate-term improvements in pain-related outcomes in patients with CP, CLBP, FM and OA, and Thurnheer et al [22] reported a decrease in pain severity in patients with several CP diagnoses (chronic cancer pain, general CP, CLBP, CNP, menstrual pain, and also acute pain) using mobile apps for their management. Furthermore, focusing on the CP condition, Du et al [20] indicated that mHealth-based self-management programs for reducing pain show clinically important effects. Similarly, Chen et al [56] showed that the use of mobile apps for delivering PA programs is associated with significant pain relief in patients with knee OA or chronic knee pain.
Regarding the QoL, improvements were observed in 7 of 15 studies [34,36,39,46,47,50,51] involving several CP conditions (OA, CNP, CLBP, IBS, and IC/BPS). This result agrees with a previous systematic review [22] reporting that patients using a mHealth app for their self-management have a higher QoL compared to patients not using that system. Nevertheless, in the meta-analysis carried out by Chen et al [56], when analyzing the type of technology used for delivering PA programs, they observed that the use of the web is associated with significant improvements in the QoL in patients with knee OA or chronic knee pain, but the use of mobile apps or smartphones is not. This may be because only few of the studies included in this meta-analysis used mobile apps to deliver the interventions, making it difficult to examine the effects of this type of technology.

In the case of functional disability, we found some significant differences between mHealth and control groups in patients with musculoskeletal pain (CLBP [41,47,53], CNP [49,51], and CMSP [38]) and OA [34,35,45]. Nevertheless, these findings are not in line with the available literature. Chen et al [56] did not find evidence for a significant improvement in physical function with technology-supported PA programs. Likewise, results of meta-analyses of telehealth-based interventions, including mHealth and eHealth systems, have suggested that these interventions have no significant effects on physical functionality [14] and disability [57] at short- and intermediate-term follow-up. However, these results are provided by different technology-based interventions and not specifically mHealth systems, which are more recent technologies not sufficiently researched yet.

The types of intervention of the studies included in this systematic review were home-based PA programs, education, CBT, mind-body therapies, and monitoring. This is in line with a large review of the recommendations from clinical practice guidelines (CPG) for musculoskeletal pain, where 3 pillar interventions were identified as key self-management approaches: education, PA, and psychosocial therapies [58]. Similarly, Geraghty et al [59] analyzed the available self-management interventions for chronic widespread pain, with PA programs and medical information being the 2 most common components, followed by psychological approaches. Our findings reported that depending on the type of interventions carried out by mHealth, there are differences in their effects on study outcomes. In this regard, home-based PA programs and education, combined or isolated, showed significant effects on all outcomes compared to other interventions, especially in the case of functional disability. We also found that PA programs and education are commonly considered as cointerventions.

The use of PA as a clinical intervention is suggested as being adequate for several of the conditions included in this systematic review. In patients with OA, it showed a moderate effect on physical functioning, with high patient acceptability and limited side effects, being strongly recommended as conservative management [60]. Similarly, van Doormaal et al [61] reported that PA reduces pain and improves physical function and QoL, with strong-to-moderate evidence. Finally, the CPG for OA include specific exercise programs as core treatment of the nonsurgical management of this condition [58,62]. Moreover, for CLBP and CNP self-management, PA showed significant improvements in pain intensity and functional disability outcomes and slightly more effects on the QoL. In line with this, Bertozzi et al [63] and Price et al [64] reported significant improvement effects of PA programs on CNP in the short and intermediate terms. Nevertheless, both studies have mentioned that the effects of PA are not maintained in the long term, although no high-quality trials are available [63,64]. In the case of FM, although only Yuan et al [42] performed a home-based PA program, this type of intervention is strongly recommended in clinical guidelines for the management of this pathology [65,66]. In fact, previous evidence supports the effectiveness of different modalities of exercise (aerobic, strength, and functional training) in common symptoms of FM and QoL [67].

Education is also considered an essential component of conservative management. In fact, the included studies on several CP conditions applied this approach in isolation or in combination with other interventions, showing improvements in pain-related outcomes, functional disability, and QoL. Education usually includes information about the condition, its prognosis, possible consequences, associated factors, the importance of maintaining a healthy lifestyle, and self-care management options [58,60]. Education promotes feelings of hope and optimism and a positive expectation of the treatment benefits in patients with CP [62].

As previously mentioned, another key purpose of the CPG was to address the psychosocial factors related to CP, for which the internet-delivered interventions may be a means of increasing remote access to psychological care. In fact, the previous literature shows beneficial effects of internet-delivered cognitive and behavioral interventions for CP on pain intensity, disability, mood states, and QoL, supporting the use of technological devices for pain management outcomes [19,68]. In that line, CBT is the most studied and used and is especially important in some CP conditions, such as FM [65]. Evidence showed that patients with FM who received CBT showed reduced pain and improved health-related QoL and functional disability more than patients receiving usual care, no treatment, or other nonpharmacological interventions [69]. Similarly, Mascarenhas et al [70] found high-quality evidence in favor of CBT for pain in the short term but with a small effect size that did not reach the minimum clinically important change. Although CBT is a common treatment strategy in FM, the studies included in our systematic review did not apply this type of intervention for FM. However, CBT was applied to patients with both IBS and IC/BPS, showing improvements in QoL and functional disability outcomes. Guidelines recommend that the management of these CP conditions should include multimodal behavioral, physical, and psychological techniques [71].

Other self-management interventions delivered by mHealth systems found in the studies included in this review were the monitoring of pain, other symptoms (mood states, disease stages and impact, and adverse events), and PA parameters, isolated or as cointerventions of other therapies. In addition, mind-body components encompassing meditation, mindfulness, and relaxation techniques were found. Nevertheless, the results of these strategies were heterogeneous, showing only some slight differences when compared to usual care or similar intervention.
by traditional methods. Thus, it suggests that these interventions have insufficient evidence in CP to provide conclusive findings.

Regarding the overall methodological quality of the studies included, almost all of them reported medium methodological quality according to the Checklist for Measuring Quality. Nevertheless, some items related to internal and external validity were frequently scored as “null” or “unable to determine,” which could limit the interpretation and generalization of the results. Likewise, the results of the Cochrane RoB 2.0 assessment tool showed some concerns and a high RoB in the domain related to deviations from intended interventions due to the nature of the study design itself. Lack of blinding of participants is a common issue reported in research where the implementation of interventions depends on the participants, making it difficult to blind them. Similarly, lack of blinding of outcome assessors poses some concerns and a high RoB in the measurement outcome domain, which could also influence the interpretation of findings. Therefore, a future RCT should address these issues to strengthen the evidence on mHealth-based interventions for the self-management of patients with CP.

**Study Limitations and Recommendations for Future Research**

Although this systematic review provides a wide perspective on the use of mHealth for self-management of CP, some limitations should be remarked. First, due to the inclusion criteria of the study population, the heterogeneity among CP conditions and patient characteristics makes generalization of the findings not suitable for a specific CP condition. In addition, the high heterogeneity in terms of study interventions and outcome measures makes a meta-analysis not congruent enough to extract a quantitative synthesis of the findings. Third, due to the nature of the RCT, patients in most studies were aware of the interventions, so the effect of a placebo cannot be rejected and could suppose a risk of performance bias. Similarly, the lack of blinding outcome assessors poses a risk of detection bias, which could influence the interpretation of results. Therefore, future research with higher quality in these methodological aspects is needed. Fourth, in some studies, the sample size was small, in addition to losses to follow-up during ongoing research, which could limit the interpretation of the results and limit the drawing of conclusive evidence. Last, because we focused our study on the adult population with CP conditions, the review did not provide information about the effects that the mHealth systems might have on children and adolescents. This could be of interest for future research, as this type of intervention may be attractive and motivating for those populations who are currently familiar with the use of mobile technologies.

**Conclusion**

This systematic review analyzed the effects of mHealth systems on self-management interventions in patients with different CP conditions, showing beneficial effects on pain intensity, QoL, and functional disability. Concretely, mHealth systems showed positive effects on pain intensity in CNP, FM, IC/BPS, and OA; on the QoL in CLBP, CNP, IBS, and OA; and on functional disability in CLBP, CMSP, CNP, and OA. No statistically significant changes for any of the study outcomes were observed in patients with unspecified CP and CPP. Despite the methodological limitations, mHealth systems seem to be a promising alternative for the management of patients with CP through a biopsychosocial framework. Indeed, there is a wide variety of mHealth systems for the management of CP, ranging from the monitoring of pain and symptoms to therapeutic approaches, mainly based on exercise, education, and psychosocial components. However, further clinical studies of high methodological quality are needed to consolidate the scientific evidence and recommendations for the use of mHealth systems in patients with CP.

**Acknowledgments**

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**Authors' Contributions**

MM-L, JAM-M, AS, and IF were responsible for conceptualization, methodology, and writing—review and editing, and MM-L and JAM-M for writing—original draft preparation. All authors have read and agreed to the published version of the manuscript.

**Conflicts of Interest**

None declared.

Multimedia Appendix 1

Complete search strategy.

[PDF File (Adobe PDF File), 49 KB - mhealth_v11i1e40844_app1.pdf ]

Multimedia Appendix 2
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**Abbreviations**

- **CBT**: cognitive behavioral therapy
- **CLBP**: chronic low back pain
- **CMSP**: chronic musculoskeletal pain
- **CNP**: chronic neck pain
- **CP**: chronic pain
- **CPG**: clinical practice guidelines
- **CPP**: chronic pelvic pain
- **FIQ**: Fibromyalgia Impact Questionnaire
- **FM**: fibromyalgia
- **HOOS**: Hip injury and Osteoarthritis Outcome Score
- **IBS**: irritable bowel syndrome
- **ICD-11**: International Classification of Diseases 11th Revision
- **IC/BPS**: interstitial cystitis/bladder pain syndrome
- **KOOS**: Knee injury and Osteoarthritis Outcome Score
- **mHealth**: mobile health
- **NDI**: Neck Disability Index
- **NRS**: numeric rating scale
- **OA**: osteoarthritis
- **OCEBM**: Oxford Centre for Evidence-Based Medicine
- **PA**: physical activity
- **PRISMA**: Preferred Reporting Items for Systematic Reviews and Meta-Analysis
- **QoL**: quality of life
- **RCT**: randomized controlled trial
- **RoB**: risk of bias
- **SF-36**: 36-item Short Form Health Survey
- **VAS**: visual analogue scale
- **WOMAC**: Western Ontario and McMaster
Review

The Feasibility of Using Smartphone Sensors to Track Insomnia, Depression, and Anxiety in Adults and Young Adults: Narrative Review

Doaa Alamoudi¹, PhD; Emma Breeze², BSc; Esther Crawley³, PhD; Ian Nabney¹, PhD

¹Department of Computer Science, University of Bristol, Bristol, United Kingdom
²Bristol Medical School, University of Bristol, Bristol, United Kingdom
³Centre for Academic Child Health, University of Bristol Medical School, University of Bristol, Bristol, United Kingdom

Corresponding Author:
Doaa Alamoudi, PhD
Department of Computer Science
University of Bristol
Merchant Venturers’ Building
Woodland Road
Bristol, BS8 1UB
United Kingdom
Phone: 44 117 928 3000
Email: d.alamoudi@bristol.ac.uk

Abstract

Background: Since the era of smartphones started in early 2007, they have steadily turned into an accepted part of our lives. Poor sleep is a health problem that needs to be closely monitored before it causes severe mental health problems, such as anxiety or depression. Sleep disorders (e.g., acute insomnia) can also develop to chronic insomnia if not treated early. More specifically, mental health problems have been recognized to have casual links to anxiety, depression, heart disease, obesity, dementia, diabetes, and cancer. Several researchers have used mobile sensors to monitor sleep and to study changes in individual mood that may cause depression and anxiety.

Objective: Extreme sleepiness and insomnia not only influence physical health, they also have a significant impact on mental health, such as by causing depression, which has a prevalence of 18% to 21% among young adults aged 16 to 24 in the United Kingdom. The main body of this narrative review explores how passive data collection through smartphone sensors can be used in predicting anxiety and depression.

Methods: A narrative review of the English language literature was performed. We investigated the use of smartphone sensors as a method of collecting data from individuals, regardless of whether the data source was active or passive. Articles were found from a search of Google Scholar records (from 2013 to 2020) with keywords including “mobile phone,” “mobile applications,” “health apps,” “insomnia,” “mental health,” “sleep monitoring,” “depression,” “anxiety,” “sleep disorder,” “lack of sleep,” “digital phenotyping,” “mobile sensing,” “smartphone sensors,” and “sleep detector.”

Results: The 12 articles presented in this paper explain the current practices of using smartphone sensors for tracking sleep patterns and detecting changes in mental health, especially depression and anxiety over a period of time. Several researchers have been exploring technological methods to detect sleep using smartphone sensors. Researchers have also investigated changes in smartphone sensors and linked them with mental health and well-being.

Conclusions: The conducted review provides an overview of the possibilities of using smartphone sensors unobtrusively to collect data related to sleeping pattern, depression, and anxiety. This provides a unique research opportunity to use smartphone sensors to detect insomnia and provide early detection or intervention for mental health problems such as depression and anxiety if insomnia is detected.

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KEYWORDS
mHealth; digital; health; mental health; insomnia; technology; sleep; risk; cardiovascular disease; diabetes; men; mortality; sleep disorder; anxiety; depression; heart disease; obesity; dementia; sensor; intervention; young adult

Introduction

Background

Insomnia is defined as inadequate sleep, with the most common causes being poor sleep conditions and stress [1]. It has also been defined as the presence of long sleep latency, also called sleep onset latency; the elapsed time from being fully awake to sleeping [2]. Sleep latency differs from person to person. Sleep latency and how quickly we reach rapid eye movement (REM) sleep can be indicators of the quantity and quality of sleep. Good sleep quality is measured by the time falling asleep (the ideal is 15 to 20 minutes), the ability to stay asleep all night without waking up, and the ability to spend at least 85% of the time asleep rather than awake [3,4].

About 40% of people who are diagnosed with insomnia symptoms also report mental health problems [5]. Mental health problems and insomnia are linked in significant ways, where insomnia is a common diagnostic symptom for depression and anxiety [5]. Compared to the longstanding perspective that regarded sleep issues as related to symptoms of mental problems, there is growing research evidence that the relationship between mental disorders and insomnia is problematic and includes bidirectional causation.

The Risk of Insomnia

Mendelson et al [6] were the first to publish findings on this topic; they found that over 90% of depressed patients complained about impaired sleep quality. Several early epidemiological studies found similar strong associations: Ford and Kamerow [7], in 1989, found that people with chronic insomnia were 40 times more likely to have major depression and 6 times more likely to have an anxiety disorder. Mellinger et al [8], in 1985, found that there was a significant association between insomnia and depression. This led to the generally accepted concept that insomnia is one of the core symptoms of psychopathology.

Insomnia and depression share multiple underlying mechanisms. Both conditions have been shown to be triggered by psychosocial stressors, which can then cause overactivity of arousal-inducing neurons in the central nervous system (CNS) compared to the sleep-promoting areas, leading to hyperarousal (Figure 1) [9,10]. Another hypothesis is that insomnia could disrupt synaptic plasticity and neural network function, both of which could precipitate depression [11].

More recent studies started to find that insomnia can be an independent indicator for depression. This is highlighted by a 2011 meta-analysis by Baglioni et al [12] of 21 longitudinal epidemiological studies, which found “an overall odds ratio for insomnia to predict depression” of 2.60 (95% CI 1.98-3.42). Results from a 2016 meta-analysis were consistent with these findings (risk ratio 2.27, 95% CI 1.89-2.71) [13]. The recent evidence triggered a change in international guidelines, with insomnia being included in the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition, a commonly used diagnostic tool, as an independent disorder. This therefore means that insomnia, although still very closely linked to depression, is no longer classified as “primary” or “secondary” and is now considered a disorder in its own right [14,15].

Nyer et al [16] conducted a study to explore the association of sleep disturbance and depressive symptoms in 287 college students with depressive symptoms. The study assumed that students with depressive symptoms and sleep disturbance would have a significant burden of psychiatric symptoms compared to those who had depressive symptoms without sleep disturbance. The study addressed its aims by using different self-report scales, such as the Beck Depression and Anxiety

Figure 1. Brain mechanisms of insomnia (adapted from Someren [9], with permission from the American Physiological Society). ANS: autonomic nervous system; REM: rapid eye movement.
inventories [17,18], the Beck Hopelessness Scale [19], the Anxiety Symptoms Questionnaire [20], the Massachusetts General Hospital Cognitive and Physical Functioning questionnaire [21], and the Quality-Of-Life Enjoyment and Satisfaction questionnaire [22]. For all measures, descriptive statistics showed that the total number of students who had depression with sleep disturbance was 220, and the remaining 67 students had depression without sleep disturbance problems. The results further showed that students who had depressive symptoms with sleep disturbance experienced a significant burden of anxiety symptoms compared to those with depressive symptoms without sleep disturbance [16].

A similar study conducted by Samarayake et al [23] among university students found that a large number of students were affected by depression and anxiety due to sleep disorders. A total of 1933 students completed a self-report survey. The study found that 39.4% of the students had a sleep disorder lasting over a month. Moreover, depression and anxiety were present in 17.3% and 19.7% of students, respectively, and 7.3% of the students had thought of self-harm.

Studies have shown the close relationship between sleep disorders and mental health problems. Poor sleep quality, defined as waking up frequently during the night, may cause mental health issues such as depression and anxiety. Also, mental health problems could affect an individual’s sleep pattern. Anxiety due to worries or repetitive thoughts might keep their brain awake. These symptoms have to occur at least 3 times a week over a period of at least 3 months in order to be diagnosed as insomnia disorder [11]. Furthermore, studies have shown that insomnia is associated with an increased risk of depression.

Methods

The main research criterion we looked at in the publications was the use of smartphone sensors to track sleep. We excluded studies that monitored sleep using other tools, such as wearable devices, electroencephalography headsets, or dream headbands. The reason for excluding these factors was the possibility of finding a method that can track sleep unobtrusively. According to Deloitte’s seventh annual mobile consumer survey, around 79% of young adults check their phones before going to sleep [24].

We looked at different studies that monitored sleep using smartphone sensors. The total sample population was up to 205 university students and adults. The designed studies used the Android operating system to collect the data. We categorized the studies based on whether they monitored sleep with a single or multiple sensors.

Anxiety and depression are common, with a prevalence of 18% to 21% among young adults aged 16 to 24 in the United Kingdom [25]. As we wanted to study the relationship between poor sleep and anxiety and depression, we looked to a range of different studies that used mobile sensors to detect individuals’ behavior. They predicted changes in mood using behavioral signals such as location, mobility, speech pattern, phone use, and activities. We excluded papers that discussed other mental health issues, such as bipolar disorder or schizophrenia, and articles that examined changes in mood using other methods, such as physiological and social signals.

Results

In the field of measuring sleep via smartphone sensors, we found a total of 7 published articles that used mobile sensors to passively collect data [8,14,26-30]. A total of 5 articles discussed the use of mobile sensors to track depression and anxiety [31-35].

Smartphone Sensors for Sleep Detection

With the widening reach of technology, several groups have carried out sleep studies relying on smartphone sensors [36-38]. The accelerometer embedded in every smartphone has been used to measure phone (hence body) movement to understand sleep stage [27]. Room environment conditions can be measured and monitored by other smartphone sensors to estimate sleep quality. Room environmental variables that can be measured by smartphone sensors to assess the quality of the environment include noise [27,39,40], luminosity or darkness [40], and temperature [41]. Screen on/off timing has been used in several studies as an indicator of sleeping time and duration [27,28,30]. Microphone sensors can also measure an individual’s snoring, which might impact their sleep quality [26]. Snoring can lead to fragmented and unrestful sleep, which often causes poor daytime functioning (tiredness and sleepiness) [41]; moreover, snoring is common among people aged 60 years or older [42,43].

Single-Sensor Method

The iSleep app, which was developed by Hao et al [26], aims to replace wearable devices in sleep tracking by relying on the built-in microphone. The algorithm was able to classify several types of extraneous noise, such as that from fans and air conditioners. However, in order to collect sleep events, the user is required to turn on the app and place the phone in a certain location, and this requires user intervention on a daily basis. That means that in order to calculate sleep duration, the user needs to manually start and close the app. Two matrices (snoring and coughing detection) are used to evaluate the accuracy of the app. During the experiment, the smartphone or tablet is used to collect acoustic data and should be placed 1.5 meters away. A second omnidirectional microphone attached on the headboard and connected to a laptop collects high-quality audio. The microphone should be placed 5 meters away from the bed to avoid noises coming from the laptop fan that might impact the quality of the collected data. Additionally, an iPod is used to record any movement on the bed. The iSleep app uses microphone sensors to collect data related to sleep pattern without considering privacy-sensitive data sets from the user’s smartphone. However, the complicated procedure used to detect sleeping patterns will be difficult to implement in daily life, as it requires a detailed room setup and user intervention, which may be difficult for young adults. Also, although the app has been tested among young adults aged between 20 and 30 years, the prevalence of snoring among young adults is only around 10%, although it increases with age [42,43].
A “tappigraphy” sensor has also been used to measure sleeping patterns [29]. Tappigraphy involves measuring touchscreen events and comparing them with both actigraphy and a daily sleep diary. The study design is based on calculating the number of times the user touches their phone and follows a 24-hour sleep-wake cycle. The longest period of not using the phone is considered to be sleeping time. Tappigraphy overestimates sleeping time compared to actigraphy when a low number of touchscreen touches are measured per day [29]. The sample size of this study was 79 users aged between 16 and 45 years. The large variation in the subjects’ age may have made the data collected an inaccurate reflection of reality, as students and workers have different phone-use styles. Usually, older people spend less time using their phone compared to younger people [44]. The 24-hour sleep-wake cycle might also not have been accurate, especially if the user was a worker or a student, as sometimes, they may need to avoid using their phone during working or class time, affecting the accuracy of predictions of sleeping time, whether this was during the day or the night.

Mobile apps that use screen on/off events to measure sleeping pattern have been discussed in several research papers [28,30,38]. A study based on computing circadian rhythm focused on detecting the chronotype, which means the activity and sleep preferences of an individual within a 24-hour period, and the impact of social jet lag on sleep duration using an unobtrusive and low-cost method based on on/off screen sensors among 9 subjects aged between 19 and 25 years [28]. In order to obtain accurate results, the sleep duration was calculated using a ground truth determined by sleep diaries that were collected daily from participants. When comparing the app performance with the sleep-diary data, there was less than 45 minutes of error. The study showed that participants with an early chronotype experienced the most social jet lag, due to social pressure applied by people with later chronotypes on weekends. However, the study was only interested in determining sleep onset that happened between late night and early morning, without taking into consideration individual preferences. For example, international students who have different sleep times in their home country may adjust their sleep time to be able to contact their family and friends when they are available.

The Know Addiction app [38] was developed to monitor the link between circadian rhythm and individual sleeping patterns using smartphone screen on/off events during a predetermined sleeping window; this window was the period between 10 PM and 10 AM among 61 subjects who were non–shift workers and aged between 20 and 56 years. The app collected total sleep duration according to different parameters. The 3 parameters that were used to measure sleeping pattern were as follows: reactive use episode, proactive use episode, and nonuse episode. A reactive use episode was defined as any notification within 1 minute prior to a screen-on event. In contrast, a proactive use episode was defined as no notifications within 1 minute prior to a screen-on event. The app excluded all reactive use episodes in the sleep indicators calculation. The third parameter was nonuse episodes, defined as a screen on/off event. Sleeping time was determined by measuring the maximal nonuse episode within the predetermined sleeping window. Overall, the study results showed that total daily duration of smartphone use was statistically significantly correlated with delayed sleep onset (correlation 0.0808, 95% CI 0.0434-0.1182; P<.05) The study was limited to tracking sleeping patterns and did not attempt to measure other health or mental health issues. However, the predetermined sleeping window of 10 PM to 10 AM could not accurately estimate all individuals’ sleep duration, as having mental health problems such as depression or anxiety means that sleep may not occur during the defined sleeping time window. An individual with depression symptoms would prefer to sleep for a longer time than the estimated sleeping time window.

The iSenseSleep app [30] lists all screen on/off events and then analyzes them to estimate sleep duration; it was validated in different groups (4 working mothers and 10 university students). The algorithm provides a list of all time points related to sleep episodes; the iSenseSleep app then considers the longest period to be the sleeping time, ignoring any disturbance that is less than 5 minutes. The app was designed to estimate sleeping time occurring during the night from 10 PM onwards. The app was designed to estimate sleep duration during the normal sleeping time, ignoring those who have changes in their sleeping pattern, for example, weekdays versus weekend days, where the sleeping time may differ. The iSenseSleep app estimates the wake-up time by checking the last screen-on event in the morning that was at least 4 hours since the last screen-off event. The app was able to predict sleep duration with an average error of 24 (SD 17) minutes (7%, SD 4% of the total duration). The estimation of sleep duration was more accurate among university students than working mothers, with an average error of 68 minutes (17% of the total) and 83 minutes (20% of the total), respectively. However, the iSenseSleep app was only used for 2 days to predict the sleeping pattern of the user for the rest of the nights, and that may not reflect the reality of changes in their sleeping pattern over time, especially for people who have problems with depression and anxiety.

Although the above studies conducted their research to understand individual sleeping patterns based on screen on/off events and tappigraphy, sleep quality was not determined in these studies. Sleep quality measures disturbance time, which is when the user wakes up in the middle of the night before going back to sleep. The user can also be asked to enter their sleeping time for working days and weekend days, so their sleeping pattern and sleep quality can be accurately predicted.

**Multiple Sensor Modalities**

Chen et al [27] developed Best Effort Sleep (BES), an Android mobile app to estimate sleep duration without user intervention by collecting data from multiple mobile sensors, including the light sensor and the microphone, as well from phone use and whether the device was in stationary mode (ie, not moving). The authors also developed another mobile app, known as Sleep With the Phone (SWP). SWP was developed to collect sleeping data using the accelerometer, with a strict protocol the user needs to follow in order to ensure accuracy while collecting the data, which includes placing the phone on the pillow when the user intends to sleep. Over 1 week with 8 participants, the accuracy of the BES app was tested with SWP and other
commercial wearable systems, such as a Jawbone wristband and Zeo headband. When evaluating the accuracy of sleep monitoring using BES, SWP, Jawbone, and Zeo, the authors found that BES achieved a sleep duration error of plus or minus 42 minutes. The use of BES can be considered as an ideal approach to sleep monitoring in terms of its low cost and reduced need for user intervention to record the data, avoiding putting a burden on the user. However, room environment observations might not be considered a good predictor to rely on when predicting sleeping time, as some people may sleep while the room light is turned on. In addition, in the case that the user forgets to recharge the phone, the app will consider that the user is sleeping, as it is in the phone-off mode. The study showed that light and phone-off features contributed to lowering error.

Toss ’N’ Turn (TNT) is an Android mobile app developed to investigate how smartphones can detect bedtime, wake time, and sleep duration without requiring changes in people’s behavior and thus estimate the regularity of sleep quality [36]. A total of 27 participants were studied who were aged between 20 and 59 years. The algorithm observes the sensor logs for the accelerometer, screen on/off events, light, microphone, and battery in a 10-minute window to classify a sleep or not-sleep state. It then eliminates possible sleep detection errors, such as noise or disturbance states, between quiet and stationary situations. The app produces errors of plus or minus 35 minutes, 31 minutes, and 49 minutes in detecting bedtime, wake time, and sleep duration, respectively. However, when the mobile smartphone sensors for detecting depression and anxiety problems. These studies have used mobile sensors to collect behavioral signals and later relate them to mental health problems.

Table 1 shows a summary of methods to determine sleep duration; column 3 shows the sample size for validation and column 4 shows the duration of the validation study.

Earlier studies have used unobtrusive methods to predict sleeping patterns without user intervention and have used various sensors to predict sleeping time and various techniques to determine sleep duration and quality. Moreover, earlier papers [28,30,38] have shown that sleep duration, bedtime, and wake time could be identified over a significant period with screen on/off events instead of complex sensors that require additional software, use protocols, or collect sensitive data, such as from the microphone.

### Table 1. Studies of mobile sensors to monitor sleep.

<table>
<thead>
<tr>
<th>Study characteristics</th>
<th>Sensors used</th>
<th>Study characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Authors</td>
<td>Year</td>
<td>Sample size, n</td>
</tr>
<tr>
<td>Hao et al [26]</td>
<td>2013</td>
<td>7</td>
</tr>
<tr>
<td>Borger et al [29]</td>
<td>2019</td>
<td>79</td>
</tr>
<tr>
<td>Abdullah et al [28]</td>
<td>2014</td>
<td>9</td>
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<tr>
<td>Lin et al [38]</td>
<td>2019</td>
<td>61</td>
</tr>
<tr>
<td>Chen et al [27]</td>
<td>2016</td>
<td>8</td>
</tr>
<tr>
<td>Min et al [36]</td>
<td>2014</td>
<td>27</td>
</tr>
</tbody>
</table>

*: indicates the type of sensor used in the study.

### Smartphone Sensors for Detecting Depression and Anxiety

The interest in studying the effectiveness of using smartphones for tracking individuals’ sleeping patterns and activities and the relationship with mental well-being has increased at a brisk pace. Over this period of technological advancement, a considerable amount of literature has been published using mobile sensors to categorize mental health and well-being. These studies have used mobile sensors to collect behavioral signals and later relate them to mental health problems. GPS has been used to study mental health problems such as depression [32,33,35]. These studies discussed a correlation between physical activities and mental health problems. DeMasi et al [32] aimed to track depression symptoms using GPS. Sleep duration was measured by estimating the longest period an individual was not physically active after 9 PM and individual physical activities during the day. A total of 47 undergraduate students installed the app over an 8-week period and completed a self-report survey related to depression and bipolar symptoms. The study showed a positive correlation between physical activities and estimated mental health status. There were limitations to activity recognition, especially that the smartphone was not in a fixed position, participants performed nonstandard activities.
activities, and the phones were set down, such as when they were left in a gym locker. Sleep duration and sleep disturbance could not be identified with a single sensor such as GPS.

Saeb et al [33] performed a study of 40 adult subjects over a 2-week period to detect daily life behavior and depression symptoms using GPS, including circadian movement (over 24 hours), location variance, and use of phone features. The data were collected and compared with self-report surveys. The accuracy achieved from this study in predicting depression symptoms through GPS and phone use was 86.5%. A similar study was conducted to study changes in mental health by tracking individuals’ activities and sleeping patterns using mobile sensors [31]. This study aimed to understand changes in depression and stress level using data collected from smartphone sensors. The data were collected from 47 young adults over a 10-week period. GPS was used to track individual daily activities while sleep duration was tracked based on light, microphone data, mobile use, and accelerometer data. The study used the algorithm developed for BES [27] to calculate sleep duration. Self-report surveys of stress and depression were collected on a daily basis. The result of the analysis showed a correlation between individual activities and sleep duration with daily stress and depression level.

StudentLife is an app that is run on smartphones and wearable devices [31,34]. The study was conducted for a 10-week period among a single class of 48 students whose age was between 19 and 30 years. The study aimed to track the engagement and performance of students on an individual level. StudentLife used different types of smartphone sensors, such as the accelerometer, microphone, light sensor, and GPS [31,34]. The microphone was coded to capture sounds every 2 minutes. In contrast, GPS was activated every 10 minutes to calculate the total daily distance moved by the individual. The accelerometer embedded in the smartphone was used to detect the ratio of movement versus being stationary. The study used data retrieved from device lock duration, the accelerometer, the microphone, and the light sensor to calculate sleep duration. A self-report was used to measure mental health status and depression (with the Patient Health Questionnaire-9) [45], perceived stress [46], flourishing [47], and loneliness scales [48]. However, the study did not consider that not carrying the phone during the day would prevent the app from accurately predicting data. For example, if the user left the phone at home, all the data from the microphone and accelerometer would not be collected on that day, and the system would assume that the person was stationary and quiet, which was interpreted as sleeping. In consequence, the predicted mental health state would not be accurate. Other difficulties arose from the app measuring sleep duration using the light level. If the user was from a high-latitude location, which is dark for most of the day, then the app would consider the dark time to be sleeping time. Also, if the user preferred to sleep while keeping the room light on, it would not predict bedtime and sleeping duration accurately.

From the previous studies, we can see that the proliferation of digital technologies and mobile sensors can provide a feasible and unobtrusive method to continuously collect behavioral data from individuals, which can help in better understanding the mental health condition of individuals. Using accelerometers and other phone [31,33] features has been shown to be an efficient way of understanding individuals’ behavior and mental well-being.

**Discussion**

**Principal Findings**

Mental health problems and sleep are linked in significant ways. Compared to the longstanding perspective that sleep issues are symptoms of mental problems, there is growing research evidence that the relationship between mental disorders and sleep is problematic and includes bidirectional causation.

Many people may not be aware of how their sleeping pattern can impact their health and well-being, seeking treatment only when physical and mental symptoms have started to manifest. Furthermore, both children and adults are reluctant to seek help, with only 1 in 3 receiving treatments for common mental health problems. These reasons, along with the increasing difficulty of accessing primary care services, leave room for an alternative method of insomnia identification. Smartphone sensor technologies in users’ phones may be a suitable method to track sleeping patterns and early sleep disorders. Using these technologies may prevent more serious symptoms arising.

Research has demonstrated the effectiveness of using mobile phone sensors to record personal data and predict mental health and well-being. Several apps have been developed to track behavioral signals and link them with individual mental health and well-being. These apps are based on wearable and nonwearable devices that collect data using accelerometers, microphones, light sensors, and screen on/off events.

**Conclusion**

This review describes the effectiveness of several sleep apps that have been used to track insomnia, which can cause depression and anxiety. Furthermore, the studies in this review found that using smartphone sensors to detect mental health problems can be useful for monitoring behavioral patterns that can cause depressive symptoms. Further study is needed in this area to understand the feasibility of using mobile sensors to track sleep disorders and provide early intervention and treatment when insomnia is detected, so as to reduce mental health problems.


Abbreviations

BES: Best Effort Sleep
CNS: central nervous system
REM: rapid eye movement
SWP: Sleep With the Phone
TNT: Toss ’N’ Turn
Effectiveness of Remote Fetal Monitoring on Maternal-Fetal Outcomes: Systematic Review and Meta-Analysis

Suya Li¹*, MSN; Qing Yang¹*, MSN; Shuya Niu², BS; Yu Liu¹, BS

¹Nursing Department, Tongji Hospital, Tongji Medical College, Huazhong University of Science and Technology, Wuhan, China
²Zhongnan Hospital of Wuhan University, Wuhan, China
*these authors contributed equally

Corresponding Author:
Yu Liu, BS
Nursing Department
Tongji Hospital, Tongji Medical College
Huazhong University of Science and Technology
No. 1095 Jiefang Rd
Wuhan, 430030
China
Phone: 86 13995579713
Email: hust512@sohu.com

Abstract

Background: To solve the disadvantages of traditional fetal monitoring such as time-consuming, cumbersome steps and low coverage, it is paramount to develop remote fetal monitoring. Remote fetal monitoring expands time and space, which is expected to popularize fetal monitoring in remote areas with the low availability of health services. Pregnant women can transmit fetal monitoring data from remote monitoring terminals to the central monitoring station so that doctors can interpret it remotely and detect fetal hypoxia in time. Fetal monitoring involving remote technology has also been carried out, but with some conflicting results.

Objective: The review aimed to (1) examine the efficacy of remote fetal monitoring in improving maternal-fetal outcomes and (2) identify research gaps in the field to make recommendations for future research.

Methods: We did a systematic literature search with PubMed, Cochrane Library, Web of Science, Embase, MEDLINE, CINAHL, ProQuest Dissertations and Theses Global, ClinicalTrials.gov, and Open Grey in March 2022. Randomized controlled trials or quasi-experimental trials of remote fetal monitoring were identified. Two reviewers independently searched articles, extracted data, and assessed each study. Primary outcomes (maternal-fetal outcomes) and secondary outcomes (health care usage) were presented as relative risks or mean difference. The review was registered on PROSPERO as CRD42020165038.

Results: Of the 9337 retrieved literature, 9 studies were included in the systematic review and meta-analysis (n=1128). Compared with a control group, remote fetal monitoring reduced the risk of neonatal asphyxia (risk ratio 0.66, 95% CI 0.45-0.97; \( P = .04 \)), with a low heterogeneity of 24%. Other maternal-fetal outcomes did not differ significantly between remote fetal monitoring and routine fetal monitoring, such as cesarean section (\( P = .21; I^2 = 0\% \)), induced labor (\( P = .50; I^2 = 0\% \)), instrumental vaginal birth (\( P = .43; I^2 = 0\% \)), spontaneous delivery (\( P = .85; I^2 = 0\% \)), gestational weeks at delivery (\( P = .35; I^2 = 0\% \)), premature delivery (\( P = .47; I^2 = 0\% \)), and low birth weight (\( P = .71; I^2 = 0\% \)). Only 2 studies performed a cost analysis, stating that remote fetal monitoring can contribute to reductions in health care costs when compared with conventional care. In addition, remote fetal monitoring might affect the number of visits and duration in the hospital, but it was not possible to draw definite conclusions about the effects due to the limited number of studies.

Conclusions: Remote fetal monitoring seems to reduce the incidence of neonatal asphyxia and health care costs compared with routine fetal monitoring. To strengthen the claims on the efficacy of remote fetal monitoring, further well-designed studies are necessary, especially in high-risk pregnant women, such as pregnant women with diabetes, pregnant women with hypertension, and so forth.

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Introduction

Fetal safety has always been a top priority for perinatal care. According to the World Health Organization, as of 2019, there were an estimated 2 million stillbirths, most of which can be prevented by safe and quality care, timely emergency care, and accurate recording [1]. Fetal monitoring is the primary means of monitoring to assess fetal safety and contributes to reducing the risk of stillbirth by detecting fetal hypoxia as early as possible [2,3]. Previous studies have repeatedly demonstrated the clinical value of fetal monitoring in reducing adverse perinatal outcomes (eg, neonatal cerebral palsy, hypoxic-ischemic encephalopathy, or stillbirth) [4,5].

Traditional antenatal care is resource intensive and not friendly to underserved settings. Beyond that, routine prenatal monitoring is only suitable for hospital settings, which means that pregnant women require regular outpatient follow-up [6]. Recurrent outpatient visits also pose additional travel risks (eg, falls, collisions, and bumps), especially for high-risk pregnant women. Telemedicine refers to the long-distance transmission of medical information between medical workers and patients through telecommunication technology [7], which has many potential advantages such as reducing outpatient time, alleviating the shortage of medical resources, reducing transportation costs and medical costs, and so forth [8-10]. Remote monitoring using telephones, websites, portable devices, and so forth during pregnancy is becoming more and more popular [11,12].

Systematic reviews have demonstrated the feasibility and superiority of telemedicine in obstetrics [13], focusing on blood pressure (BP) management [14,15], blood glucose management [16], and weight management [17] during pregnancy. However, we are not yet clear about the benefits or dangers of remote fetal monitoring. The primary objective of this systematic review was to assess the effectiveness of remote fetal monitoring for improving maternal-fetal outcomes. In addition, we also sought to analyze the cost-effectiveness of remote fetal monitoring compared to conventional prenatal monitoring.

Methods

Reporting Standards

This systematic review and meta-analysis was carried out according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines of 2009 [18] and was registered on PROSPERO as CRD42020165038.

Literature Retrieval

In total, 9 web-based databases were searched in March 2022, including PubMed (January 1966-March 2022), Cochrane Library (January 1947-March 2022), Web of Science (January 1990-Mar 2022), Embase (January 1974-March 2022), MEDLINE (January 1950-March 2022), CINAHL (January 1982-March 2022), ProQuest Dissertations and Theses Global (January 1899-March 2022), ClinicalTrials.gov (January 1997-March 2022), and Open Grey (January 1980-March 2022).

Search terms generated from the inspection of relevant papers were wielded to search for eligible studies, such as fetal, remote, telemetry, monitor, and so forth. The full search strategy was available in Multimedia Appendix 1 and was rerun before the final analysis.

Inclusion Criteria

Studies were considered eligible if they simultaneously met the following criteria: (1) pregnant women; (2) randomized controlled trials (RCTs) or quasi-experimental trials; (3) fetal monitoring data were transmitted to the central monitoring station by remote monitoring terminals; and (4) outcomes included at least 1 maternal-fetal outcome or health resource usage. There were no restrictions on language, nationality, or publication status.

Exclusion Criteria

Studies meeting any of the following criteria were excluded: (1) no control group in the study; (2) comparative studies of 2 or more remote monitoring technologies; and (3) the full text was still unavailable after contacting the original authors. Studies were not excluded due to monitoring settings (hospital, home, community setting, or mixed).

Outcome Measures

The primary outcomes were maternal-fetal outcomes (cesarean section, induced labor or miscarriage, instrumental vaginal birth, spontaneous delivery, gestational weeks at delivery, premature delivery, birth weight, and so on). The secondary outcomes were health care usage, which was assessed by on-site appointments, home visits, duration in the hospital, prenatal costs, and so on.

Study Selection

A 3-step screening identified articles that met the inclusion and exclusion criteria were literature retrieval, preliminary screening (title and abstract), and full-text screening. Literature retrieval was conducted by 2 investigators. All searched articles were uploaded into the reference management tool of EndNote. Articles with the same author, year, title, and so on were identified and removed by EndNote. Subsequently, 2 independent investigators (SYL and QY) selected all articles by evaluating the title and abstract after the removal of duplicates. Finally, the same 2 investigators (SYL and QY) identified the ultimately eligible articles by screening independently the full text according to the inclusion and exclusion criteria. In addition, the first author (SYL) hand-searched the references of the ultimately included literature to identify further publications. Any discrepancies and disagreements were finally resolved by consultation with a third reviewer (YL). We also contacted the original authors for verification if there were any uncertain technical types.

Data Extraction

Data from included studies were extracted by SYL and then cross-checked by another author (QY). A standardized data extraction form was designed by the research team and included...
the following data: (1) basic information of included studies (first author, year of publication, country, and study design); (2) characteristics of participants (maternal age, gestational weeks, sample size, and attrition rate); (3) characteristics of interventions (trial settings, duration of the intervention, monitoring personnel, monitoring content, feedback types, and technical support); and (4) outcomes measurement (maternal-fetal outcomes and health care usage). For insufficient data, we contacted the original authors via email. The standardized data extraction form was available in Multimedia Appendix 2.

Quality Assessment
Independently, the quality of eligible studies was assessed by 2 reviewers (SYL and QY) according to the Cochrane Risk of Bias Tool [19], which consisted of 7 items (random sequence generation, allocation concealment, blinding of participants and personnel, blinding of outcome assessment, incomplete outcome data, selective reporting, and other bias) with the responses of “low risk,” “high risk,” and “unclear risk.” The research was considered high quality with a low risk score on at least 4 domains, which must include 3 key domains (random sequence generation, allocation concealment, and incomplete outcome data) [20]. Consensuses between 2 investigators (SYL and QY) were reached by discussion with a third reviewer (YL).

Data Synthesis and Statistical Analysis
Quantitative analysis of included studies was carried out in Review Manager (RevMan) software (version 5.4). Continuous variables were presented as mean difference (MD), and dichotomous variables were described as risk ratio (RR) with a 95% CI. The statistical heterogeneity of selected studies was assessed by the chi-square test combined with $I^2$. Heterogeneity was divided into nonignorable heterogeneity ($I^2$ ranging from 0% to 40%), moderate heterogeneity ($I^2$ ranging from 30% to 60%), substantial heterogeneity ($I^2$ ranging from 50% to 90%) and considerable heterogeneity ($I^2$ ranging from 75% to 100%) [19]. When $I^2<40\%$, the fixed-effects model was adopted; otherwise, a random effect model was considered. In addition, sensitivity analysis and subgroup analysis were used to explore the sources of heterogeneity if needed.

Results
Study Selection
A total of 9337 studies were initially retrieved by searching 9 databases. After the 3-step screening, 8 studies met the inclusion and exclusion criteria. From a manual search of related references, 1 additional study was included. Finally, 9 RCTs were included in the systematic review and meta-analysis. The results of 1 study were published in 2 articles [21,22]. The detailed flow diagram of study selection is shown in Figure 1.

Figure 1. Flow diagram of study selection.
Study Characteristics

The characteristics of 9 RCTs are outlined in Table 1, involving 1128 participants from 6 countries. Seven studies were from developed countries (1 from the United States [23], 3 from the United Kingdom [24-26], 2 from the Netherlands [21,22], and 1 from Finland [27]). Only 2 studies were performed in developing countries (1 from China [28] and 1 from Mexico [29]). Eight of the screened studies were monocentric, and 1 was multicenter [26]. On the duration of interventions, 7 studies were carried out in the prenatal period [21-23,25,26,28,29], and 2 studies were conducted during labor [24,27]. In terms of participants, most of the included studies recruited high-risk pregnant women [21,22,25,26], and the remaining studies recruited low-risk pregnant women [23], late pregnant women [28], and pregnant women facing labor [24,25], respectively. The pooled mean age of pregnant women was 29.28 (SD 5.03) years in 6 RCTs [21-23,25-27].
<table>
<thead>
<tr>
<th>Author, year, country</th>
<th>Study design</th>
<th>Participants</th>
<th>Duration</th>
<th>Sample, N</th>
<th>Attrition rate (%)</th>
<th>Major characterization</th>
<th>Major results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Butler Tobah et al, 2019, United States [23]</td>
<td>2-arm RCT, monocentric</td>
<td>Low-risk pregnancies (IG: 29.5±3.3 years; CG: 29.7±3.6 years)</td>
<td>&lt;13 weeks of gestation to deliver</td>
<td>IG: N=134; CG: N=133</td>
<td>11</td>
<td>IG: OB Nest care (8 on-site appointments, 6 remote visits via phone or web-based communication) CG: usual care (12 prescheduled prenatal clinic appointments)</td>
<td>Pregnancy outcomes (cesarean, delivery, miscarriage, and preterm delivery); neonatal outcomes (low birth weight, and neonatal asphyxia); health care usage (on-site appointments, remote visits, and inpatient days)</td>
</tr>
<tr>
<td>Wang et al, 2019, China [28]</td>
<td>2-arm RCT, monocentric</td>
<td>Late pregnancies (IG: 22-40 years; CG: 22-38 years)</td>
<td>36-41 weeks of gestation to deliver</td>
<td>IG: N=80; CG: N=80</td>
<td>0</td>
<td>IG: remote FHR monitoring (3-4 times daily); CG: own fetal movement count (3 times daily) and routine outpatient FHR monitoring</td>
<td>Neonatal outcomes (neonatal asphyxia and nonstress test)</td>
</tr>
<tr>
<td>Tapia-Conyer et al, 2015, Mexico [29]</td>
<td>2-arm RCT, monocentric</td>
<td>High-risk pregnancies (&lt;19 or &gt;35 years)</td>
<td>27-29 weeks of gestation to deliver</td>
<td>IG: N=74; CG: N=79</td>
<td>12</td>
<td>IG: wireless maternal-fetal monitoring (1- to 2-week intervals); CG: conventional care (standard midwifery visits)</td>
<td>Pregnancy outcomes (preterm, preeclampsia, and eclampsia); neonatal outcomes (low birth weight); adherence</td>
</tr>
<tr>
<td>Dawson et al, 1999, United Kingdom [26]</td>
<td>2-arm RCT, multicenter</td>
<td>High-risk pregnancies (IG: 25.7 ± 5.0 years; CG: 27.2 ± 6.3 years)</td>
<td>12 weeks of gestation to deliver</td>
<td>IG: N=43; CG: N=38</td>
<td>0</td>
<td>IG: domiciliary monitoring daily via DFM system; CG: conventional care (standard midwifery visits)</td>
<td>Pregnancy outcomes (weeks of gestation at delivery, spontaneous delivery, cesarean delivery, operative vaginal delivery, and induced labor); neonatal outcomes (neonatal asphyxia); health care usage (on-site appointments, home visits, inpatient days, and cost-effectiveness)</td>
</tr>
<tr>
<td>Birnie et al, 1997, the Netherlands [21]</td>
<td>2-arm RCT, monocentric</td>
<td>High-risk pregnancies (IG: 29.6±5.8 years; CG: 30.9±5.8 years)</td>
<td>32-43 weeks of gestation to deliver</td>
<td>IG: N=76; CG: N=74</td>
<td>0</td>
<td>IG: domiciliary monitoring daily via portable cardiotocography; CG: in-hospital monitoring daily</td>
<td>Pregnancy outcomes (weeks of gestation at delivery, cesarean delivery, and induced labor); neonatal outcomes (birth weight); health care usage (inpatient days and cost-effectiveness)</td>
</tr>
<tr>
<td>Monincx et al, 1997, the Netherlands [22]</td>
<td>2-arm RCT, monocentric</td>
<td>High-risk pregnancies (IG: 29.6±5.8 years; CG: 30.9±5.8 years)</td>
<td>32-43 weeks of gestation to deliver</td>
<td>IG: N=76; CG: N=74</td>
<td>0</td>
<td>IG: domiciliary monitoring daily via portable cardiotocography; CG: in-hospital monitoring daily</td>
<td>Pregnancy outcomes (spontaneous delivery, operative vaginal delivery, and perinatal mortality); neonatal outcomes (neonatal asphyxia and neurological optimality scores)</td>
</tr>
<tr>
<td>Author, year, country</td>
<td>Study design</td>
<td>Participants</td>
<td>Duration</td>
<td>Sample, N</td>
<td>Attrition rate (%)</td>
<td>Major characterization</td>
<td>Major results</td>
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<tr>
<td>Calvert et al, 1982, United Kingdom [24]</td>
<td>3-arm RCT, monocentric</td>
<td>Patients facing labor (≤37 weeks of gestation)</td>
<td>During labor</td>
<td>IG: N=100; CG: N=100</td>
<td>0</td>
<td>IG: remote monitor cardiotocography (patients could get out of bed to walk or sit); CG: conventional bedside cardiotocography</td>
<td>Pregnancy outcomes (spontaneous delivery, cesarean delivery, and operative vaginal delivery); Neonatal outcomes (neonatal asphyxia)</td>
</tr>
<tr>
<td>Haukkamaa et al, 1982, Finland [27]</td>
<td>2-arm RCT, monocentric</td>
<td>Patients facing labor (IG: 28.35±3.75 years; CG: 28.1±3.7 years)</td>
<td>During labor</td>
<td>IG: N=31; CG: N=29</td>
<td>0</td>
<td>IG: FHR monitored by telemetry (patients were encouraged to sit or walk); CG: FHR monitored by conventional cardiotocography</td>
<td>Pregnancy outcomes (cesarean delivery, operative vaginal delivery, and induced labor)</td>
</tr>
</tbody>
</table>

\[\text{aRCT: randomized controlled trial.} \]
\[\text{bIG: intervention group.} \]
\[\text{cCG: control group.} \]
\[\text{dFHR: fetal heart rate.} \]
\[\text{eDFM: domiciliary fetal monitoring.} \]

**Characteristics of Interventions**

The characteristics of interventions are described in Table 2. Most of the included studies were undertaken at home [21-23,25,26,28], with 3 exceptions occurring in rural clinics [29] and hospitals [24,27]. Pregnant women in the control groups received “conventional care,” including routine outpatient monitoring, in-hospital monitoring, or conventional bedside cardiotocography. Pregnant women in the intervention groups received remote fetal monitoring with web, Bluetooth, or telephone. Of the included studies, 5 RCTs only supervised fetal heart rate [24-28], and the remaining 4 RCTs monitored extra BP [21-23,29], blood glucose [29], height [29], weight [29], or temperature [21,22].

The frequency of fetal monitoring and guidance varied among the included studies as did the form of feedback. Due to the different stages of pregnancy, the frequency of fetal monitoring ranged from 3 to 4 times daily to biweekly. There were many ways to achieve one-to-one, personalized, and exclusive guidance, including phone visits, on-site appointments, or family visits. In addition, 2 other studies, which occurred during labor, used the obstetrical telemetry system to remotely monitor the fetus in real time [24,27]. During the birth process, the pregnant women in the conventional group were nursed in bed, whereas those with telemetry equipment were encouraged to get out of bed to walk or sit on a chair.
### Table 2. Characteristics of interventions.

<table>
<thead>
<tr>
<th>Author, year, country</th>
<th>Monitoring personnel</th>
<th>Monitoring locus</th>
<th>Monitoring content</th>
<th>Feedback</th>
<th>Technical support</th>
</tr>
</thead>
</table>
| Butler Tobah et al, 2019, United States [23] | Patient, nurse, and obstetrician | Domiciliary | FHR, BP<sup>a</sup> | • Transmission of data via a phone or the institution’s electronic medical record system  
• Personalized guidance by telephone visits or on-site appointments | Home digital sphygmomonometer, handheld fetal Doppler, and patient web portal |
| Wang et al 2019, China [28] | Patient and obstetrician | Domiciliary | FHR | • Transmission of data via phone  
• Personalized guidance via telephone if necessary | Portable intelligent medical terminal system |
| Tapia-Conyer et al, 2015, Mexico [29] | Nurse and obstetrician | Rural clinics | FHR, BP, blood glucose, height, and weight | • Transmission of data through a Bluetooth interface and web access  
• Personalized consultations via fetal monitoring visits | MiBebe fetal remote monitor prototype, Bluetooth, and patient web portal |
| Dawson et al 1999, United Kingdom [26] | Patient, community midwife | Domiciliary | FHR | • Transmission of data via telephone using modems  
• Personalized surveillance and care for each pregnant woman | DFM<sup>c</sup> system |
| Birnie et al 1997, the Netherlands [21] | Investigator, midwife, and physician | Domiciliary | FHR, BP, and temperature | • Transmission of data via telephone  
• Personalized consultations via telephone if necessary | Portable cardiotocography and public telephone network |
| Monincx et al 1997, the Netherlands [22] | Investigator, midwife, and physician | Domiciliary | FHR, BP, and temperature | • Transmission of data via telephone  
• Personalized consultations via telephone if necessary | Portable cardiotocography and public telephone network |
| Dawson et al 1989, United Kingdom [25] | Patient, midwife | Domiciliary | FHR | • Transmission of data via telephone fetal monitoring systems  
• Personalized guidance via regular family visits | DFM system |
| Calvert et al 1982, United Kingdom [24] | Midwife | Hospital | FHR | • Transmission of data via an obstetrical telemetry system | Obstetrical telemetry system |
| Haukkamaa et al 1982, Finland [27] | Midwife | Hospital | FHR | • Transmission of data via an obstetrical telemetry system | Obstetrical telemetry system |

<sup>a</sup>FHR: fetal heart rate.  
<sup>b</sup>BP: blood pressure.  
<sup>c</sup>DFM: domiciliary fetal monitoring.

### Risk of Bias

Overall, the quality of included studies was moderate, 4 of which (44%) were high-quality research [21-23,26]. The studies showed the main bias in the blinding of participants and personnel, which might be caused by the nature of interventions. In addition, 1 study (11%) showed a high risk of bias for random sequence generation because of grouping according to the hospital number [24]. Fortunately, all outcomes were obtained from medical records, so the outcome assessment would not be influenced by the lack of blinding. Based on the above reasons, the blinding of outcome assessment of included studies was assessed as “low risk of bias.” Three RCTs (22%) reported clear data loss, with attrition of 11% [23], 12% [29], and 5% [25], respectively. One of the studies had a relatively large difference in attrition between the groups (20% and 4%, respectively), and it was unclear whether the loss to follow-up varied [29]. Three studies (22%) used intention-to-analysis [21-23] (Figures 2 and 3).
Synthesis of Results

The review extracted 8 maternal-fetal outcomes and the pooled analyses are presented in Table 3.
Table 3. Effect estimates of 8 outcomes.

<table>
<thead>
<tr>
<th>Outcomes</th>
<th>Studies, n</th>
<th>Participants, n</th>
<th>Statistical methods</th>
<th>Effect estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cesarean section</td>
<td>6</td>
<td>815</td>
<td>Risk ratio (M-H, fixed, 95% CI)</td>
<td>0.81 (0.59 to 1.12)</td>
</tr>
<tr>
<td>Neonatal asphyxia</td>
<td>5</td>
<td>859</td>
<td>Risk ratio (M-H, fixed, 95% CI)</td>
<td>0.66 (0.45 to 0.97)</td>
</tr>
<tr>
<td>Instrumental vaginal birth</td>
<td>4</td>
<td>492</td>
<td>Risk ratio (M-H, fixed, 95% CI)</td>
<td>1.21 (0.74 to 1.98)</td>
</tr>
<tr>
<td>Induced labor</td>
<td>4</td>
<td>348</td>
<td>Risk ratio (M-H, fixed, 95% CI)</td>
<td>0.90 (0.66 to 1.22)</td>
</tr>
<tr>
<td>Spontaneous delivery</td>
<td>3</td>
<td>432</td>
<td>Risk ratio (M-H, fixed, 95% CI)</td>
<td>0.99 (0.89 to 1.10)</td>
</tr>
<tr>
<td>Gestational weeks at delivery</td>
<td>3</td>
<td>288</td>
<td>Mean difference (IV, fixed, 95% CI)</td>
<td>−0.28 (−0.86 to 0.30)</td>
</tr>
<tr>
<td>Premature delivery</td>
<td>2</td>
<td>420</td>
<td>Risk ratio (M-H, fixed, 95% CI)</td>
<td>0.80 (0.44 to 1.46)</td>
</tr>
<tr>
<td>Low birth weight</td>
<td>2</td>
<td>420</td>
<td>Risk ratio (M-H, fixed, 95% CI)</td>
<td>1.20 (0.45 to 3.20)</td>
</tr>
</tbody>
</table>

\( ^a \) M-H: Mantel-Haenszel.
\( ^b \) Statistically significant at \( P = .04 \) level.
\( ^c \) IV: inverse variance.

Maternal Outcomes

Cesarean section was the most assessed in the included studies, involving 815 pregnant women from 6 RCTs [21,23-27]. Under the fixed effect model, the pooled results showed a nonsignificant difference between the intervention group and the control group (RR 0.81, 95% CI 0.59-1.12; \( P = .21 \)), without any heterogeneity (\( I^2 = 0\%; \ P = .93 \); Figure 4).

Instrumental vaginal birth was mentioned in 4 studies involving 492 pregnant women [22,24,26,27]. There was no evidence of heterogeneity when pooling the 4 studies (\( I^2 = 0\%; \ P = .88 \)). With a fixed effect model, the prevalence of instrumental vaginal birth did not significantly differ between the remote monitoring group and the routine monitoring group (RR 1.21, 95% CI 0.74-1.98; \( P = .45 \); Figure 5).

Four RCTs (n=348) reported induced labor with an overall rate of 32% [21,25-27]. Moreover, no significant difference (RR 0.90, 95% CI 0.66-1.22; \( P = .50 \)) between groups and the heterogeneity (\( I^2 = 0\%; \ P = .42 \)) in pooling 4 studies was demonstrated (Figure 6).

Similarly, no significant difference was found in the risk of spontaneous delivery (RR 0.99, 95% CI 0.89 - 1.10; \( P = .85 \)) [22,24,26] or premature delivery (RR 0.80, 95% CI 0.44 - 1.46; \( P = .47 \)) [23,29], both with no heterogeneity (\( I^2 = 0\%; \ P = .68 \) and \( P = .45 \), respectively; Figures 7 and 8). For gestational weeks at delivery, the overall effect of 3 studies [21,25,26] was also insignificant (MD −0.28, 95% CI −0.86 to 0.30; \( P = .35 \)) in the absence of heterogeneity (\( I^2 = 0\%; \ P = .68 \); Figure 9).

**Figure 4.** Forest plot of cesarean section.
Figure 5. Forest plot of instrumental vaginal birth.

<table>
<thead>
<tr>
<th>Study or Subgroup</th>
<th>Experimental</th>
<th>Control</th>
<th>Risk Ratio</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dawson 1999</td>
<td>3</td>
<td>43</td>
<td>1</td>
<td>38</td>
</tr>
<tr>
<td>Monincox 1997</td>
<td>6</td>
<td>77</td>
<td>6</td>
<td>74</td>
</tr>
<tr>
<td>Calvert 1982</td>
<td>18</td>
<td>100</td>
<td>15</td>
<td>100</td>
</tr>
<tr>
<td>Haukkamaa 1982</td>
<td>4</td>
<td>31</td>
<td>3</td>
<td>29</td>
</tr>
</tbody>
</table>

Total (95% CI) 251 241 100.0% 1.21 [0.74, 1.96]

Total events 31 25

Heterogeneity: Chi² = 0.65, df = 3 (P = 0.88); I² = 0%

Test for overall effect: Z = 0.76 (P = 0.45)

Figure 6. Forest plot of induced labor.

<table>
<thead>
<tr>
<th>Study or Subgroup</th>
<th>Experimental</th>
<th>Control</th>
<th>Risk Ratio</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dawson 1999</td>
<td>14</td>
<td>43</td>
<td>18</td>
<td>38</td>
</tr>
<tr>
<td>Binmeier 1997</td>
<td>23</td>
<td>76</td>
<td>27</td>
<td>74</td>
</tr>
<tr>
<td>Dawson 1989</td>
<td>11</td>
<td>40</td>
<td>3</td>
<td>17</td>
</tr>
<tr>
<td>Haukkamaa 1982</td>
<td>10</td>
<td>31</td>
<td>7</td>
<td>29</td>
</tr>
</tbody>
</table>

Total (95% CI) 190 158 100.0% 0.90 [0.66, 1.22]

Total events 58 55

Heterogeneity: Chi² = 2.83, df = 3 (P = 0.42); I² = 0%

Test for overall effect: Z = 0.68 (P = 0.50)

Figure 7. Forest plot of spontaneous delivery.

<table>
<thead>
<tr>
<th>Study or Subgroup</th>
<th>Experimental</th>
<th>Control</th>
<th>Risk Ratio</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dawson 1999</td>
<td>30</td>
<td>43</td>
<td>24</td>
<td>38</td>
</tr>
<tr>
<td>Monincox 1997</td>
<td>58</td>
<td>77</td>
<td>59</td>
<td>74</td>
</tr>
<tr>
<td>Calvert 1982</td>
<td>77</td>
<td>100</td>
<td>78</td>
<td>100</td>
</tr>
</tbody>
</table>

Total (95% CI) 220 212 100.0% 0.99 [0.89, 1.10]

Total events 165 161

Heterogeneity: Chi² = 0.76, df = 2 (P = 0.68); I² = 0%

Test for overall effect: Z = 0.19 (P = 0.85)

Figure 8. Forest plot of premature delivery.

<table>
<thead>
<tr>
<th>Study or Subgroup</th>
<th>Experimental</th>
<th>Control</th>
<th>Risk Ratio</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Butler Tobah 2019</td>
<td>4</td>
<td>134</td>
<td>3</td>
<td>133</td>
</tr>
<tr>
<td>Tapia-Connor 2015</td>
<td>12</td>
<td>74</td>
<td>18</td>
<td>79</td>
</tr>
</tbody>
</table>

Total (95% CI) 208 212 100.0% 0.80 [0.44, 1.46]

Total events 16 21

Heterogeneity: Chi² = 0.57, df = 1 (P = 0.45); I² = 0%

Test for overall effect: Z = 0.72 (P = 0.47)

Figure 9. Forest plot of gestational weeks at delivery.

<table>
<thead>
<tr>
<th>Study or Subgroup</th>
<th>Experimental</th>
<th>Control</th>
<th>Mean Difference</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dawson 1999</td>
<td>38.3 2.9</td>
<td>43 38.5 2.6</td>
<td>38 23.5% -0.20 [-1.40, 1.00]</td>
<td>1999</td>
</tr>
<tr>
<td>Binmeier 1997</td>
<td>39.9 2.5</td>
<td>76 40.4 2.5</td>
<td>74 52.7% -0.50 [-1.30, 0.30]</td>
<td>1997</td>
</tr>
<tr>
<td>Dawson 1989</td>
<td>38.78 2.12</td>
<td>40 38.65 2.09</td>
<td>17 23.8% 0.13 [-1.06, 1.32]</td>
<td>1989</td>
</tr>
</tbody>
</table>

Total (95% CI) 159 129 100.0% -0.28 [-0.86, 0.30]

Heterogeneity: Chi² = 0.76, df = 2 (P = 0.68); I² = 0%

Test for overall effect: Z = 0.94 (P = 0.35)
Outcomes of Infants

Five studies (n=859) compared the incidence of neonatal asphyxia between the intervention group and the control groups, with an overall prevalence of 11% [22-24,26,28]. Furthermore, the overall effect of neonatal asphyxia was significant, and the combined risk ratio was 0.66 (95% CI 0.45-0.97; P=.04) with an acceptable heterogeneity across studies (I²=24%: P=.26; Figure 10).

For low birth weight, the pooled results of 2 studies involving 420 newborns showed that no significant difference was discovered between the intervention group and the control group (RR 1.20, 95% CI 0.45-3.20; P=.71), without any heterogeneity (I²=0%; P=.41; Figure 11) [23,29].

Figure 10. Forest plot of neonatal asphyxia.

Figure 11. Forest plot of low birth weight.

Health Care Usage

The outcomes of health care usage were investigated in 3 studies [21,23,26], involving the number of on-site appointments or home visits, duration in hospital, medical cost, and so on. However, none of them was suitable for meta-analysis due to heterogeneity of evaluation methods and assessment timing or to a lack of sufficient data.

Butler Tobah et al [23] reported that compared with conventional nursing, the number of on-site appointments with clinicians and nurses decreased significantly in the intervention group (11.25 vs 14.69 visits; P<.01), while the duration of time spent on coordinating care and connected care appointments by phone or on the internet was higher in the intervention group (401.20 vs 167.10 minutes per woman; P<.01). Similarly, Dawson et al [26] also reported that the remote group received more home visits (3.7 vs 1.4 visits; P=.002) and longer home visits (33.5 vs 12.8 minutes per visit; P=.001). There was no significant difference in the number of antenatal clinic visits between the 2 groups (2.4 vs 3.2 visits; P=.11) [26]. For antenatal inpatient days, Dawson et al [26] found there were no significant differences between the 2 groups (3.58 vs 5.13 days; P=.12), whereas Birnie et al [21] reported longer hospital stays in the control group (1 vs 7 days; P<.001). Furthermore, no significant differences in hospital length of stay after delivery [21,23] were observed across groups.

Two studies reported cost-effectiveness [21,26]. Birnie et al [21] indicated that domiciliary monitoring had lower prenatal costs than in-hospital monitoring (US $1521 vs US $3558 per woman; P<.001), mainly focusing on nursing care, domiciliary monitoring, and informal family care. Dawson et al [26] also supported that the total cost of domiciliary care was €223.83 (US $239.89 in 2023) per woman less than that of conventional care, consisting of community midwife (time and travel), home monitoring equipment (capital cost and maintenance), lost productive output (women and partners), and antenatal clinic attendances (visits, ultrasound scans, and antenatal inpatient care) [26].

Discussion

Principal Findings

As far as we know, this is the first article to quantitatively analyze the effects of remote fetal monitoring. The systematic review and meta-analysis highlighted that remote fetal monitoring significantly reduced the risk of neonatal asphyxia by 34%. Beyond that, remote fetal monitoring was also beneficial for reducing prenatal costs, which showed some potential for greater cost-effectiveness.

Comparison With Prior Studies

In previous reviews, the superiority of obstetric remote monitoring has also been repeatedly emphasized because of...
real-time, periodic, and remote monitoring [3,30,31]. By integrating 14 studies involving blood glucose, fetal heart rate, and uterine activity, Lanssens et al found that remote monitoring reduced low neonatal birth weight and neonatal intensive care unit admissions, as well as prolonged gestational age [31]. Likewise, a recent systematic review, focusing on obstetric remote monitoring of BP, uterine contractions, weight, heart rate, and so forth also supported that telemonitoring during pregnancy had great potential for promoting better pregnancy outcomes [3]. However, due to limited research on prenatal remote monitoring, no further quantitative analysis was carried out in the above reviews.

This systematic review and meta-analysis, the first to focus remote monitoring on the fetus, revealed that remote fetal monitoring reduced the risk of neonatal asphyxia by 34%. Remote fetal monitoring can identify signs of fetal hypoxia in time by monitoring wherever and whenever, which is essential to reduce neonatal asphyxia, especially in high-risk pregnant women [32]. In terms of cost-effectiveness, only 2 RCTs out of 9 studies reported cost-effectiveness [21,26]. Both demonstrated that remote monitoring significantly reduced prenatal costs, which was consistent with previous studies [31,33,34]. In Lanssens’ [31] review, 2 retrospective studies found that remote monitoring significantly reduced health care costs. In the studies reviewed, cost analysis focused on health care costs, patient costs, caregiver costs, and productivity costs. Remote fetal monitoring had additional equipment costs and maintenance costs, but in the long run, it saved much more than that, such as time costs, travel costs, or outpatient costs.

In addition, the disadvantages of remote fetal monitoring remained controversial, such as whether additional cesarean sections would be added. In this regard, this meta-analysis covering 9 studies found no consistent evidence of adverse effects on maternal and infant outcomes, with a small heterogeneity ranging from 0% to 24%. This might be related to accurate guidance from midwives or obstetricians on the remote monitoring team. Nonetheless, a recent review in 2019 evaluated information involving decreased fetal movement in 24 mobile applications, revealing that the information varied widely and lacked evidence-based clinical advice [35]. Accurate information about fetal movement is essential for improving maternal and infant outcomes. Therefore, it is recommended that health care personnel cooperate with software developers to jointly develop high-quality prenatal education tools, which will help to promote more pregnant women to obtain timely and accurate guidance.

Notably, in the current systematic review and meta-analysis, 7 of the 9 studies were carried out in developed countries, which were inseparable from the rich medical resources and advanced medical technologies of developed countries. The latest global figures showed that in 2020, there were 26 and 17 deaths per 1000 live births in low- and middle-income countries (LMICs), respectively. However, in high-income countries, the rate only stood at 3 per 1000 [36]. Given the higher perinatal mortality rate, the need for remote fetal monitoring in developing countries may be more urgent. Furthermore, a recent review focused on LMICs concluded that mobile technology can overcome economic and geographic barriers by transmitting clinical information collected using low-cost devices, thereby increasing the perinatal care coverage of LMICs [5]. It can be argued that remote fetal monitoring supported by mobile technology appears to have greater potential in LMICs, where antenatal care services need to be improved. Therefore, we encourage remote fetal monitoring in LMICs to alleviate the shortage of medical resources and further complement the benefits of remote fetal monitoring.

Suggestions for Clinical Practice
This systematic review has demonstrated that remote fetal monitoring has a significant effect on improving maternal and infant outcomes, but this does not mean that remote fetal monitoring can replace face-to-face communication between doctors and patients, which is necessary for shared decision-making. Remote monitoring breaks through the barriers of time and distance, so it is reasonable as an effective complement to traditional outpatient monitoring [37]. Especially during the COVID-19 pandemic, pregnant women, as a high-risk group, should not gather in outpatient clinics for a long time. At this time, remote fetal monitoring not only realizes noncontact medical services but also ensures the safety of mothers and babies. Unfortunately, remote fetal monitoring is rarely implemented in developing countries, especially in areas with limited medical resources [3]. Therefore, the development and implementation of remote monitoring technology urgently need to be put on the agenda. Aside from the technical issues, another concern of remote fetal monitoring is that authentication rules, reimbursement policies, data security, legal responsibilities, and so forth are not yet clear [38]. Although remote fetal monitoring has not yet shown adverse consequences, it is still necessary to conduct relevant research cautiously in combination with the local medical level.

Limitations
There were some limitations worth noting. The diversity of pregnant women in the current systematic review was the major limitation, involving low-risk pregnancies, high-risk pregnancies, late pregnancies, and patients facing labor. Future research can continue to explore which types of pregnant women are more suitable for remote fetal monitoring. In addition, several RCTs included in this meta-analysis were relatively old, which might limit the direct applicability of the evidence to current clinical practice. Finally, due to the limited literature, it was difficult to quantitatively analyze the efficacy of remote fetal monitoring in health resource usage. Future studies are expected to assess the cost-effectiveness of remote fetal monitoring, including implementation costs (technology costs, medical costs, etc), intervention costs (patient resource costs, commuting costs, etc), and downstream costs (productivity costs, future costs, etc) [39]. Likewise, the number of consultations, length of hospital stay, and patient compliance or satisfaction cannot be ignored and need to be explored further.

Conclusions
The present systematic review and meta-analysis of 9 studies highlighted that remote fetal monitoring had a favorable effect on reducing neonatal asphyxia. Remote fetal monitoring has not yet found hidden dangers, but more large-scale, multicenter,
and high-quality studies are still expected to explore its safety and efficacy. At the same time, more research is also recommended to further carry out the cost analysis of remote fetal monitoring, which will help alleviate the huge medical expenses.

Conflicts of Interest
None declared.

Multimedia Appendix 1
Search strategy.
[DOCX File, 15 KB - mhealth_v11i1e41508_app1.docx ]

Multimedia Appendix 2
Data extraction form.
[DOCX File, 25 KB - mhealth_v11i1e41508_app2.docx ]

References


Community Health Worker Use of Smart Devices for Health Promotion: Scoping Review

Merlin Greuel1, BA, MGH, MD; Frithjof Sy1, BSc, MD; Till Bärnighausen1,2,3, MSc, MD, SCD; Maya Adam1,4, BA, MD; Alain Vandormael1, MSc, PhD; Jennifer Gates5, BA; Guy Harling2,6,7,8,9, BSc, MA, MPH, SCD

1Heidelberg Institute of Global Health, Heidelberg University, Heidelberg, Germany
2Africa Health Research Institute, KwaZulu-Natal, South Africa
3Department of Global Health and Population, Harvard TH Chan School of Public Health, Harvard University, Boston, MA, United States
4Department of Pediatrics, School of Medicine, Stanford University, Stanford, CA, United States
5Icahn School of Medicine at Mount Sinai, New York, NY, United States
6Institute for Global Health, University College London, London, United Kingdom
7Department of Epidemiology and Harvard Center for Population and Development Studies, Harvard TH Chan School of Public Health, Harvard University, Boston, MA, United States
8Medical Research Council/Wits Rural Public Health and Health Transitions Research Unit (Agincourt), Faculty of Health Sciences, University of the Witwatersrand, Johannesburg, South Africa
9School of Nursing and Public Health, College of Health Sciences, University of KwaZulu-Natal, KwaZulu-Natal, South Africa

Corresponding Author:
Merlin Greuel, BA, MGH, MD
Heidelberg Institute of Global Health
Heidelberg University
Im Neuenheimer Feld 130.3
Heidelberg, 69120
Germany
Phone: 49 17625498934
Email: merlin.greuel@gmail.com

Abstract

Background: Community health workers (CHWs) have become essential to the promotion of healthy behaviors, yet their work is complicated by challenges both within and beyond their control. These challenges include resistance to the change of existing behaviors, disbelief of health messages, limited community health literacy, insufficient CHW communication skills and knowledge, lack of community interest and respect for CHWs, and CHWs’ lack of adequate supplies. The rising penetration of “smart” technology (eg, smartphones and tablets) in low- and middle-income countries facilitates the use of portable electronic devices in the field.

Objective: This scoping review examines to what extent mobile health in the form of smart devices may enhance the delivery of public health messages in CHW-client interactions, thereby addressing the aforementioned challenges and inducing client behavior change.

Methods: We conducted a structured search of the PubMed and LILACS databases using subject heading terms in 4 categories: technology user, technology device, use of technology, and outcome. Eligibility criteria included publication since January 2007, CHWs delivering a health message aided by a smart device, and face-to-face communication between CHWs and clients. Eligible studies were analyzed qualitatively using a modified version of the Partners in Health conceptual framework.

Results: We identified 12 eligible studies, 10 (83%) of which used qualitative or mixed methods approaches. We found that smart devices mitigate challenges encountered by CHWs by improving their knowledge, motivation, and creativity (eg, through self-made videos); their status within the community; and the credibility of their health messages. The technology stimulated interest in both CHWs and clients—and sometimes even in bystanders and neighbors. Media content produced locally or reflecting local customs was strongly embraced. Yet, the effect of smart devices on the quality of CHW-client interactions was inconclusive. Interactions suffered as CHWs were tempted to replace educational conversations with clients by passively watching video content. Furthermore, a series of technical difficulties experienced especially by older and less educated CHWs compromised
some of the advantages brought about by mobile devices. Adequate CHW training ameliorated these difficulties. Only 1 study (8%) considered client health behavior change as an end point, thus revealing a major research gap.

**Conclusions:** Smart mobile devices may augment CHWs’ field performance and enhance face-to-face interactions with clients, yet they also generate new challenges. The available evidence is scarce, mostly qualitative, and focused on a limited range of health outcomes. Future research should include larger-scale interventions across a wide range of health outcomes and feature client health behavior change as an end point.

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**KEYWORDS**

mobile health; community health workers; smart phones; tablets; health promotion; public health; health worker; smart devices; health behaviour; smart technology; health message; health outcome

**Introduction**

Community health workers (CHWs) have become central to health promotion activities, with more than 5 million CHWs working worldwide in 2014 [1]. In part, CHWs’ impact is a result of speaking the local language and identifying with the community they serve. Therefore, they have the potential to convey health messages more effectively than other health cadres [2] and may be able to “improve key health-related behaviors” [1]. Katigbak and colleagues [3] have developed the Partners in Health conceptual framework for how CHWs can facilitate the adoption of healthy behaviors. In this framework, client characteristics, the environment, and CHW activities reciprocally influence each other to generate behavior change. Nevertheless, factors both within and beyond CHWs’ control can impede their health promotion activities. Based on the literature cited below, we have identified challenges to CHW health promotion activities and have integrated them into the Partners in Health framework (Figure 1).

![Figure 1. Conceptual framework of facilitators and barriers to community health workers (CHWs) and patients acting as partners in health. Challenges to the CHW-client interaction are shown in red (adapted from Katigbak et al [3] with permission from the American Journal of Public Health).](https://mhealth.jmir.org/2023/1/e42023)

One challenge is the way humans manage change, as promoting healthy behavior often entails encouraging changes in existing behavior. Since multiple social, emotional, and cognitive factors interact to mediate [4] and sustain behavior change [5], harmful behaviors are often resistant to change. A second challenge to promoting healthy behaviors is community literacy. In particular, limited health literacy, the ability to comprehend and act on health-related information, is associated with negative health outcomes [6,7] and may complicate health message uptake. In contrast, adequate health literacy can promote healthy behaviors, such as physical activity, by increasing knowledge and self-efficacy related to these behaviors, resulting in positive health outcomes [7]. While low health literacy is certainly a problem in higher-income countries [6], it constitutes a larger problem in low- and middle-income countries (LMIC). For example, basic literacy in many sub-Saharan African countries ranges from 24% to 60% [8].

Other challenges relate to the characteristics of CHWs and their interaction with community members. These include insufficient CHW communication skills [9]. In addition, a lack of...
community participation and interest, CHWs’ own limitations in understanding complex health information due to low levels of education, a lack of respect for CHW knowledge, and disbelief in health promotion messages may complicate the work of CHWs [10]. The lack of community recognition and the low community status of CHWs may pose additional challenges [11], and this problem may be aggravated if CHWs lack adequate supplies and equipment [12]. Facing these challenges, CHWs have demanded educational communication materials that can be carried to the households they visit [9] and suggested using media to reinforce health messages [10].

Mobile electronic media—in particular “smart” devices such as smartphones and tablets—may constitute powerful tools to deliver public health messages. Smart devices can provide learning via videos or mobile apps, providing information through multiple modes (eg, verbally and visually). Learners presented with visual information in addition to verbal information generate a multimedia effect that deepens learning [13]. Dual coding theory suggests that this deeper learning occurs because learners process visual and verbal information separately and then select pieces of information from each before unifying them into a coherent mental representation of knowledge [14]. This theory has been used to optimize multimedia learning materials for e-learning [15] and medical education [16].

The rapidly rising smartphone ownership in LMIC [17] presents an opportunity for increased access to health-related information and resources extending health system reach [18]. However, the comparatively low penetration of smart devices in low-income settings may limit their usefulness as health promotion vehicles; in several Sub-Saharan African countries, adult smartphone ownership is less than 20% [17]. Equipping CHWs with mobile smart devices provides an intermediate solution, allowing electronic multimedia education to be accessed even in low device-penetration communities. For example, tablet-displayed videos have transmitted agricultural knowledge and induced abstractive learning in rural Uganda [19].

Given the potential of smart devices as health promotion vehicles, equipping CHWs with such devices may address several of the aforementioned health promotion challenges. Past reviews of mobile health (mHealth) and CHWs have not focused specifically on the use of mHealth as a health promotion tool. Braun and colleagues’ [20] review of CHW mHealth use concentrated on how mHealth improved intra-CHW communication and learning. Hall and colleagues’ [21] review of mHealth interventions in LMIC included client education and behavior change but focused on the role of mHealth in improving treatment adherence and appointment compliance rather than multimedia applications. Kallander and colleagues’ [22] review considered SMS text messaging rather than multimedia applications, while the review by White et al [23] focused on how mHealth improved CHW-patient communication broadly but did not focus specifically on educational uses. Thus, there has not been a systematic review of how smart mobile devices can facilitate the delivery of public health messages by CHWs.

Accordingly, we conducted a scoping review of how multimedia features of smart mobile devices have been used to enhance knowledge transfer and behavior change by CHWs. We excluded distance-based media approaches such as SMS text messaging, automated voice messages, and phone calls and focused instead on studies involving direct face-to-face communication between CHWs and community members. Our fundamental question is whether smart mobile devices can enhance CHW face-to-face delivery of public health messages and thereby enhance client health behavior change. The aim of this study was to identify the type of evidence available, point out knowledge gaps, and indicate possible directions for future research. Given these objectives, we deemed a scoping review approach as the most suitable [24].

Methods

Following the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-analyses extension for Scoping Reviews) methodology [25], we used a scoping approach to review the literature published between January 1, 2007, and January 5, 2022. The start date was chosen because the first publicly available smartphones using capacitive touch screens were released in 2007 (tablet computers became more common after 2010). The search was performed in English, but no articles were excluded from the full-text assessment if they were published in another language. We consulted the PubMed and Lilacs databases, modifying White and colleagues’ [23] strategy to capture the intersection of 4 search categories: technology user, technology device, use of technology, and outcome.

We defined our “technology users” as CHWs using smart devices to deliver public health messages and client recipients. As definitions for CHWs vary [26], we employed the common definition used in a World Health Organization study group review, in that CHWs should be “members of the communities where they work, should be selected by the communities, should be answerable to the communities for their activities, should be supported by the health system but not necessarily a part of its organization, and have shorter training than professional workers” [27]. Clients are defined as community and household members of any age or gender who receive a health message outside the context of health facilities.

For “technology device” and “use of technology,” we focused on digital content requiring portable computer-like “smart” devices that distinguish themselves from regular cell phones by the ability to run apps, show video content, and connect to the internet. We excluded technological features not requiring “smart” devices that can be used by traditional cell phones, (eg, SMS text messages, automated voice messages, and phone calls). We also required direct, person-to-person communication between CHWs and clients (as opposed to CHWs sending messages from a distance) since we were interested in whether technology enhances the effectiveness of person-to-person communication. The person-to-person communication had to be primary health education (ie, the delivery of a preventative health message such as the promotion of healthy behaviors). We excluded secondary prevention messages such as treatment...
dissemination or medication reminders. Finally, we included any qualitative or quantitative “outcome” that allowed us to assess the effectiveness, advantages, or disadvantages of the use of smart devices for health promotion from the viewpoint of any stakeholder.

For each category, we identified relevant Medical Subject Headings (MeSH) for PubMed and the corresponding multilingual Descriptores en Ciencias de la Salud in LILACS. The complete search process including all MeSH terms used is shown in Multimedia Appendix 1. For each article fulfilling the inclusion criteria, we screened all references for other potentially relevant articles and used Google Scholar to search for relevant publications citing these included studies, as well as additional publications by the same authors.

Details of all articles found through these searches were extracted to a spreadsheet and deduplicated. Two authors (MG and FS) independently screened the article titles and abstracts for relevance with respect to the inclusion criteria defined above. If deemed relevant by at least 1 of the 2 authors, the article was included in the following stage of review. The same authors then independently reviewed the full text of all retained articles from the abstract screen. All full-text articles deemed relevant by at least 1 of the 2 authors were then discussed in-depth to reach the final agreement on inclusion. Disagreements were resolved through mutual consent or consultation with a third author (GH). We grouped all included studies by methodology, extracting methods and findings into tables, and used these to qualitatively describe the literature in the context of our original conceptual framework. The PRISMA-ScR checklist [25] that guided our approach can be found in Multimedia Appendix 2.

Results

Identified Articles

The PubMed search yielded 1045 results, and the LILACS search 52, all but 2 (96%) of them duplicates of PubMed articles. Of all articles in either database, 168 articles (16%) were included after the title review, 33 (3%) after the abstract review, and 4 after the full paper review. Of these, 1 was chosen to be included in the results of this publication. From the Google Scholar search and reference screenings, 21 additional abstracts were selected, 11 (52%) of which met our inclusion criteria. All 11 studies were included. Hence, of the 1118 initially identified studies (1068 after deduplication), 12 (1%) were retained for analysis (Figure 2 [28]).

Overview of Studies

The included studies—all published between 2010 and 2021—were conducted in South Africa [29,30], Nigeria [31], Burkina Faso [32], Lesotho [33-35], and India [36-40] (Table 1). Among them, 9 (75%) studies were rural, 2 (17%) urban, and 1 (8%) both. Moreover, 2 (17%) studies were quantitative, 7 (58%) were qualitative, and 3 (25%) were a combination of both. Five (42%) articles were published in peer-reviewed journals, and 7 (58%) were conference papers. Eight (67%) studies addressed maternal and child health (MCH), 1 (8%) addressed polio immunization, and 3 studies (25%) included multiple health themes. Moreover, 11 (92%) studies included between 7 and 81 CHW participants. Of these, CHWs were the sole or primary participants in 6 (50%) studies; in other cases, they constituted 1 group of participants, alongside mothers, field staff, or mobile shop/laptop owners. The remaining 1 (8%) study examined only clients. Note that sample sizes reported both in the text and Table 1 refer to the participants relevant to our research question and in some cases do not reflect the overall sample size of all participants featured in the study.
<table>
<thead>
<tr>
<th>Citation</th>
<th>Title</th>
<th>Health issue</th>
<th>Location</th>
<th>Sample</th>
<th>Study type</th>
<th>Publication</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coetze et al, 2018 [29]</td>
<td>Community health workers’ experiences of using video teaching tools during home visits—A pilot study</td>
<td>Maternal and child health (HIV, alcohol, nutrition, and breastfeeding)</td>
<td>South Africa (urban)</td>
<td>24 CHWs&lt;sup&gt;c&lt;/sup&gt;</td>
<td>Qualitative</td>
<td>Journal</td>
</tr>
<tr>
<td>Gopalakrishnan et al (2020)</td>
<td>Using mHealth to improve health care delivery in India: A qualitative examination of the perspectives of community health workers and beneficiaries</td>
<td>Maternal and newborn health</td>
<td>India (rural)</td>
<td>32 CHWs, 55 clients</td>
<td>Qualitative (interviews)</td>
<td>Journal</td>
</tr>
<tr>
<td>Isler et al, 2019 [32]</td>
<td>Iterative adaptation of a mobile nutrition video-based intervention across countries using human-centered design: Qualitative study</td>
<td>Maternal and child health (nutrition during pregnancy and breastfeeding)</td>
<td>Burkina Faso (rural)</td>
<td>CHWs, mothers, field staff (N not specified)</td>
<td>Qualitative (focus groups, interviews, observations)</td>
<td>Journal</td>
</tr>
<tr>
<td>Kumar et al, 2015 [37]</td>
<td>Projecting health: Community-led video education for maternal health</td>
<td>Maternal and newborn health</td>
<td>India (rural)</td>
<td>CHWs, mothers, field staff (N not specified)</td>
<td>Qualitative (observations, interviews, focus groups)</td>
<td>Conference paper</td>
</tr>
<tr>
<td>Molapo et al, 2017 [33]</td>
<td>Video consumption patterns for first-time smartphone users – community health workers in Lesotho</td>
<td>Various</td>
<td>Lesotho (rural)</td>
<td>42 CHWs</td>
<td>Qualitative (observations, interviews, focus groups)</td>
<td>Conference paper</td>
</tr>
<tr>
<td>Molapo et al, 2016 [34]</td>
<td>Designing with community health workers: enabling productive participation through exploration</td>
<td>Various</td>
<td>Lesotho (rural)</td>
<td>54 CHWs</td>
<td>Qualitative (discussions, focus groups, workshops)</td>
<td>Conference paper</td>
</tr>
<tr>
<td>Molapo and Marsden, 2013 [35]</td>
<td>Software support for creating digital health training materials in the field</td>
<td>Various (eg, tuberculosis, sexual health)</td>
<td>Lesotho (rural)</td>
<td>15 CHWs</td>
<td>Qualitative (observations, interviews, focus groups, video logs)</td>
<td>Conference paper</td>
</tr>
<tr>
<td>Ramachandran et al, 2010 [38]</td>
<td>Mobile-izing health workers in rural India</td>
<td>Anemia and maternal health</td>
<td>India (rural)</td>
<td>7 CHWs</td>
<td>Qualitative (interviews, observations) and quantitative</td>
<td>Conference paper</td>
</tr>
<tr>
<td>Treatman and Lesh, 2012 [39]</td>
<td>Strengthening community health systems with localized multimedia</td>
<td>Maternal health, child nutrition, newborn health</td>
<td>India (rural)</td>
<td>8 CHWs</td>
<td>Qualitative (interviews)</td>
<td>Conference paper</td>
</tr>
<tr>
<td>Vashistha and Kumar, 2016 [40]</td>
<td>Mobile video dissemination for community health</td>
<td>Maternal and newborn health (birth preparedness, hand washing, exclusive breastfeeding, thermal care, delayed bathing)</td>
<td>India (rural)</td>
<td>84 mobile phone shop owners, 71 laptop owners, 81 CHWs</td>
<td>Quantitative (number of phone calls) and qualitative (interviews, focus groups, discussions)</td>
<td>Conference paper</td>
</tr>
</tbody>
</table>

<sup>a</sup>MOVIE: Mobile Video Intervention for Exclusive Breastfeeding.

<sup>b</sup>RCT: randomized controlled trial.

<sup>c</sup>CHW: community health worker.
Quantitative Assessments

Birukila et al [31] assessed the acceptance of videos containing messages to promote polio immunization in rural and urban Nigeria. The videos—described as pictorial, digitalized flipcharts—were shown to parents and caregivers in 21,242 households on CHWs’ smartphones. Almost all (99.9%) of the 11,612 caregivers who watched the videos claimed that these videos met their health information needs, and 85.4% of the 12,418 mobile phone owners agreed to receive the videos via Bluetooth. Over the study period, CHWs shared the videos around 100 times a day.

The only randomized controlled trial (RCT) we encountered was the intervention by Adam et al [30] in South Africa, wherein 1502 pregnant mothers were randomized into 2 groups. The control group received standard of care (SOC) home-based infant feeding counseling by CHWs. Using tablets, the intervention group was shown videos on infant feeding in addition to the SOC. No differences in behavior (infant feeding practices) were observed between the groups at 1 month and 5 months follow-up, but the videos had replaced around 40% of the CHWs’ face-to-face counseling, thereby freeing up time for other health-related tasks. The small increase in maternal knowledge, observed at the 1-month follow-up, was no longer present after 5 months.

Qualitative and Mixed Assessments

Ramachandran et al [38] evaluated portable multimedia content in rural India. In their study, 7 CHWs used smartphones to show educational videos on maternal health and anemia to pregnant women during weekly household visits. Some of the material was produced by CHWs and featured influential community members. CHWs approached the videos with enthusiasm, yet older CHWs struggled with the technical features of the smartphones. The devices were often used in a noninteractive manner due to a lack of training. However, CHW coaching mitigated these issues. A written test administered before and after the intervention revealed improvements in CHW knowledge of pregnancy danger signs and self-efficacy after the intervention.

Treatman et al [39] developed a smartphone app featuring culturally appropriate color illustrations and audio recordings in the local language containing health messages about topics in MCH. In their study, 8 CHWs in rural India tested the app and were then interviewed. The audio messages were considered more significant than the illustrations; an engaging speaker was deemed especially important. CHWs described the devices as fun to use and impressive to clients, who considered the health messages credible and trustworthy. CHWs preferred the phones over other job aides since they were easier to carry. However, CHWs doubted the effectiveness of the multimedia content if presented without facilitation and thus highlighted the importance of interaction with clients. Moreover, smartphones appeared inept for use in noisy environments or with groups of clients.

In urban South Africa, Coetzee et al [29] provided 24 CHWs with tablets to show videos to pregnant women and mothers during home visits. Pre- and postintervention focus groups were conducted. The tablets increased CHW motivation by amplifying the perceived importance of their work. The videos stimulated clients’ interest and attention, improved CHW credibility and time efficiency, and triggered interest even among nontargeted household members. However, some CHWs worried about tablet theft and their credibility and social status being compromised by insufficient technologic capability. Sometimes, tablets were regarded as a means to avoid interaction with clients, especially when CHWs were tired. Moreover, some clients were concerned that the tablets might be recording them, compromising confidentiality.

Molapo et al [33-35] carried out a series of qualitative assessments based on interviews, focus groups, and observations in Lesotho, one of which [33] also contained a quantitative component. In the first intervention [35], a computer application allowed rural trainers of CHWs to create educational videos with local content transferable to the smartphones of 15 CHWs via Bluetooth. Repeated video views helped CHWs deepen their knowledge, and CHWs requested video material deemed especially important. Surprisingly, CHWs not only used the videos for their own education, as was intended, but they also shared them with community members and peers who did not possess smartphones. The health workers experienced a sense of pride, respect from others, and empowerment, and the videos helped them talk about topics that made them feel uncomfortable, such as sexual health.

During the second intervention [34], the existing video content was improved through community feedback. Since CHWs had started showing the videos to community members, their trainers created videos catered to this purpose. Different versions of the application were tested in the field by 54 CHWs, each equipped with a smartphone. CHWs usually showed the videos to groups of clients; they disliked pausing the videos for feedback or questions because the interruptions limited their perceived professionalism.

In the last of the 3 interventions, Molapo et al [33] analyzed the results of their 17 months of fieldwork both qualitatively and quantitatively using log data of video views. The 42 CHWs preferred to watch the videos to completion and interact with their clients afterward instead of pausing the videos. Older CHWs handled the smartphones as well as their younger peers after appropriate instructions. In general, CHWs found the smartphones easy to use, though a lack of English literacy sometimes caused problems. Explicit graphic images, such as in videos about sexually transmitted infections, were popular and triggered discussion. The average number of views per video per CHW declined 24% to 87% percent in 16 months, which the authors attribute to a waning novelty effect. However, video views tended to increase shortly after CHW educational workshops, with views increasing for around 3 months. The number of views per video depended on the video’s perceived importance and individual features, with a preference for videos showing influential community members.

In the study by Kumar et al [37] spanning 24 months, Indian CHWs showed educational videos on MCH to community members in 84 rural villages during monthly group gatherings. These events became so popular that CHWs began to organize
them independently, thereby exceeding the researchers’ expectations. The videos were played on small, battery-powered projectors; they facilitated CHWs’ explanations, generated discussions, and highly elevated their social status. The latter was especially true for videos starring CHWs, giving them “celebrity status” [37]. Locally filmed videos were the most popular, as community members could relate to the content. Other advantages included the videos’ repeatability and credibility boost for health messages.

Vashistha et al [40] attempted to identify the most effective means of distributing offline health videos on personal mobile phones. They equipped 81 CHWs, 84 mobile shop owners, and 71 laptop owners in rural India with videos promoting MCH. The videos featured unique phone numbers, and viewers were urged to call if they liked the video. The number of calls was recorded, and callbacks were conducted to gather viewers’ opinions. By the end of the 14-week study period, mobile shop owners had distributed the video material to 6 times as many clients compared to laptop owners and CHWs. However, the number of calls received from videos distributed by CHWs far exceeded the calls from those disseminated by mobile shop or laptop owners. The authors provided 3 reasons for this finding: the CHWs had stronger ties with their clients, they were considered experts in their domain, and they seemed to have emphasized the importance of making the phone calls. CHWs regarded the technology as an effective way to enable clients to learn, review, and share health-related knowledge.

Gopalakrishnan et al [36] developed a software for smartphones and tested how its use would affect CHW-client interactions. In their study, 32 CHWs showed videos with health messages on MCH to 55 clients during home visits. Postintervention interviews revealed a divergence in the software’s perceived utility between CHWs and beneficiaries; some initial technical difficulties notwithstanding, the former reported increases in CHW authority, the credibility of health messages, client attention, and the involvement of key household decision makers. They also noted a positive impact on behavior change (vaccination rates). However, for most beneficiaries, the software failed to improve interactions with CHWs. On the contrary, CHW-client interactions were harmed by rushed and short visits and the failure of CHWs to mediate interactions appropriately.

Finally, Isler et al [32] adapted a series of videos related to MCH and nutrition from 1 cultural setting (South Africa) to another (Burkina Faso). Animated videos with South African content and design received input from Burkanese CHWs and clients and were then modified to represent the Burkina Faso cultural, linguistic, and physical setting. Clients emphasized that the characters portrayed should reflect community members in appearance, behavior, and financial situation. Moreover, they recommended acknowledging local household structures and hierarchies during video presentations. The ease of tablet usage varied by CHW education and age. Some CHWs expressed technical concerns and preferred reducing the amount of information transmitted in each video viewing session.

Discussion

Principal Findings

Studies to date have been conducted in India and across Africa and have largely evaluated the practicability of smartphones or tablets as health promotion vehicles. Despite the diversity of study designs and cultural contexts, the studies have common findings regarding both the ability of mHealth to alleviate some challenges encountered by CHWs and some key drawbacks, such as equivocal effects on CHW-client interactions and frequent technical difficulties in the field. While locally produced media content proved popular, the potential of smart devices as catalysts for health behavior change remains elusive and merits larger-scale, quantitative interventions in the future.

Overcoming Challenges

mHealth technologies may mitigate some of the challenges experienced by CHWs in the promotion of healthy behaviors. mHealth can increase CHW health knowledge [35,38], thereby addressing CHWs’ own educational deficits. CHWs themselves stressed that the ability to carry mobile videos helped them remember crucial health concepts [35], an assertion verified objectively in a written test [38]. Increased CHW health knowledge should benefit their interactions with clients and increase clients’ respect for the health workers and their work. As a novel technology, mHealth use by CHWs may stimulate community interest [29,32-35,37,39]. Clients, bystanders, and neighbors were interested mHealth deliveries [29,39], as were CHWs not possessing electronic devices [35]. While this interest may wane over time as recipients become accustomed to the technology, it appears possible to rekindle interest through the introduction of new material [33]. Constant innovations (in the form of new videos, apps, etc) may therefore be necessary to maintain interest. The rising personal ownership of mobile electronic devices in LMIC may limit such novelty effects in the future, making the case for constant technological or creative progress even stronger.

Part of the creativity required for this progress may well be shown by the CHWs themselves, as the introduction of the technology motivated them [29,38] and was overall enjoyable [39]. CHWs became innovative in the development of new media [38] and took ownership of the technology, for example, by independently organizing events going beyond the aims set out by the researchers [37]. At times, CHW motivation also extended to influential community members who became involved in the projects [38]. The increased levels of CHW motivation may be explained to some extent by their elevated levels of self-efficacy [38] and community recognition [29,30,35-37]. The mHealth technology gave CHWs a sense of pride and empowerment [35] and elevated their social status [30,37]. This, in turn, affected the extent to which clients accepted health messages, as they considered them trustworthy and credible [29,30,37,39]. Thus, by boosting CHW motivation, self-efficacy, and community status and by raising the credibility of health messages, mHealth may help CHWs promote healthy behaviors more effectively in their interactions with clients. However, the question remains whether these interactions improved with the use of mobile technology.
CHW-Client Interactions

The impact of mHealth on CHW-client interactions was ambivalent. On the one hand, CHWs sometimes viewed smart devices as complementary to their interaction with clients [39]. For instance, CHW-moderated group video sessions generated considerable discussion [37]. Devices were particularly beneficial for sensitive topics such as sexual health [35]. On the other hand, CHWs also used portable media to replace client conversations [29,30,38], for example, because they did not know what else to do [38], they were tired [29], or they wanted to save time [30]. In other cases, CHWs preferred to interact with clients only after the videos had played until completion [33,34]. Beneficiaries frequently considered video-assisted health promotion sessions as rushed or too short [36]. In 1 study [36], there was a considerable divergence in how CHWs and clients assessed the use of smartphones; while CHWs embraced them, beneficiaries criticized the quality of interactions. This suggests that mHealth-facilitated health promotion may simplify CHWs’ work by replacing discussions with screen time—at the expense of clients’ experience.

Personal interaction with clients is one of the factors that distinguish CHWs from other health-promoting agents. It is thus questionable whether mHealth can benefit CHWs’ health-promoting efforts should the quality of face-to-face interactions be undermined. However, appropriate CHW training in how to use videos to stimulate discussions may reduce or eliminate the risk of noninteraction, as 1 study showed [38]. Further research should focus on mHealth’s influence on the quality of CHW-client interactions and how a stimulating synergy between technology and interactions can be achieved.

Technical Difficulties

Even the best electronic device is of no avail if a CHW lacks the knowledge on how to use it. Some CHWs initially struggled when using portable media [32,36,38]. Younger CHWs generally adapted more quickly than their older colleagues [32,38], and higher education levels facilitated the adoption of the technology [32,38]. Due to the technological challenges, CHWs reported feeling anxious [29], nervous [32], and even worried about their community status being compromised [29,34]. However, the technical difficulties were reduced after CHWs received appropriate training [33,38], and even older CHWs learned to use the devices as effectively as their younger peers [33]. Having overcome the initial problems, CHWs enjoyed using the devices [33,39], considered touchscreens user friendly [33], and preferred portable devices over other, bulkier job aides [39]. Some CHWs reported that their skillful usage of the technology enhanced their perceived authority in the community [30]. Hence, proper CHW instruction is the key to converting smart devices from stressors and sources of discomfort into pleasant companions at work.

Go Local

Both CHWs and clients highlighted the importance of the media featuring local content [32,35,37-39]. When given the opportunity to create their own educational videos, CHWs chose to include testimonials from influential community members [38]. Videos featuring sequences of CHWs raised their social status in the community and enabled clients to identify with the content [37]. Clients preferred locally filmed videos over those shot in different locations [37]. The inclusion of locally appropriate color illustrations and the local language was also appreciated by clients [32,39], who emphasized that animated video content should resemble the local population in appearance and behaviors [32]. Hence, mHealth promotional strategies should adopt local features to maximize client identification with the material. Locally produced content thus has the potential to affect health behaviors more powerfully than material conceptualized elsewhere.

Client Learning and Behaviors

Perhaps the most important question in the context of mHealth and health promotion is whether mHealth helps CHWs improve clients’ health behaviors. The reviewed literature contained almost no evidence relating to changes in clients’ behaviors or process measures such as behavioral intent or health knowledge. Both clients [31] and CHWs [29,40] regarded the portable devices as enriching educational tools for the recipients of the interventions. Some CHWs provided anecdotal evidence that the use of the devices could have contributed to the adoption of health behaviors such as vaccinations [36]. However, only 1 (8%) of the 12 studies featured behavior change as an end point [30]. In this long-term RCT, the researchers observed no effect of the mHealth video intervention on health behaviors and only a small positive effect on health knowledge [30]. Thus, the potential of mHealth to bring about behavior change when employed by CHWs remains unclear.

Looking Ahead

The studies included in this review contain valuable information on the impact of mobile electronic devices on the delivery of health messages by CHWs. mHealth can empower CHWs and potentially help alleviate many challenges faced in the field. By stimulating community interest, health messages may be conveyed more effectively. Media content informed by the targeted communities themselves has been shown to be especially persuasive. However, the use of mobile media will always require careful training to maximize benefits and minimize potential pitfalls. CHWs should be familiarized with the technology and instructed on employing it as a complement to their interactions with clients, not as a replacement thereof. If used appropriately, smart devices may catalyze health promotion, benefiting CHWs and clients alike (Figure 3).

Nevertheless, our primary research question—whether mHealth improves CHW-led face-to-face delivery of public health messages and behavior change interventions—remains unanswered. Notably, all but 2 (83%) of the studies in this review are qualitative. While these are invaluable for planning, improvement, and evaluation, more large-scale quantitative studies, such as the included RCT [30], are needed with behavior change end points. In addition, 8 (67%) of the 12 studies in this review focus on MCH. This reflects the importance of MCH in low-income settings, but a wider scope of mHealth assessments would be desirable.
Limitations
Our review has some limitations. First, we only used 2 databases which, while wide-ranging in scope, did not capture all the relevant published studies we finally used. Therefore, we may have missed other published studies. Second, capturing all relevant research in this fast-moving field is difficult, as highlighted by most of the included work being only available as conference papers. These findings suggest the importance of future updates to this review.

Conclusions
Novel technological improvements may increase the effectiveness of CHW-led promotion of healthy behaviors. In this review, we show that smart mobile devices have the potential to enhance face-to-face interactions between CHWs and their clients, as these job aides address many of the challenges that CHWs commonly encounter in the field. However, we also find that the available evidence on our research question is scarce, largely qualitative, and focused on a limited scope of health outcomes. In particular, it is unclear whether mHealth helps CHWs change clients' health behaviors. Moreover, the impact of employing mHealth in the field is not all positive, as smart devices may burden CHWs with technological difficulties and lead them to act more passively in their interactions with clients. Further research is required to develop interventions to address this issue, along with large-scale quantitative interventions across a wider range of health outcomes to determine the full potential for interactive mHealth interventions to support CHW behavior change work in low-resource settings.

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Authors' Contributions
GH, TB, and MG conceived and designed the study. MG screened the titles, abstracts, and full texts and led the quality assessment, data extraction, and drafting of the manuscript. FS screened titles, abstracts, and full texts and participated in quality assessment and data extraction. GH judged over disagreements. MG, GH, FS, MA, AV, and JG interpreted the results and participated in the manuscript drafts and finalization. All authors approved the final manuscript.

Conflicts of Interest
None declared.

Multimedia Appendix 1
Database search entries.
[DOCX File, 13 KB - mhealth_v11i1e42023_app1.docx ]

Multimedia Appendix 2
PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-analyses extension for Scoping Reviews) checklist.
[DOCX File, 84 KB - mhealth_v11i1e42023_app2.docx ]
References


Abbreviations

CHW: community health worker
LMIC: low- and middle-income countries
MCH: maternal and child health

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Design Features Associated With Engagement in Mobile Health Physical Activity Interventions Among Youth: Systematic Review of Qualitative and Quantitative Studies

Ayla Schwarz¹, PhD; Laura H H Winkens¹, PhD; Emely de Vet¹, PhD; Dian Ossendrijver¹, MSc; Kirsten Bouwsema¹, MSc; Monique Simons¹, PhD
Department of Social Sciences, Chair Group Consumption & Healthy Lifestyles, Wageningen University & Research, Wageningen, Netherlands

Corresponding Author:
Ayla Schwarz, PhD
Department of Social Sciences, Chair Group Consumption & Healthy Lifestyles
Wageningen University & Research
Hollandseweg 1
Wageningen, 6706KN
Netherlands
Phone: 31 0639187108
Email: ayla.schwarz@wur.nl

Abstract

Background: Globally, 81% of youth do not meet the physical activity (PA) guidelines. Youth of families with a low socioeconomic position are less likely to meet the recommended PA guidelines. Mobile health (mHealth) interventions are preferred by youth over traditional in-person approaches and are in line with their media preferences. Despite the promise of mHealth interventions in promoting PA, a common challenge is to engage users in the long term or effectively. Earlier reviews highlighted the association of different design features (e.g., notifications and rewards) with engagement among adults. However, little is known about which design features are important for increasing engagement among youth.

Objective: To inform the design process of future mHealth tools, it is important to investigate the design features that can yield effective user engagement. This systematic review aimed to identify which design features are associated with engagement in mHealth PA interventions among youth who were aged between 4 and 18 years.

Methods: A systematic search was conducted in EBSCOhost (MEDLINE, APA PsycINFO, and Psychology & Behavioral Sciences Collection) and Scopus. Qualitative and quantitative studies were included if they documented design features associated with engagement. Design features and related behavior change techniques and engagement measures were extracted. Study quality was assessed according to the Mixed Method Assessment Tool, and one-third of all screening and data extraction were double coded by a second reviewer.

Results: Studies (n=21) showed that various features were associated with engagement, such as a clear interface, rewards, multiplayer game mode, social interaction, variety of challenges with personalized difficulty level, self-monitoring, and variety of customization options among others, including self-set goals, personalized feedback, progress, and a narrative. In contrast, various features need to be carefully considered while designing mHealth PA interventions, such as sounds, competition, instructions, notifications, virtual maps, or self-monitoring, facilitated by manual input. In addition, technical functionality can be considered as a prerequisite for engagement. Research addressing youth from low socioeconomic position families is very limited with regard to engagement in mHealth apps.

Conclusions: Mismatches between different design features in terms of target group, study design, and content translation from behavior change techniques to design features are highlighted and set up in a design guideline and future research agenda.

Trial Registration: PROSPERO CRD42021254989; https://tinyurl.com/5n6ppz24

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KEYWORDS
systematic review; youth; physical activity; design features; engagement; mHealth; mobile health; mobile phone
**Introduction**

**Background**

Physical activity (PA) in youth is associated with a variety of health benefits [1], including physical [2] and mental health benefits [3]. Despite the health benefits, 81% of youth (ie, those in childhood and adolescence) globally do not meet the PA guidelines [4,5] of daily 60 minutes of moderate- to vigorous-intensity physical activity (MVPA) and vigorous activities 3 days per week [1]. In Europe, only 19% of adolescents comply with the MVPA guidelines, and higher family affluence is associated with higher levels of MVPA [6]. Moreover, PA in youth is reported to track into adulthood, underlying the importance of promoting PA in the youth [7,8]. Also, the youth of families with a low socioeconomic position (SEP) are less likely to meet the recommended PA guidelines [9,10]. Therefore, effective and socially acceptable PA interventions are needed [11], especially among youth of families with a low SEP. SEP is often measured in terms of education (attainment), income, and occupation status, which are often interrelated and related to the social and economic resources available [12].

Mobile health (mHealth) tools such as smartphone apps can be cost-effective [13] in changing total PA [14,15] and daily steps [14]. mHealth interventions are preferred by youth over traditional in-person approaches [16-18] and are in line with preferences of youth, with regard to multimedia formats (ie, text, sound, and video) [19]. Mobile devices and apps have gained popularity in the daily life of increasingly younger age groups of youth, starting at the age of 3 or 4 years already [20-24]. Families of young children, especially those with a low-SEP background, indicate concern about inappropriate content [20], which might suggest that appropriate content might rather be supported by guardians. Appropriate content may refer to different forms of app use that might not necessarily increase current screen time use, as the design of the mHealth intervention may have considered a limited use time frame, only stimulating sporadic screen time (eg, integration to the direct physical environment to stimulate children to go outside and be physically active instead of the requirement of using the digital tool when being physically active) or stimulating the co-use of young children and guardians [25]. Earlier systematic reviews indicated that currently, foremost, adults are included in mHealth effectiveness studies, and limited research has been conducted among youth [26]. People with high SEP compared with people with low SEP report foremost positive health effects of the same digital intervention [27]. Apps are primarily designed for people with high SEP, and people with low SEP are often reported as being difficult to reach [28]. In contrast to mHealth apps, youth from low-SEP families engage in more screen time [29] and are more involved on the web [30] and active [31] gaming. This suggests that approaching youth with low SEP via apps (eg, screen and games) can be useful and beneficial, yet other ingredients (eg, tailoring) are needed to reach them effectively in mHealth apps [32].

Despite the promise of digital or mHealth interventions in promoting PA [26], a common challenge is to engage users in the long term [14] or effectively [26]. With regard to including people with a low-SEP background in research, studies identified challenges in reaching the target group [33] and engaging them in research [28] and in the digital health intervention [34]. In addition, eHealth and mHealth studies focus on a general target group and often do not research subgroups (ie, low-SEP groups) [35].

Engagement refers to the involvement and motivation of the user in the intervention [36]. It refers to “(1) the extent (e.g., amount, frequency, duration, depth) of usage and (2) the subjective experience characterized by attention, interest and affect” (ie, enjoyment) [37]. Attention refers to the degree of focus or absorption versus distraction in the intervention. Interest refers to feelings of interest or fascination versus boredom with the intervention. Enjoyment reflects the enjoyable experience of fun or pleasure versus frustration and annoyance while using the intervention [37,38]. Engagement can contribute to the overall effectiveness of digital interventions [26,39], meaning that to be effective, it is important that the user experiences a sufficient degree of engagement. The extent of use or dose is less predictive of engagement than the subjective experience to achieve the intended outcomes of the intervention (ie, effective engagement) [40]. This means that frequently engaging with the intervention is not always required to be effectively engaged with the intervention or the behavior eventually.

Currently, engagement is still not commonly reported in terms of use data (ie, extent) [26] and experience data (ie, subjective engagement) [41]. To improve intervention exposure and related intervention efficacy, it is important to better understand the design features (ie, active ingredients of an app that are in best cases informed by theory and translated into design, often referred to as “persuasive features,” features, and elements) contributing to engagement [26]. A review of commercial apps indicated low engagement scores and suggested investigating features that improve engagement with an app among youth [42], as the features may differ with those studied in adults [37]. Earlier studies reported a common decline in app use over time and called for investigating features that contribute to intervention uptake and engagement [14,26] also among particular subgroups, such as people with a low-SEP background [27,32,43,44]. For example, research among low-SEP groups indicated that frustration with particular design features and navigations (eg, data log) hampered app use [45].

When designing mHealth interventions, several active ingredients, otherwise indicated as behavior change techniques (BCTs), are applied and translated to app features to foster behavior change. In addition to low engagement scores, existing reviews reveal that a limited number of BCTs, such as instructions, encouragement, rewards, and feedback on performance, which are essential components of interventions to promote behavior change [46], are currently applied in mHealth apps [42]. BCTs can be directly translated into gamification or app features (eg, goal-setting translated into challenges), here referred to as design features [47]. Studies suggest that applying either a larger number of BCTs [42]—particular BCTs (eg, self-monitoring, feedback, goal-setting, rewards, reminders, and social support under certain circumstances) or a particular combination of BCTs (eg,
problem-solving and rewards) [48]—may contribute to engagement in digital interventions [44,47,48].

**Objective**

To inform the design process of future mHealth tools, it is important to investigate the design features that can yield effective user engagement. Research has demonstrated that for adults, user guidance, well-designed reminders, self-monitoring, positive feedback, rewards (eg, lottery), goal-setting, personalization, social networking, and health message framing [43,44,49] were associated with higher user engagement. However, most studies included adult samples, targeted mental health instead of PA among adolescents, or did not focus on low-SEP groups [50-52]. To our knowledge, no systematic review that primarily seeks to identify design features in mHealth PA intervention among youth, especially youth from low-SEP families that have been associated with engagement, has yet been conducted. Therefore, this systematic review aimed to identify which features are associated with engagement in mHealth PA interventions among youth who were aged between 4 and 18 years. This could help inform app developers and (digital) behavior change intervention researchers to better integrate engagement during the design process of mobile behavioral change interventions.

**Methods**

**Systematic Review**

The research protocol of the review was registered with the International Prospective Register of Systematic Reviews (PROSPERO; #CRD42021254989). Reporting complied with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses; Multimedia Appendix 1 [53]) statement [54].

**Search Strategy**

A systematic search was conducted on June 2, 2021, updated on June 24, 2022, and included the following databases: EBSCOhost (MEDLINE, APA PsycINFO, and Psychology & Behavioral Sciences Collection) and Scopus. The search terms that included synonyms relating to engagement and the population (youth), the intervention (mHealth), and outcome (PA) were informed by earlier reviews [37,55,56] and were eventually reviewed by an academic librarian. Multimedia Appendix 2 provides the complete search terms and synonyms used.

**Eligibility Criteria**

Quantitative, qualitative, and mixed methods studies were included in the review, as engagement is an emerging field of research, and the aim of this review was to gain a broad overview of features that are considered engaging. Available full-text research articles or conference papers were eligible in case they (1) described the development (ie, user-testing) or evaluation of an mHealth intervention (or more broadly the use of healthy lifestyles as long as specific information about PA could be retrieved), designed for PA promotion; (2) reported on the extent of use or subjective experience; (3) reported an association (ie, relation of design features with engagement, either assessed qualitatively and referred to “self-perceived association” or quantitatively referred to “association”); (4) included an intervention that was designed for healthy youth who were aged between 4 and 18 years (in line with Dutch PA guidelines [57] and in line with the increasing popularity of mobile devices in the daily life of [increasingly younger] youth) [20-24] or if the mean sample age was within this range; (5) were written in English; and (6) were published between 2010 and 2021 (owing to the smartphone use increase among youth, the use of mHealth interventions has been increasing since 2010).

Papers were excluded in case they (1) included a PA intervention that was not mobile based; (2) did not report on the extent of use or subjective experience; (3) did not report an association between a particular intervention feature and engagement; and (4) included either a study population of children who were aged <4 years, adults, or older adults or a population whose mean sample age was not within the range of 4 to 18 years (in line with Dutch national PA recommendation age range). Moreover, editorials, opinion papers, case studies, research protocols, design papers not including any user-testing, book chapters, systematic reviews, or meta-analyses were excluded (Textbox 1).
Textbox 1. Inclusion and exclusion criteria.

**Inclusion criteria**

- **Population**
  - Youth was defined as individuals who were:
    - healthy
    - aged between 4 and 18 years or the mean age of sample in the same age range

- **Intervention**
  - Physical activity mobile health interventions that are:
    - developed (ie, offered for user-testing) or evaluated
    - mobile
    - designed for physical activity promotion (or healthy lifestyle, including physical activity)
    - designed for the target group of youth (4-18 years old)

- **Comparison**
  - Not applicable

- **Outcome**
  - Drivers of the extent of use or subjective experience with regard to physical activity

- **Study type**
  - Quantitative, qualitative, and mixed methods studies that:
    - report on behavioral or subjective engagement
    - report a relation or association between the particular feature and engagement
    - are original and available full-text research articles or conference paper

**Exclusion criteria**

- **Population**
  - Youth in disease recovery and rehabilitation, experiencing a chronic disease (ie, overweight, obesity, and diabetes)
  - Children aged <4 years or mean age not within the age range of 4 to 18 years and adults or older adults

- **Intervention**
  - Physical activity interventions that:
    - were still in the early development phase (ie, not offering an app but, for example, only a general discussion about apps, paper mock-ups)
    - used different formats than mobile
    - only included wearables (eg, smartwatches) without a mobile health app

- **Comparison**
  - Not applicable

- **Outcome**
  - No drivers of the extent of use or subjective experience with regard to physical activity

- **Study type**
  - Quantitative, qualitative, and mixed methods studies that:
    - do not report on behavioral or subjective engagement
    - do not report a relation or association between the particular feature and engagement, for example, engagement is only described in general without any relation to the particular feature
Screening and Data Extraction

All the papers identified through the searches were downloaded into Rayyan software (Rayyan Systems Inc), a systematic review software, and duplicates were removed. A multistep strategy was applied. First, titles and abstracts were screened, followed by full-text reading to determine eligibility (DO). One-third of the titles and abstracts and full texts were reviewed by a second reviewer (KB). Interrater reliability for the titles and abstracts and full texts was substantial and moderate (Cohen $\kappa = 0.73$ and Cohen $\kappa = 0.54$), respectively. Disagreements regarding the title and abstract and full texts were resolved through discussion between the reviewers (DO and KB). Any disagreement between the 2 reviewers was discussed, and a third reviewer (AS) was consulted if necessary.

Data extraction was completed by both reviewers (DO and KB). Disagreement regarding data extraction was resolved through discussion between the reviewers (DO and KB). Background information (1-3) was extracted by one reviewer (DO), and the rest of the data (4-7) were extracted by two reviewers (DO and KB): (1) publication information (author and year); (2) study information (country and target group [number, percentage of female, percentage of people of low SEP, mean age, and age range]), and 3) app description (name, device, operating system, aim, and theory used; based on the mHealth taxonomy) [58]; (4) engagement measures (engagement measure or definition); (5) presence of BCT and, if present, behavioral change measures (based on the ABACUS scale) [59]; (6) design features (type of feature and 1 feature vs multiple features); and (7) association with engagement (short summary of association of particular features and engagement). The engagement measure of the original individual study was extracted (ie, usability, motivation, enjoyment, and liking) and then coded according to attention (ie, paying attention to mHealth app), interest (ie, feeling interested in mHealth app), and enjoyment (ie, experiencing enjoyment while using it; Textbox 2) [37].

As the researchers of this study were not aware of one framework of design features, 3 (digital) behavior scientist researchers (AS, LW, and MS) developed a coding frame to code all design features based on earlier studies on PA apps; gamification (ie, application of any features [eg, badges, points, avatars etc] in a nongame setting); and game research (ie, full-fledged and rule-based games) [61]. Free codes were created if they did not suit 1 category. Owing to the design process of translating BCTs into design features, obviously, overlap between the features and BCTs occurs (ie, goals vs goal-setting). Design features were coded as interface esthetics, challenges, narrative, levels, feedback, monitoring, customization or personalization, reinforcement, navigation, goals, social, progress, and credibility (Textbox 3).

Textbox 2. Coding scheme of engagement and definitions.

<table>
<thead>
<tr>
<th>Interest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experiencing interest, boredom, fascination, intrigue, or indifference [37]</td>
</tr>
<tr>
<td>Cognitive state that is occurring spontaneously and relates to liking and willful engagement [60]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Attention</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experiencing focus, inattention, absorption, distraction, or mindfulness [37]</td>
</tr>
<tr>
<td>Cognitive state of focused awareness and relates to focalization and concentration [60]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Enjoyment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experiencing frustration, annoyance, enjoyment, fun, or pleasure [37]</td>
</tr>
<tr>
<td>Relates to the sensory experience and relates to pleasure and activation [60]</td>
</tr>
</tbody>
</table>
### Quality Assessment

Quality was assessed according to the Mixed Method Assessment Tool [66], and it was not used as a basis for study exclusion but to support the interpretation of results (Multimedia Appendix 3 [67-87]). All the studies were coded by 1 reviewer (DO), and one-third of the studies were double coded (KB). Interrater reliability was substantial ($\kappa=0.63$). Any disagreement between the 2 reviewers was discussed, and a third reviewer (AS) was consulted if necessary.

### Synthesis of Results

A systematic narrative format [88] structured around the design features that were associated with engagement was applied. All the features that have been actually tested (ie, user-testing) were reported. In case the same study also provided suggestions by participants to further develop the app (ie, hypothetical design features not tested but suggested), this was marked explicitly as a suggestion. In addition, the presence or absence of BCTs was outlined, indicating whether theories had been applied in the design phase of design features or not. A subgroup analysis was conducted for youth from low-SEP families. The categorization of SEP was derived from the classification of the original studies. Research results were not grouped by the origin of the data (ie, qualitative, quantitative, or mixed methods), but it was indicated explicitly for each research outcome.

### Results

#### Description of Included Studies

In total, 21 studies were included in this review (Figure 1). The studies originated from different countries (15) and were conducted in Europe (n=10), North America (n=4), Australia (n=3), Asia (n=3), and South America (n=1). These studies were
published between 2012 and 2021. Mobile interventions were used and evaluated by youth who were aged between 3 and 18 years. Sample sizes ranged from 5 to 354 youths, with a total sample size of 1443 youths. All the studies retrieved informed consents from parents and youth participants, except for 5 studies that only collected consent from the youth participants alone [67,68] or from the school principal [70], were conducted in parent-child dyads [69], or did not clearly state this [71]. Studies included different engagement measures varying from acceptability, experience, usability, motivation, feasibility, enjoyment, engagement, satisfaction, or interest. When categorizing the measures in terms of interest, attention, or enjoyment, most studies (15/21, 71%) measured solely interest, especially in terms of features that were in general liked by the users. A combination of interest and attention (1/21, 10%), solely attention (1/21, 5%), solely enjoyment (1/21, 5%), or solely engagement (2/21, 10%) was rarely studied. Engagement was mainly measured as the primary outcome in some studies (14/21, 67%). Most studies (12/21, 57%) used a mixed methods design, ranging from posttest prototype studies to quasi-experimental studies to randomized controlled trials, mixed with designs such as qualitative exit interviews, focus groups, or think-aloud studies. In total, 24% (5/21) of studies included a qualitative study design (interview and focus group study), and 19% (4/21) of studies included a quantitative study design (experimental design with quantitative survey). Studies relevant to this review included qualitative data (10/21, 48%), quantitative data (4/21, 19%), or mixed methods data (7/21, 33%) to determine the association between design features and engagement.

Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart illustrating the inclusion and exclusion of studies. PA: physical activity.

On the basis of Mixed Method Assessment Tool [66], the quality of the included studies was mixed. In general, the studies that measured engagement as the primary study outcome had a moderate to high quality, especially scoring high on transparency regarding the data collection methods and analysis. Studies that focused on engagement as a secondary outcome scored rather low on the quality of the study design applicable to measure engagement (eg, including nonvalidated methods such as a number of open exit questions in a larger randomized controlled trial), although the studies scored high on the design (eg, randomized controlled trial) to measure the primary outcome (eg, PA).

mHealth Interventions

In general, the mobile interventions tested in the included studies (N=21) were either developed for commercial purposes (n=4, 19%) or for study purposes (n=17, 81%). Most of the interventions (14/21, 67%) were designed to improve PA behavior. In addition, 33% (7/21) of studies focused also on additional health behaviors associated with a healthy lifestyle (eg, nutrition or sleep) in addition to PA behavior. The studies included different types of mHealth interventions, ranging from mobile games (10/21, 48%) to mobile apps (8/21, 38%) to mobile text messaging systems (3/21, 14%). Mobile games mainly focused on PA (9/10, 90% studies); included different PA activities (ie, ranging from simple arm movements such as swinging arm to complex full-body movement such as running); and applied different inputs (ie, ranging from manual input to camera data to Bluetooth, GPS, or PA sensor data). Games ranged from short-term activities (eg, push-ups) to long-term gameplay (eg, location-based treasure hunt games). Mobile apps ranged from narrative-driven PA guidance to GPS-tracking.
information. Mobile text messaging systems especially focused on generating and adapting goal-setting, facilitating self-monitoring, and providing feedback [72,73] and informative content (ie, quizzes and factoids) [74]. Furthermore, 67% (2/3) of the studies focused also on health behaviors other than PA (Multimedia Appendix 4 [67-87]). The interventions tested in the included studies were perceived as engaging by the youth. Youth liked to play games that aimed to increase their PA level and evaluated apps or text messaging systems as easy to use and supportive in improving PA or lifestyle behaviors. Multiple studies (6/21, 29%) found that poor functionality and technical issues are considered a barrier for engagement with mobile interventions [67,68,75-77] and suggested to include technical improvements [76].

In the following section, all the design features are summarized, starting with the design feature researched most often. A detailed overview of the results is presented in Table 1. All tested design features (ie, features offered to participants via an app and actually tested) are outlined as an association between the particular design feature and engagement (either as self-perceived association in qualitative studies or as tested association in quantitative studies). In case the participants provided further suggestions on design features that might be included in a future version (ie, feature not tested or only hypothetical), it was explicitly referred to as a suggestion. The results section concludes with a subanalysis on BCTs and low-SEP subgroups.
Table 1. Design features and association with user engagement.

<table>
<thead>
<tr>
<th>Details</th>
<th>Association (ie, tested)</th>
<th>Suggestion (ie, hypothetical)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Interface aesthetics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Language</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PA(^a) and nutrition messages (ranging from information to quizzes)</td>
<td>([74]^{b,c}[67]^{b,d}[74]^{b,c})</td>
<td>([67]^{d})</td>
</tr>
<tr>
<td>Familiar content</td>
<td>([74]^{e}e)</td>
<td>N/A (^f)</td>
</tr>
<tr>
<td>Short messages</td>
<td>([78]^{b,f}[74]^{b,c})</td>
<td>N/A</td>
</tr>
<tr>
<td>Cheerful and personal tone</td>
<td>([78]^{b,f}[74]^{b,c})</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Visual</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clearly presented text</td>
<td>([68]^{b})</td>
<td>N/A</td>
</tr>
<tr>
<td>Large text blocks and complicated language</td>
<td>([68]^{e}e)</td>
<td>N/A</td>
</tr>
<tr>
<td>Clear and realistic visualization (eg, infographics, figures, tables, pictures, symbols, and videos)</td>
<td>([79]^{b,f}[68]^{b,g})</td>
<td>([68]^{e}[67]^{d}[76]^{f}[77]^{d})</td>
</tr>
<tr>
<td>Quality not reflecting reality</td>
<td>([70]^{e}e)</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Sound</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sounds associated with arm movements or game activities</td>
<td>([75,80]^{b,c})</td>
<td>N/A</td>
</tr>
<tr>
<td>Sounds associated with every click</td>
<td>([81]^{e}e)</td>
<td>N/A</td>
</tr>
<tr>
<td>Monotone and robotic voice</td>
<td>([75]^{c}e)</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>General interface</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lack of sophistication</td>
<td>([75]^{c}e[79]^{e}e)</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Reinforcement</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Rewards</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tangible rewards (prize, medal, new Pokémon, and healthy real-world actions)</td>
<td>([75,82]^{b,c}[78]^{h,b}[83]^{e}[78]^{d})</td>
<td>([83]^{e}[78]^{d})</td>
</tr>
<tr>
<td>Intangible rewards (achievement, encouragement, evolving Pokémon, and comparisons)</td>
<td>([70,81]^{b,f}[82,84]^{b,c})</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Messages</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Messages sent at random times, maximum frequency &lt;2 times per day</td>
<td>([74]^{b,c})</td>
<td>N/A</td>
</tr>
<tr>
<td>Frequency and timing of messages</td>
<td>([78]^{e}e)</td>
<td>N/A</td>
</tr>
<tr>
<td>Receiving reminders</td>
<td>([79]^{e}e)</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Reinforcement</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leaderboard</td>
<td>([76]^{b,c}[87]^{b,d}[85]^{c}c)</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Navigation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>PA instructions</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instructions on PA (eg, video)</td>
<td>([67]^{b,d})</td>
<td>([71]^{e}[86]^{e})</td>
</tr>
<tr>
<td>Textual and unclear instructions on physical missions</td>
<td>([71]^{e}e[83,85,86]^{c}e)</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>In-app instructions</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clear and intuitive in-app instructions</td>
<td>([84]^{b,c})</td>
<td>([80]^{c})</td>
</tr>
<tr>
<td>Written manual and unclear instructions</td>
<td>([78]^{e}e[76]^{c}e)</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Layout</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Straightforward and simple layout</td>
<td>([84]^{b,c})</td>
<td>([67]^{d}[83]^{f})</td>
</tr>
<tr>
<td>Scrolling to find information</td>
<td>([68]^{e}e)</td>
<td>N/A</td>
</tr>
<tr>
<td>Details</td>
<td>Association (ie, tested)</td>
<td>Suggestion (ie, hypothetical)</td>
</tr>
<tr>
<td>------------------------------------------------------------------------</td>
<td>--------------------------</td>
<td>-------------------------------</td>
</tr>
<tr>
<td>Lack of logical flow between different modules</td>
<td>N/A</td>
<td></td>
</tr>
<tr>
<td><strong>Navigation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Finding and recognizing items on a map</td>
<td>[68] e,g</td>
<td>N/A</td>
</tr>
<tr>
<td>Difficulty reading the map</td>
<td>[70] e,g</td>
<td>N/A</td>
</tr>
<tr>
<td>Controls reacting slowly</td>
<td>[76] f,e</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Social</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Multiplayer</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socializing and multiplayer capabilities (eg, friends)</td>
<td>[80] b,c [70,78,81] b,g</td>
<td>[76,80,82] f [71] d</td>
</tr>
<tr>
<td><strong>Social messages</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sharing results and postings</td>
<td>[78] b,d [83] b,c</td>
<td>N/A</td>
</tr>
<tr>
<td>Social networking</td>
<td>[84] f,e</td>
<td>N/A</td>
</tr>
<tr>
<td>Replying messages or chat</td>
<td>[74] b,c</td>
<td>[82] c</td>
</tr>
<tr>
<td><strong>Competition</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Competing against classmates</td>
<td>[71] e,h [82] e,h [87] d,h</td>
<td>N/A</td>
</tr>
<tr>
<td>Competing with friends</td>
<td>[87] d,b [78] b,g</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Cooperation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cooperation and togetherness</td>
<td>[82] b,c</td>
<td>[82] c</td>
</tr>
<tr>
<td><strong>Challenges</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Types of challenges</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Searching for items (eg, QR codes, bombs, Pokémon, and tags)</td>
<td>[70,71,81] b,g [82] b,c</td>
<td>N/A</td>
</tr>
<tr>
<td>PA missions</td>
<td>[84] b,c [69,71,78] b,g</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Variety</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Repetitive game with lack of progression or clear end goal</td>
<td>[78] f,g</td>
<td>N/A</td>
</tr>
<tr>
<td>Larger variety of actions (eg, special events, season-themed challenges, and new missions or minigames)</td>
<td>N/A</td>
<td>[78] f [76,82] f [77] d</td>
</tr>
<tr>
<td><strong>Difficulty level</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difficulty level of the challenges that suit a player’s skill level</td>
<td>[81] b,g</td>
<td>[80] c</td>
</tr>
<tr>
<td><strong>Time limit</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time given (to diffuse bombs)</td>
<td>[70] e,h</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Monitoring</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Manual input</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manual input of multiple activities or behaviors</td>
<td>[68,69] e,g</td>
<td>N/A</td>
</tr>
<tr>
<td>Remembering multiple behaviors</td>
<td>[79] e,g</td>
<td>N/A</td>
</tr>
<tr>
<td>Run logs and PA diary</td>
<td>[84] b,c [67] b,d</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Device</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monitoring via phone (eg, SMS text messaging and smartphone)</td>
<td>[73] b,d [71] b,g</td>
<td>N/A</td>
</tr>
<tr>
<td>Monitoring via external sensor (eg, pedometer, wearables, and heart rate monitor)</td>
<td>[73] b,d [71] b,g</td>
<td>N/A</td>
</tr>
<tr>
<td>Monitoring with real-time information</td>
<td>[83] b,c [77] d,h</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Self-monitoring</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Details</td>
<td>Association (ie, tested)</td>
<td>Suggestion (ie, hypothetical)</td>
</tr>
<tr>
<td>---------</td>
<td>--------------------------</td>
<td>-----------------------------</td>
</tr>
<tr>
<td>Self-reflection</td>
<td>[72]c, h</td>
<td>N/A</td>
</tr>
<tr>
<td>Ability to track multiple behaviors</td>
<td>[79]f, h</td>
<td>N/A</td>
</tr>
<tr>
<td>Goals</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Self-set goals</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Personal, self-selected goals</td>
<td>[67]b, d [78,79]b, g</td>
<td>N/A</td>
</tr>
<tr>
<td>Type of goals</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Choosing between different types of goals</td>
<td>[84]b, c</td>
<td>N/A</td>
</tr>
<tr>
<td>Goals helped to perform PA</td>
<td>[83]b, c [67]b, d</td>
<td>N/A</td>
</tr>
<tr>
<td>Goals</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Goal reminders</td>
<td>[72,76]b, c</td>
<td>N/A</td>
</tr>
<tr>
<td>Customization</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Types of customization</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ability to customize user account, own music, choosing the type of PA, and personal goals</td>
<td>[78,79]b, f [83,84]b, c</td>
<td>[83]c</td>
</tr>
<tr>
<td>Avatars</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avatars (and additional sports equipment)</td>
<td>[69]b, g</td>
<td>[69]g</td>
</tr>
<tr>
<td>Feedback</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Types of feedback</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Feedback message on goals, weekly PA, real-time information, and individualized feedback</td>
<td>[67]b, d [83]b, c [79]b, g [77]d, h</td>
<td>N/A</td>
</tr>
<tr>
<td>Representation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Feedback presented in graphs or via SMS text messages</td>
<td>[67,73]b, d</td>
<td>N/A</td>
</tr>
<tr>
<td>PA input</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PA input</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variety of arm movements and physical exercise</td>
<td>[80]b, c [71]b, g</td>
<td>N/A</td>
</tr>
<tr>
<td>Running, PA, and FMS¹ components</td>
<td>[70,81]g, h</td>
<td>N/A</td>
</tr>
<tr>
<td>Narrative</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Characters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variety of virtual components (eg, zombies), weapons, and ways to increase character abilities</td>
<td>[80,84]b, c</td>
<td>[78]g</td>
</tr>
<tr>
<td>Setting</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Realistic</td>
<td>[80]b, c</td>
<td>N/A</td>
</tr>
<tr>
<td>More world to explore</td>
<td>N/A</td>
<td>[78]g</td>
</tr>
<tr>
<td>Story</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Complex story line</td>
<td>N/A</td>
<td>[70]g [80,86]c</td>
</tr>
<tr>
<td>Levels</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Increasing levels</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gradually increasing levels</td>
<td>[84]b, c</td>
<td>[69]g</td>
</tr>
<tr>
<td>Credibility</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Messages originating from nutrition professionals</td>
<td>[74]b, c</td>
<td>N/A</td>
</tr>
</tbody>
</table>
Other features

- **Push notifications**
  - Additional push notifications
  - N/A

- **GPS**
  - Reduce GPS latency
  - N/A

Navigation

Instructions related on the one hand to instructions of the in-app functions and on the other hand to instructions related to PA activities. In both cases, well-outlined instructions could support engagement [67,84], and suggestions were made to design clear, simple, and intuitive instructions [80] with the addition of visual components [71,86]. Unclear instructions on requested movements [83,85,86] or unclear [76] textual [71,78] instructions could hamper engagement. The wish for clear instructions had been underlined by a straightforward and simple layout [67,68,76,84]. Working with a map was considered difficult [70,76]. Laine and Suk [70] reported that the quality of the map tile was perceived as poor, which made it difficult to identify one’s current location. In addition, Robertson et al [76] reported that children experienced difficulties in understanding the map representation in the game interface. Interestingly, both studies integrated the Google Maps (Google Inc) services, which hampered PA and interrupted engagement. To find and recognize targets, the map resolution and targets should be clear. Furthermore, controls facilitating navigation through the app were negatively associated with engagement in case they were reacting slowly [78,85].

Social

Multiplayer gameplay was considered important for engaging, socializing [80,81], and playing with friends [70] and setting challenges for friends [78]. In different studies, multiplayer gameplay was suggested to include in future versions of the app [76,77,80,82]. However, competing with friends revealed mixed results. Martin et al [78] found a positive association with engagement [78], and as outlined previously, leaderboards could affect high competition (see Reinforcement section); however, when competition was compared with cooperation, the latter was preferred [71,82,87]. This was also quantitatively assessed by Nuijten et al [87], who found that intergroup competition (ie, collaboration within class and competing against other classes) increased engagement in comparison with intragroup competition (ie, individual competition). Competing with others was suggested by youth for future app versions [80].

\[\text{PA: physical activity.}\]
\[\text{Qualitative studies, assessing self-perceived association.}\]
\[\text{Quantitative studies, assessing association.}\]
\[\text{Negative association between features and engagement.}\]
\[\text{N/A: not applicable.}\]
\[\text{Mixed methods studies.}\]
\[\text{Positive and negative associations between features and engagement.}\]
\[\text{Fundamental movement skills.}\]

Interface Esthetics

Clear and short messages with positive and personal tone and relevant content were associated with engagement in youth [67,74,78]. Engagement was hampered by lack of sophistication in the interface (eg. game graphics, sound effects, and camera use) [75,79]. Youth preferred a clear and understandable layout [67,68,76] and text with clear headlines and a large font size supported with infographics, figures, and tables [68]. The design of progress graphs was identified as an important contributor to engagement in terms of readability [79]. Too much text or large text blocks, as well as heavy and complicated language, were considered to hamper usability [68]. Participants suggested to include more pictures, symbols, and videos to make the app more attractive [68]; improved or realistic visuals [67,76,77]; or general interfaces [76]. Youth liked sounds that were associated with their movements or game activities [75,80]. However, robotic and monotonic voices [75] or sound associated with clicks could negatively impact engagement [81].

Reinforcement

Youth enjoyed winning tangible rewards [70,75,78,82] and suggested offering rewards (ie, in apps that have not introduced rewards earlier) [78,83]. Intangible rewards (eg, feeling of achievement [81] and encouragement [84]) were especially interesting for the youth. Messages that were sent at random times were preferred over messages sent at preset times. The preferred frequency of the messages was less than twice per day [74]. In the study by Martin et al [78], participants expressed concerns about the frequency and timing of messages. The timing should be appropriate, for example, not receiving messages at a moment when one is not able to act on the messages [74,78]. Mixed results with regard to leaderboards were noted. Youth enjoyed leaderboards when beating persons placed above them but they did not enjoy being at the top of the leaderboard. In addition, leaderboards could lead to too much competition that could result in teasing [76]. In another study, adolescents particularly indicated that they missed seeing the other player’s scores [85].
Cooperation and togetherness were considered important during gameplay [82,87], and an extension to collaborate with others was suggested for future app versions [82]. Social interaction in terms of messages to the research team [74], postings [83], and sharing results [78] was considered to contribute to engagement. A chat function [82] or a social platform [80] was suggested for a future app version. Direito et al [84] described that children seldom or never used the social networking features and disliked sharing their runs or status updates.

**Challenges**

Youth suggested increasing the variety of actions or (mini) games available, indicating that they liked a wide variety of challenges to choose from when playing a game [77,78]. In addition, the new content was considered important, for example, season-themed challenges or special events [76,78,82]. Youth liked activities organized around a hunt, including activities of finding and scanning objects [70,71,81,82] or missions, for example, PA-related workout missions [69,71,78,84]. Youth liked games that made a connection between energy expenditure in real life and the energy level in a game [78]. Repetitive challenges with a lack of progression or clear end goals negatively impacted engagement [78]. The difficulty level of the challenges needed to fit the users’ level [80,81], as challenges that were not adjusted to a younger age appeared to negatively impact young kids’ enjoyment [81]. This finding was supported by the study done by Arteaga et al [80], in which children suggested including multiple challenges that fit the different levels of individual players. The study by Laine and Suk [70] reported mixed results regarding a time limit paired with challenges.

**Monitoring**

Manual input hampered engagement [68,69,79], although youth liked to make use of logbooks [84] and diaries [67]. Using devices [71,73] to track real-time information was appreciated and perceived as useful [77,83]. Youth endorsed the self-monitoring function but had complaints relating to discomfort while wearing the monitoring device [72]. The accelerometer that was used in this study was not part of the intervention but was used to measure the PA outcome. The perceived discomfort might have influenced the use of the intervention. Including the function to track multiple health behaviors, on the one hand, engaged youth but, on the other hand, challenged them by the need to remember multiple behaviors [79].

**Goals**

Self-set goals were considered important [67,76,78,79]. However, choosing a goal was considered cognitively challenging [76]. Specific goals on PA or different types of goals were considered to contribute to engagement [67,83,84]. The feeling of achieving a goal contributed to enjoyment [76]. Reminders to set goals were considered useful [72].

**Customization**

Youth liked to customize their accounts (eg, removing features such as friends, goal-setting, and training plans) [79,83]; choose the type of PA they wanted to perform [83]; sort their personal goals [78]; and listen to their own music [84]. Youth in general suggested including the possibility of customizing one’s account [83]. Youth liked to engage with avatars [69], and children (10-12 years old) suggested including dragons (35%), followed by a dinosaur (25%), and suggested to upgrade their avatar with personal equipment [69].

**Feedback**

Participants considered regular feedback on achievements and goals [67], which is individualized and in real time to contribute to engagement [79,83]. However, feedback based on dynamic tailoring did not reveal to contribute to overall engagement but contributed to narrative sensation (ie, feeling of presence) [77]. Feedback that was shared via SMS text messaging and presented in graphs was highly valued [67,73].

**PA Input**

Youth enjoyed upper-body movements [80] compared with full-body movement such as running. However, requiring running to proceed in the game achieved mixed results (ie, facilitating and hampering) on engagement [70,71,81].

**Narrative**

Youth liked the addition of a narrative, including a variety of characters [78,80,84] and settings [78] that are realistic [80], and the addition of a (complex) story, which was suggested by various studies [70,80,86].

**Levels**

Gradually increasing levels [84] were considered important, and higher upgrade levels, referring to unlocking new levels as the player proceeds, were suggested to be added [69].

**Credibility**

Youth found it important to receive information from a credible source as nutrition professionals [74].

**Other Features**

Youth suggested including additional push notifications [80] and reducing the GPS latency [76].

**Included BCTs**

In total, 19% (4/21) of the studies did not include any reference to BCTs [68,71,82,86]; 19% (4/21) of studies did only include a reference to BCTs in the results [70,73,74,80]; and 33% (7/21) of studies did include a reference to BCTs in the methods and results; however, they did not particularly refer to it as BCT [67,69,75,77,78,84,87]. Furthermore, 29% (6/21) of studies included a particular reference to BCTs and included the outline of the BCT in the methods and results [72,76,79,81,83,85]. In general, 57% (12/21) of studies included theory in the development of the app (4/21, 19% excluded as apps developed for commercial purposes). In addition, 81% (17/21) of studies included several BCTs (ranging from 2-10), which were partly related to the design features outlined in Table 1. The particular BCTs were not adopted in Table 1, as they have been translated into design features. The BCTs that were most often mentioned were feedback (11/21, 52%), social comparison (11/21, 52%), goal-setting (10/21, 48%), rewards (10/21, 48%), monitoring (9/21, 43%), and encouragement (6/21, 29%).
Subanalysis SEP

In total, 29% (6/21) of the studies (all from countries that form the Global North) included a substantial target population of low SEP [72,75,77,86,87]; however, 33% (2/6) of studies eventually included a large percentage of high-SEP children (34% to 75%) [72,76]. In only 33% (2/6) of studies [75,76], the SEP was indicated as a direct study aim, and in 33% (2/6) of studies [77,86], a mix in SEP was desired. Low SEP was defined differently (ie, neighborhood site, family income, family affluence, parents’ education level, and youth education level), which made it difficult to compare studies, and engaging design features were not presented for different SEP categories. Therefore, subanalysis of the different design features could not be conducted.

Discussion

Principal Findings

This systematic review presents the results of 21 studies that assessed the associations between features and engagement with mHealth PA interventions. According to our knowledge, this is the first mHealth intervention review that focused on PA and youth, with an additional focus on low-SEP background.

The results showed that various design features, such as a clear interface; rewards; multiplayer game mode; facilitation of social interaction; variety of challenges with personalized difficulty level; self-monitoring options; and a variety of customization options among others, including self-set goals, personalized feedback, progress, and a narrative, were positively associated with engagement. In contrast, various features, such as sounds, leaderboards, competition, instructions, timing of messages or notifications, maps, or self-monitoring facilitated by manual input, that have been negatively associated with engagement need to be carefully considered while designing mHealth PA interventions. In addition, technical functionality can be considered as a prerequisite for engagement.

When comparing the results with those of research in adults, several features are shared, such as a simple and structured interface, tailored and positive feedback on PA levels [43,44,89,90], progress [90], well-designed reminders (eg, timing and frequency of notifications) [26,43,44,89], rewards [43,44,49,91-93], self-monitoring [26,43,44], goal-setting [43,44], clear navigation [43,44], accurate tracking function [43], personalization (eg, goals) [94], and the offer of a variety of features [43,95]. Technical difficulties were also negatively influencing engagement in adults [43,89].

Several features that have been in particular noted for adults, yet not in this review on youth, are credential sources, adequate privacy settings [43], and content preventing the occurrence of surprises [26,43]. Sharing accomplishments via social media was considered less engaging in adults [90] than in youth. Although the studies among youth provided mixed results on competition, literature on adults suggests including competition [44,90], leaderboards [91], and hierarchical status (eg, progressive status report) [91]. In gamification research, leaderboards are considered the most common feature implemented (alongside points, goals, and progress) [96,97], and this seems to be considered with care when addressing youth for PA promotion. In studies including adults, no direct links with narratives, avatars, a hunt, difficulties with manual input, sounds, or virtual location maps were found. Research on using these design features for interventions in youth is limited, according to the results of this review.

This review focused on design features that have been tested by youth and included hypothetical or suggested features of the same studies but did not extend the search to studies that only provided ideas or suggestions that have not been tested (ie, cocreation study on app development without user-testing). Earlier studies have indicated that what users may request and what they actually engage with in practice do not have to match [44,98]. In the studies in this review, several features were tested and included as further suggestions, which may underline the importance of the match between what youth would like to have included and what they actually engage with. The following results are in line with existing research on app development (ie, no user-testing) among youth: (1) clear user interface aesthetics (ie, youthful visuals) [99,100]; (2) rewards, referring to a fair reward system [100,101], rewards that progressively increase [102], and social rewards (ie, storybooks with interactive questions) [103]; and (3) multiplayer mode, facilitating competition [55,100] and comparison (eg, leaderboards) [55], as well as cooperation [103,104]. Several features that have been suggested and tested in the studies included in this review were not found in existing research, and these include (1) chat functions (although with mixed results), (2) increasing difficulty level, (3) customizing user content, and (4) adding a variety of avatars and characters. In addition, several features have been suggested but have not been tested, and these include (1) meaningful information [99,100], including PA-related tips and plans [101], and (2) variety and content updates [102].

Features that have been solely suggested in this review (ie, not tested) relate to (1) adding video and moving figures that navigate the PA and app instructions, (2) adding a storyline, and (3) including additional push notifications. Other research suggests that a clear navigation that is self-explanatory is important [99], yet that notifications evoke mixed results on engagement [101]. Features that have been suggested in other research, but not in this review, include (1) in-app events [104] and (2) GPS and map editors [105,106]. This review contributes to the body of research and highlights that although maps can be suggested by youth, they can be very challenging when applied in practice, risking hampering engagement. Additional features that especially could hamper engagement include a small number of available minigames [106], no instant feedback [102] or personalized feedback by email [101], lengthy texts, and difficult navigation [99]. Future studies are needed to conduct experimental testing on features that yield inconclusive evidence so far among others competition, leaderboards, and notifications, as it may be possible that the results may differ for different subgroups of youth. We recommend that designers and health researchers consider designing a clear interface and an appropriate and fair reward system, enabling social interaction, and providing a variety of content, which is preferably customizable.
Earlier research indicates how a variety of design features are designed and implemented in mobile apps [65,107]. This is also indicated in other research outlining the challenges of how BCTs are operationalized [65,108-110]. In other words, the content or the active ingredient of the intervention may still differ by how it is delivered, in which context, or in which combinations (ie, design features, including gamification elements and BCTs) it is applied [111]. An ontology, as proposed by West and Michie [112], and tools such as SciModeller that integrate multiple pieces of empirical data [113] can eventually contribute to this knowledge and help researchers and mHealth developers apply and build on this knowledge. This review focused on whether the app design has been informed by or has been based on relating BCTs or behavioral theories and concluded that BCTs are often not outlined in detail, and there is no particular translation of BCTs to app content. This review only included 33% (7/21) of studies that made a clear translation from a particular BCT to a design feature. A scoping review not only summarized the challenges in mHealth design in translating BCTs to an mHealth feature but also raised challenges with regard to integrating ideas from different perspectives (ie, BCTs, user needs, and stakeholder views), which can result in conflicting ideas [110]. Existing research on mHealth, focusing on app features, BCTs, or both, points to the challenge of mapping which features or BCTs work in isolation or in combination with others [47,114]. Furthermore, a wide applicability exists with regard to creating design features that are often designed from scratch. In light of the Open Digital Health initiative [115], we recommend making mHealth apps and data accessible to be able to reuse or continue working on existing design features that have been proven to be effective for engagement. By this, we can start mapping working design features for different user groups in different contexts [115,116].

Different systematic reviews focusing on the effectiveness of mHealth interventions have also focused on BCTs. However, a large number of the reviews map the number of BCTs that have been included in an intervention [42,117] or the BCTs that have been included [42,117]. However, there is dearth of research that identifies the individual or interaction effects of design features or BCTs in mHealth interventions among youth. Several studies have identified that modeling is an effective BCT for children. With regard to adolescents, providing consequences for behavior, providing information on others’ approval, facilitating intention formation, self-monitoring, using behavioral contract [118], and providing individualization support [25] were positive predictors of PA effect size. Providing instructions was negatively predictive of study effect size [118]. In future reviews, it would be interesting to map the similarities and differences between design features that contribute to engagement in the mHealth intervention (ie, microengagement) and BCTs that contribute to the behavioral change effectiveness (ie, macroengagement) to identify effective design features [40]. However, limited BCTs are researched in effectiveness studies, especially among youth [119]. Therefore, more individual studies are needed before this comparison can be made. Future studies may, therefore, test the effectiveness of individual BCTs and combinations of BCTs on behavioral changes in factorial designs [120] in youth. Future studies should also consider testing both microengagement and macroengagement in the same mHealth intervention [40] to better inform how to increase engagement in the mHealth intervention (ie, microengagement) and translate this to behavioral change, which can be engaged in the long term in the absence of any intervention (ie, macroengagement).

This review underlines that research addressing youth from low-SEP families is very limited with regard to engagement in mHealth apps. Although it is often argued that apps can be a suitable platform to reach diverse groups of youth, it is striking that only 7 studies have been identified that aim to involve youth from different SEP backgrounds. Unfortunately, it was not possible to conduct a subanalysis because the features were not directly linked to the SEP position. Studies that succeeded in addressing a large percentage of children with low SEP recruited participants via schools [49,77,86]. From this review, it cannot be directly derived which recruitment strategy leads to lower percentages of children with low SEP, as especially, the measures of low SEP differ greatly. We advocate for more research that includes youth from low-SEP families early in the development phase and user-testing and suggest recruiting youth from low-SEP background via schools. Further research in adults suggested that personal contact between study staff and participants is essential and that community sites (comparable with school settings) created a sense of community and support [121]. Thereby, youth who have the potential to book the greatest health gains (ie, often youth with low-SEP or low-PA levels) are addressed appropriately, which may contribute to reducing health inequalities and the digital divide [44]. A scoping review highlighted the need to further investigate user engagement studies in low-SEP groups and called for future in-depth formative studies [95]. Existing research indicates that multimedia, personalization, variation, and gamification [95], such as competition [116], can contribute to engagement in mHealth apps among young adults with low-SEP backgrounds. We advocate to start testing these features in youth with low SEP.

In this review, we identified a heterogeneity of engagement measures, which has also been identified in earlier reviews [55,60,114,122,123]. In addition, several measures only reflect one construct of engagement and do not measure the multidimensional concept of engagement [55]. Furthermore, research studies included in this review did not distinguish between different features that can be considered in different stages of engagement. Research suggests that engagement is a dynamic process rather than a state, although it is often measured as a state (ie, 1 postintervention questionnaire on engagement instead of cyclic measurement) [124]. On the basis of earlier research, it may however be stated that features such as a clear interface are especially important for the initial stage of engagement (ie, attention grabbing) [124]. Features that sustain engagement may relate to social interaction, a variety of challenges with personalized difficulty level, self-monitoring and customization options, and narratives [77]. Disengaging may relate to certain types of sounds, leaderboards, instructions, messages or notifications, competition, and self-monitoring facilitated by manual input. Features that reengaged or nonengaged users have not been identified in this review. However, for example, Janko et al [69] discussed unblockable
avatars and upgrading levels as possible features that may contribute to reengagement. Research on young adults indicated that users did not engage (ie, nonengagement) owing to low uptake of the intervention among peers [49]. The reasons for disengagement mentioned in this review relate to factors outside the mHealth intervention (eg, holidays, competing after-school activities, weather, school policies, and unstructured or leisure settings) [76,77,81,83,87], yet nonadherence has not been linked to design features. Future research is needed to identify particular features in different stages of engagement to grasp engagement as a multidimensional and dynamic process [124]. Thereby, designers can improve design features according to the stage of engagement (eg, include particular features to reengage users and prevent them from sustained disengagement). Furthermore, engagement may also be related to the setting in which the mHealth tool is implemented. The activity that competes with the mHealth tool is central. Earlier research indicated that pupils tend to choose to engage with an mHealth tool in order not to participate in class in a school setting [125]. In comparison, mHealth tools are often challenged in leisure time, and the competition with other apps or leisure activities is central [126,127]. Future studies should focus on the implementation of mHealth tool and investigate differences in engagement in either voluntary versus more obligatory settings.

In terms of comparability, the Persuasive Systems Design (PSD) model could have helped map the different design features. PSD is often used in research to outline persuasive design elements. The model maps different persuasive design elements in primary task support, dialogue support, system credibility support, and social support. When comparing the PSD model with the coding scheme applied in this systematic review, a number of similarities can be identified. In terms of primary task support, navigation (PSD model: tunneling), personalization, and self-monitoring are identified. In terms of dialogue support, rewards, messages (PSD model: reminders), and interface aesthetics (PSD model: liking) can be identified. Liking is very broadly defined as “visually attractive” in the PSD model and has been criticized in earlier research [128]. It finds more detail in the coding of our systematic review (ie, interplay of interface elements such as sounds, visuals, and language). In terms of system credibility support, only credibility (PSD model: expertise) can be identified. In terms of social support, reinforcement (PSD model: social comparison), social messages (PSD model: social facilitation), cooperation, and competition can be identified. Design features that are difficult to code in terms of the PSD model are challenges, levels, feedback, avatars, and narratives and are predominately game elements and refer to achievement- and immersion-based features [96]. These have also been identified in earlier research, distinguishing their research from the PSD model [129,130]. On the one hand, this emphasizes the challenge to identify and apply a complete list of design elements. As a proposed solution, Geuens et al [128] created a website that derived from the PSD model and mapped a working list of adaptable features. However, it should be noted that this list is currently not complete in terms of gamification elements. On the other hand, the large number of similarities between the PSD model and the coding frame of this systematic review suggest that various research studies may have found (to a certain degree) a consensus on design features. A revision of the PSD model, adapted by, for example, gamification elements, could help create an updated list of design features that are widely applicable to designers and researchers.

**Strengths and Limitations**

As identified in an earlier review [55], this review included a larger number of studies reporting the foremost positive associations, which may bias the overview in features that are either unrelated or negatively associated and may not be reported (ie, publication bias). In addition, the strength of associations has not been included in the individual studies, owing to a lack of high-quality experimental studies. In addition, heterogeneity among studies with regard to engagement measures was identified, making direct comparison challenging; this has also been identified in earlier studies [114]. This systematic review maps a large number of features that are associated with engagement individually. The interaction of different features and their effect on engagement is still not researched and needs to be considered in future engagement studies, for example, experimental factorial designs [41]. Individual studies included small sample sizes, and only a small number of studies focused on low SEP. Using different SEP measures and mixing them with high-SEP measures made it challenging to compare studies and prevented us from conducting a subanalysis based on the SEP background. Therefore, the findings might not be transferable to low-SEP groups and this underlines the need for future research. In addition, the variability in SEP measures made it difficult to standardize SEP thresholds and compare between countries, as youth from a low-SEP background may not be equivalent in terms of studies and countries, and disparity occurs even in different parts of one country. Studies that included SEP measures were exclusively from countries of the Global North, emphasizing that in general, a minority of studies focused on the Global South (4/21, 19%), and none focused on SEP. As the search was limited to English, this review may not have included all available and relevant research on this topic. Earlier research outlines the differences in the effectiveness of mHealth intervention on behavioral outcomes and engagement among very young children and older children. Research further suggests that preferences for design features may differ between different age groups of youth. This systematic review did not cluster for different age groups because of the limited number of studies that, for example, focus on the very young children (aged <4 years) [25]. More individual studies are needed among very young children to identify whether age differences exist. Earlier research suggests that gender differences in games may exist [131-137]. None of the included studies in this systematic review distinguished between gender for design features in mHealth interventions. In future research, it can therefore be considered to investigate possible differences in future user-testing. The quality of the studies was mixed, indicating in general that study designs with regard to measuring engagement need to evolve. Especially, studies that focus on engagement as a secondary outcome need to operationalize engagement clearly and report the methods transparently. In this review, no validated design feature taxonomy has been used for coding, although it was based on existing overviews of design features [114]. In this review, all study designs were included, and this provided a comprehensive overview of...
relating research on engagement and triangulated evidence. This is the first review identifying mHealth design features among youth with the aim of promoting PA. This review was based on the PRISMA guidelines and succeeded in providing a coherent overview of all nuances relating to a good quality assessment and high interrater reliability.

**Conclusions**

The results indicate that a clear interface; an appropriate and fair reward system; social interaction; and a variety of app content (i.e., missions, content, and characters) that are preferably customizable can contribute to engagement in mHealth PA interventions for youth. Design features, such as sounds, competition, instructions, notifications, virtual maps, or self-monitoring facilitated by manual input, that were negatively associated with engagement need to be carefully considered when designing mHealth PA interventions. In addition, technical functionality can be considered a prerequisite for engagement. Research addressing youth from low-SEP families is very limited with regard to engagement in mHealth apps, and design features often lack a sufficient degree of operationalization based on behavioral change theories or techniques. Future studies are needed to further test design features in youth, particularly youth from low-SEP families, and to evolve engagement measures.

**Acknowledgments**

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**Authors’ Contributions**

AS was responsible for leading all stages of the review. AS established the research protocol, which was reviewed by MS and LHHW. DO conducted the search and data extraction under the supervision of LHHW and drafted the first version of the methods and results. KB served as the second reviewer for search and data extraction. The search was updated by AS. AS was responsible for drafting the manuscript, which was written together with MS, LHHW, and EdV. The manuscript was eventually reviewed and adapted by MS, LHHW, EdV, DO, and KB.

**Conflicts of Interest**

None declared.

Multimedia Appendix 1

PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist.

[DOCX File , 40 KB - mhealth_v11i1e40898_app1.docx ]

Multimedia Appendix 2

Full search strategy.

[DOCX File , 29 KB - mhealth_v11i1e40898_app2.docx ]

Multimedia Appendix 3

Quality check Mixed Method Assessment Tool.

[XLSX File (Microsoft Excel File), 58 KB - mhealth_v11i1e40898_app3.xlsx ]

Multimedia Appendix 4

Data extraction of the studies included in the systematic review.

[XLSX File (Microsoft Excel File), 53 KB - mhealth_v11i1e40898_app4.xlsx ]

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Abbreviations

BCT: behavior change technique
mHealth: mobile health
MVPA: moderate- to vigorous-intensity physical activity
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PROSPERO: International Prospective Register of Systematic Reviews
PSD: Persuasive Systems Design
SEP: socioeconomic position

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Review

Smartphone and Mobile App Use Among Physicians in Clinical Practice: Scoping Review

Mauricette Lee¹, BSc; Abu Bakar Shakran Bin Mahmood¹; Eng Sing Lee²,³, PhD; Helen Elizabeth Smith², PhD; Lorainne Tudor Car¹,⁴, MSc, MD, PhD

¹Lee Kong Chian School of Medicine, Nanyang Technological University, Singapore, Singapore
²Family Medicine and Primary Care, Lee Kong Chian School of Medicine, Nanyang Technological University, Singapore, Singapore
³National Health Group Polyclinics, Singapore, Singapore
⁴Department of Primary Care and Public Health, School of Public Health, Imperial College London, London, United Kingdom

Corresponding Author:
Lorainne Tudor Car, MSc, MD, PhD
Lee Kong Chian School of Medicine
Nanyang Technological University
11 Mandalay Road
Singapore, 308232
Singapore
Phone: 65 69041258
Email: lorainne.tudor.car@ntu.edu.sg

Abstract

Background: Health care professionals are increasingly using smartphones in clinical care. Smartphone use can affect patient quality of care and clinical outcomes.

Objective: This scoping review aimed to describe how physicians use smartphones and mobile apps in clinical settings.

Methods: We conducted a scoping review using the Joanna Briggs Institute methodology and reported the results according to PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) guidelines. We used the following databases in our literature search: MEDLINE, Embase, Cochrane Library, Web of Science, Google Scholar, and gray literature for studies published since 2010. An additional search was also performed by scanning the reference lists of included studies. A narrative synthesis approach was used.

Results: A total of 10 studies, published between 2016 and 2021, were included in this review. Of these studies, 8 used surveys and 2 used surveys with focus group study designs to explore smartphone use, its adoption, experience of using it, and views on the use of smartphones among physicians. There were studies with only general practitioners (n=3), studies with only specialists (n=3), and studies with both general practitioners and specialists (n=4). Physicians use smartphones and mobile apps for communication (n=9), clinical decision-making (n=7), drug compendium (n=7), medical education and training (n=7), maintaining health records (n=4), managing time (n=4), and monitoring patients (n=2) in clinical practice. The Medscape medical app was frequently used for information gathering. WhatsApp, a nonmedical app, was commonly used for physician-patient communication. The commonly reported barriers were lack of regulatory oversight, privacy concerns, and limited Wi-Fi or internet access. The commonly reported facilitator was convenience and having access to evidence-based medicine, clinical decision-making support, and a wide array of apps.

Conclusions: Smartphones and mobile apps were used for communication, medical education and training, clinical decision-making, and drug compendia in most studies. Although the benefits of smartphones and mobile apps for physicians at work were promising, there were concerns about patient privacy and confidentiality. Legislation is urgently needed to protect the liability of health care professionals using smartphones.

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KEYWORDS

evidence-based medicine; specialist; general practitioners; GP; primary care physicians; mobile apps; consultants; surgeons; pediatricians; clinical care; mobile phone
Introduction

Background
The use of smartphones has become increasingly indispensable [1]. This technology has revolutionized how people live, learn, work, communicate, and entertain themselves [2]. The use of smartphones among health care professionals is also widespread and affects the clinical care they provide [3]. Studies in various settings reported that most health care professionals use smartphones daily in their practice [4-8].

Smartphones and mobile apps offer an important and diverse set of clinical tools for health care professionals. They enable direct communication with colleagues and patients, instant access to medical knowledge, education, remote patient management, research, and digital diagnostics, to name a few [2]. However, the widespread adoption and use of smartphones in medical practice can affect the quality of care [9,10]. There are concerns about the impact of smartphones on professionalism, patient safety, and data confidentiality as well as the trustworthiness of sources accessed via smartphones [6-8,11-14].

The use of smartphones may vary between different groups of health care professionals and in different settings. For instance, some studies report that medical trainees mobile apps are more commonly used by physicians than by nurses [15,16]. In contrast, medical calculators or drug compendium apps are used by both physicians and nurses [7,16]. Many medical mobile apps targeting health care professionals are available, and their number is growing. Studies have reported that the daily use of medical apps ranges from 1 to 20 minutes among physicians [7]. Knowing what types of apps are commonly used by various health care professionals can help discern their needs, guide the future evaluation of the quality of such apps, and inform the development of new apps.

Objectives
A growing number of studies are exploring the use of smartphones among health care professionals as well as their experiences and perceptions of the role of smartphones in clinical care [4,6,7,9-11,13-15,17-22]. However, to date, there are no existing scoping reviews, systematic reviews, and research syntheses available on this topic. Our objective was to collate and describe how smartphones and mobile apps were used by physicians, specifically, specialists and family physicians, within clinical settings. We presented the barriers, facilitators, and opinions of physicians regarding smartphones and mobile apps.

Methods

Overview
A scoping review was conducted using the Joanna Briggs Institute methodology and reported according to PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) [23]. The scoping review methodology consisted of five key steps: (1) identifying the research question; (2) identifying relevant studies; (3) study selection; (4) charting the data; and (5) collating, summarizing, and reporting the results. The study protocol was registered in the Open Science Framework registries [24].

Step 1: Identifying the Research Question
This review aimed to collate and describe studies focusing on the use of smartphones among physicians. The overarching question for this scoping review was as follows: “How do physicians use smartphones in clinical practice?” More specifically, the research questions for this scoping review are as follows:

- What are the smartphone apps and features physicians access and why?
- How do physicians use their smartphones as an information source?
- What are physicians’ opinions of the impact of smartphones on clinical care?

Step 2: Identifying Relevant Studies
We developed the MEDLINE (Ovid) search strategy collaboratively and iteratively with support from an experienced medical librarian. The search strategy was guided by relevant articles identified from previous manual searches, based on our research questions, and eligibility criteria (Multimedia Appendix 1). The same strategy was adopted to search for applicable studies in Embase, Cochrane Library, and Web of Science. Similar to previous studies, we also searched the reference lists of the included studies and gray literature in the first 10 pages of the search results in Google Scholar using the search terms in our search strategy and titles of the included studies [25,26]. Only studies published in the English language were included. Results were imported to EndNote 20 (Clarivate Analytics) [27].

The included studies in this review had to meet the inclusion and exclusion criteria presented in Textbox 1. We included studies published between January 2010 and January 2022 to capture data that aligned with the proliferation of smartphone ownership [28]. This review aimed to understand practicing physicians’, defined as specialists, and family physicians’ use of smartphones in clinical settings. Owing to the differences in training needs between medical trainees and nontrainees, medical trainees were excluded [29].
Textbox 1. Inclusion and exclusion criteria.

### Inclusion criteria
- Studies focusing on the use of smartphones among physicians defined as specialists and family physicians
- Studies exploring the use of mobile apps and the use of social media if this is done explicitly using smartphones (only if the motivation for use was physician driven)
- Studies focusing on personal smartphones, organizationally provided smartphones, or both
- Studies focusing on a mix of physicians if more than 50% of the physicians were specialists and family physicians
- Survey, observational, mixed methods, or qualitative studies
- Published between January 2010 and January 2022
- Printed in the English language

### Exclusion criteria
- Studies that focused on patients, medical students, medical trainees, medical residents, house officers, health intervention, or medical education
- If the smartphones were implemented for research purposes
- Studies that focused on infection control of personal smartphones
- Editorials, opinion pieces, conference posters, and abstracts

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**Step 3: Study Selection**

Studies were identified using the search criteria presented in Textbox 1. The search results from different electronic databases were combined in a single EndNote (Clarivate Analytics) library [27], and duplicate records were removed. The first reviewer (MLM) independently screened titles and abstracts on ASReview v1.0 (ASReview Lab) [30] to identify studies that potentially met the inclusion criteria. Only 33% of the titles and abstracts were screened. This was 1 rule that was predetermined and adhered to before screening commenced on ASReview [30]. This rule was set based on a study that found that 95% of eligible studies would be found after screening between 8% and 33% of studies on ASReview [31]. In parallel, a second reviewer (ABSBM) independently screened all titles and abstracts, including 33% of titles and abstracts that were screened by MLM on Covidence (Veritas Health Innovation) [32] to identify studies that potentially met the inclusion criteria. Disagreements on the included titles and abstracts were resolved through discussion between the first and second reviewers. Conflicts between the 2 reviewers were resolved through consensus, and when required, a third reviewer (Ahmad Ishqi Jabir) acted as an arbiter. In total, 2 reviewers (MLM and ABSBM) independently retrieved the full texts of the included titles and abstracts and read and assessed the studies against the eligibility criteria. Disagreements on the included full-text articles were resolved through discussion between the first and second reviewers. Conflicts between the 2 reviewers were resolved through consensus, and when required, a third reviewer (AIJ) acted as an arbiter. A total of 2 reviewers (MLM and ABSBM) independently extracted the data for each included study using a structured data extraction form. Figure 1 shows a flow diagram of the article selection process.
Step 4: Charting the Data

After the screening process was completed, EndNote Library [27] was set up to share articles between the reviewers. A data charting form was created using Microsoft Excel and used to extract data from the included studies. The data extracted from each study included the name of the first authors, year of publication, title, aims of the study, study design, study location, study time frame, sample size, participant characteristics, type of smartphone used, and study findings (Multimedia Appendix 2 [5,22,33-40]). Adapted from previous studies by Lee and De Jong [41,42], the data extracted from the included studies were categorized into functions, benefits, and challenges of smartphones and mobile apps for health care professionals. We used coding frames from these studies, as they captured data that were aligned with the proliferation of smartphone ownership. The data charting form was piloted by 2 reviewers (MLM and ABSBM), with 4 studies either different in study designs or population specialties to ensure consistent, reliable, and efficient data extraction. Conflicts between the 2 reviewers were resolved through consensus, and when required, a third reviewer (AIJ) served as an arbiter.

Step 5: Collating, Summarizing, and Reporting the Results

A comprehensive summary of the included studies, number of studies, study design, data collection methods, population types, and the aims of the study were presented. The use of smartphones was organized according to themes presented in a previous paper [41]. The framework we developed was aligned with all our research questions. The collated findings were ownership rates, type of mobile apps used, type of information sources used, type of websites accessed, use of smartphones for contact with colleagues and patients, and physicians’ experiences of using smartphones. Relationships between population characteristics and the use of smartphones (differences in the use of smartphones among physicians in primary and secondary care) were identified. A narrative synthesis of the findings without the use of a qualitative analysis program was presented.

Results

Search Findings

Database searches yielded 11,447 records, and another 3 records were retrieved from the gray literature source. After removing 2784 duplicates, 8663 titles and abstracts were screened. Title and abstract screening led to the exclusion of 8625 records, resulting in 40 full texts that needed to be assessed for eligibility. Of these, 30 articles were excluded, resulting in 10 studies for the review (Figure 1). We used a sensitive search strategy that aimed to retrieve all relevant research in this novel area and as such had a high number of citations initially. We then screened citations in parallel and independently to ensure the reliability of our screening.

Study Characteristics

The 10 studies included in this review (Table 1 [5,22,33-40]) were conducted across 9 countries and published between 2016 and 2021. The study data collection time frames were reported in 4 studies [5,22,37,38], and data were collected between 2014 and 2019. Of the 10 included studies, 8 (80%) used surveys [5,22,33-38] and 2 (20%) used surveys with focus groups study designs [39,40]. A total of 3 studies recruited only general practitioners (GPs) [22,37,39], another 3 studies recruited only specialists [34,35,37], and 4 studies recruited both GPs and specialists [5,36,38,40]. The participants in the remaining studies were addressed as anesthetist consultants [34], pediatricians [35], specialists, or surgeons. Overall, 4 studies did not provide information on their clinical settings [5,33,35,36], 2 studies were conducted in hospitals [34,38], and the remaining studies...
were conducted in community health centers [22], large university surgical departments [37], rural practices [39], and health institutions [40]. The characteristics and details of the included studies on the use of smartphones and mobile apps by physicians are presented in Tables 1 and 2 (Multimedia Appendix 2). One study reported that physicians possessed more than 6 different work-related mobile apps on their smartphones [34]. Another study reported that most GPs had 1 to 3 medical apps, with very few owning more than 4 [22]. Only 1 study found that young GPs (aged <35 years) were more likely to own smartphones [22]. Another study found that younger physicians (aged ≤44 years) were less likely to allow their patients to communicate with them via the internet or phone, and they used medical apps more often [5]. One study reported that 10% (5/50) of physicians used organizationally provided smartphones, whereas the rest used personal smartphones for clinical use [38]. The results are presented in Tables 1 and 2 and are consistent with the PRISMA-ScR guidelines [43].
Table 1. Summary table of included studies (N=10).

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<tr>
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<td>Mostly female</td>
<td>3 (30)</td>
</tr>
<tr>
<td>Intersex</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Not applicable</td>
<td>2 (20)</td>
</tr>
<tr>
<td><strong>Type of smartphone used</strong></td>
<td></td>
</tr>
<tr>
<td>Mostly Android</td>
<td>1 (10)</td>
</tr>
<tr>
<td>Mostly iPhone</td>
<td>3 (30)</td>
</tr>
<tr>
<td>Others</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Not applicable</td>
<td>6 (60)</td>
</tr>
<tr>
<td><strong>Most commonly reported frequency of smartphone use</strong></td>
<td></td>
</tr>
<tr>
<td>Daily</td>
<td>2 (20)</td>
</tr>
<tr>
<td>Weekly</td>
<td>1 (10)</td>
</tr>
<tr>
<td>Monthly</td>
<td>0 (0)</td>
</tr>
</tbody>
</table>
Of the 10 included studies, 7 (70%) reported the use of communication [5,22,33,36,37,39,40]. One study reported that participants allowed their patients to contact them by phone and via web-based communication tools [5]. However, the study did not report on the smartphone features or apps used. Another study reported that smartphones allowed faster access to information, especially for communication among peers [40]. More than half of the physicians preferred using smartphones and mobile apps over other alternatives for communication with other physicians [36]. Of the 10 studies, 3 (30%) did not explicitly report how smartphones and mobile apps were used by physicians for communication [34,35,38]. One study reported using smartphones to contact other specialists for referrals or advice [34], another study reported using smartphones for communication [38], and the last study did not report on communication at all [35].

### Information Seeking and Management

Of the 10 included studies, 7 (70%) reported the use of mobile apps for medical education and training [5,34-38,40]. Of the 7 studies, 3 did not provide examples of mobile apps used by GPs and specialists in medical education and training [5,37,38]. Of the 3 studies, 1 reported that most physicians perceived that they were provided with reliable clinical content and continuing medical education when using mobile apps for medical education and training [5]. Another study reported that most surgeons felt that texting improved the educational experience of their trainees [37]. Of the 10 studies, 7 (70%) reported the use of mobile apps for clinical decision-making [5,22,34-36,38,40]. Of the 7 studies, 1 reported that anesthetists used mobile apps for clinical algorithms, clinical planning, and
assessments [34]. Another study reported that mobile apps for disease diagnosis were used by GPs [22], but the identity of the mobile apps used was not provided in those 2 studies.

Frequent use of drug compendium apps was reported in 7 studies [5,22,34,36,38,40]. A total of 4 studies found that the most frequent type of medical apps used by physicians were drug compendium apps [5,22,34,40]. The other most common types of reference tools were the literature search portals [5,22,35,36,38] and medical literature [5,22,34-36]. These were followed by medical journals [34-36], medical news [5,35,36], and medical textbooks [5,40]. Of the 7 studies, 1 reported that anesthetists used mobile apps for drug compendium, prescription, and dosing, and academic journals [34]. However, no examples of the mobile apps used were provided in this study. Another study reported that the Diagnosia and Embryotox medical apps were most often used [5]. Physicians were less familiar with medical apps such as Antibiotika (Thalhammer) from Germany, MedCalc (United States), Laborwerte (Germany), Arzneimittel Pocket (Germany), and Labormedizin Pocket (Germany) [5].

Of the 10 included studies, 4 (40%) reported the use of mobile apps for health record maintenance to access local appointment systems developed by their local health ministry [5,34,38,40]. Of the 4 studies, 1 reported the types of smartphone apps used by anesthetists, including apps for billing and accessing patient results and those that allowed access to hospital electronic medical records [34]. Another study reported that Enlili (Turkey), a national hospital management information system, was the most used app [40]. It was followed by other medical health recording systems from Turkey, such as Meddata, E-nabiz, PACSapp, and Acibadem [40].

Clinical Care
The use of mobile apps for time management was reported in 40% (4/10) of the included studies [22,34,35,40]. Only 1 study reported Google Calendar as the most used app among GPs, followed by the default mobile calendar and appointment app [40]. The other 3 studies did not provide examples of mobile apps used for time management [22,34,35].

Only 20% (2/10) of studies reported the use of mobile apps for patient monitoring [38,40]. According to Sezgin et al [40], patient-monitoring apps were the least prevalent among all mobile apps. Examples of the types of patient-monitoring smartphone apps provided in that study were pedometers, calorie trackers, and heart rate and information tracker tools (cardiograph) [40]. The study also reported that patients had been using the tracking apps and sharing them with their physicians [40]. Teferi et al [38] reported using an app to document the procedures for patient monitoring.

Smartphone Features Used and Web Access by Physicians
Of the 10 studies, only 1 (10%) reported the use of built-in features in the smartphone, such as torchlight, stopwatch, and camera [34]. The same study also reported the use of a smartphone to distract pediatric patients [34]. However, the study did not report on how the smartphone features were used by physicians. A total of 2 studies reported that physicians used nonmedical apps more frequently than medical apps [22,42]. These nonmedical apps were used by physicians for calendar [22] and web access [22,42]. Overall, 4 studies reported on the use of smartphones for web access [22,35,38,40]. However, 3 of the 4 studies neither reported the reasons for physicians to access the internet nor stated the websites that were accessed [22,38,40]. Web browsers and search engines were also used for medical information searches, sometimes outperforming medical apps [40].

Barriers to the Use of Smartphones and Mobile Apps by Physicians
Overview
In addition to depicting the use of smartphones and mobile apps by physicians, many studies have described the factors that prevented physicians from using smartphones. This review found a wide variety of barriers to the use of smartphones and mobile apps by physicians, including the infringement of patient privacy and confidentiality, lack of regulatory oversight, negative impact on physician-patient and collegial relationships, quality concerns, limited Wi-Fi or internet access, lack of workplace integration, and lack of smartphone savviness.

Infringement of Patient Privacy and Confidentiality
The potential confidentiality breach of patient privacy was the most common barrier to the use of smartphones and mobile apps by physicians [33,36,37,39,40]. Only one study reported on privacy concerns, which included the fear of sending the message to the wrong person or number and the uncertainty around the receipt of the messages [33]. The lack of security and control over the apps’ content were also perceived to be risks related to the infringement of patient privacy and confidentiality when using smartphones and mobile apps for communication at work [40]. However, the study did not report the names of these apps.

Lack of Regulatory Oversight
The included studies also addressed barriers to the regulation of smartphones and mobile apps used by physicians [33,37,39,40]. One study reported that only 27% of GPs have a written text policy for texting patients [33]. GPs who used texts always documented patient consent, and when texting medically sensitive information, they always obtained specific consent [33,39]. In the hospital setting, some physicians were unaware that they had any organizational policy on the use of smartphones [34] and sharing patient information via text messages [37]. Most surgeons in 1 study agreed that texting patient-related information should be regulated by a hospital policy (74%) or legislation (57%) [37].

Negative Impact on Physician-Patient and Collegial Relationships
Several studies in this review referenced barriers related to professional relationships. Hofer and Haluza [5] reported that employees were not allowed to use their smartphones at work, as it was found to be disruptive to the relationship with patients during consultation. It was also reported that, among consultant anesthetists with more than 3 years of experience as a consultant,
up to 27% agreed that their smartphone was a distraction from their work [34]. However, none of those with less than 3 years in post believed that their smartphones were a distraction from their work [34]. In addition to distraction, GPs found that text messaging increased patient anxiety [39]. Some physicians also reported feeling uncomfortable using smartphones in front of patients [40].

**Quality Concerns**

Another reported barrier was concern about the quality of the information provided by medical apps [5,40]. For example, physicians expected professional organizations to inform evidence-based medical apps, including assessing the quality of medical information in the medical apps recommended by the organization [5].

**Limited Wi-Fi or Internet Access**

In total, 2 studies reported limited internet access as a barrier [5,36]. Physicians mentioned that they would use many more apps if smartphone reception was better in the hospital [5]. Hence, they suggested that the availability of an offline version of an app is important [5].

**Lack of Workplace Integration**

Sezgin et al [40] also raised the issue of the lack of extensive use of smartphones and mobile apps in the hospital system. This has been demonstrated by the lack of interoperability between the use of smartphones and other hospital devices [40].

**Lack of Smartphone Savviness**

Only one study reported the lack of advanced skills as a barrier to the use of smartphones and mobile apps [40]. For example, some physicians indicated that they were not aware and unsure of the appropriate apps that could be used to help them with their daily clinical tasks. Their lack of knowledge on smartphone use prevented them from using it in clinical settings.

**Facilitators for the Use of Smartphones and Mobile Apps by Physicians**

**Overview**

Numerous studies have reported on the facilitators for the use of smartphones and mobile apps by physicians. Facilitators included convenience and access to evidence-based medicine and clinical decision-making support. One study reported that smartphones and mobile apps were useful for conducting research. However, the authors did not elaborate further [36]. The user-friendliness of medical apps was perceived to facilitate the ease of use of mobile apps [5].

**Convenience**

Physicians used smartphones and mobile apps primarily for convenience [5,33,34,36,37,39,40]. For example, flexible communication channels [5,33,34,36,37,40] as well as a selection of powerful apps to accomplish a variety of tasks at work were readily available [5,36]. Portability [36,41], rapid access to information [37], and multimedia resources [5,36,41] were also examples of convenience.

**Access to Evidence-Based Medicine and Clinical Decision-making Support**

Access to various evidence-based and clinical decision-making support mobile apps was highlighted as a facilitator in this review [5,34,40]. The evidence-based medical mobile apps included apps for medical education and training and reference tools, as listed in Table 2.

**Discussion**

**Summary of Key Findings**

According to the studies included in this review, physicians primarily use smartphones and mobile apps for communication, medical education and training, clinical decision-making, and accessing the drug compendium. Medscape was frequently mentioned as a medical app used for information gathering. WhatsApp has been widely reported as a nonmedical app used for physician-physician and physician-patient communication. The most common barriers reported in the included studies were the risk of infringing on patient privacy and confidentiality, lack of regulatory oversight, limited Wi-Fi or internet access, the lack of extensive use of mobile apps in the hospital system, and the lack of smartphone savviness. The most common facilitators reported in the included studies were the availability of having flexible communication methods, easy access to evidence-based medicine, clinical decision-making support, availability of mobile app choices to accomplish many different purposes at work, and portability.

We found that physicians are more likely to use smartphones for work-related purposes because of the increasing availability of mobile apps. Prior studies showed that only 13% of physicians used their smartphones to watch web-based videos weekly for professional purposes, and continuing medical education activities were the most frequently viewed content [44]. However, this review found that studies frequently reported the daily and weekly use of smartphones and mobile apps by physicians [5,22,40]. In addition, smartphones and mobile apps were widely used not only for medical education and training but also for communication, clinical decision-making, and reference tools. We found mixed views regarding the use of smartphones for work-related purposes as a distraction for physicians [5,34]. For instance, physicians believe that using a smartphone during a consultation could negatively affect the patient-physician relationship [5]. This finding is consistent with a recent systematic review on the effect of web-based information-seeking behavior on the physician-patient relationship [45]. Another study found a correlation between the number of years of experience as a specialist and whether smartphones were perceived as a distraction [34]. Younger physicians tended to use smartphones more and were more likely to accept them in the workplace [34]. This was also found to be consistent with a recent systematic review of distraction with smartphones during nursing care [46]. Future research should conduct a review on the distraction of smartphones from physicians in the clinical setting and perhaps derive a precise estimate of the effect that smartphone distraction has on clinical care outcomes.
Our review identified some challenges to the use of smartphones and mobile apps by physicians. First, we found that physicians were unaware of their hospital’s policy [41] on the use of smartphones at work. Only a minority of GPs had written a text policy for texting patients [32]. As a result, while our review found that most GPs who used text messaging always documented patient consent when texting medically sensitive information [33], there remains the potential for a breach in confidentiality. Although previous studies have suggested that the use of strong authentication mechanisms helps to mitigate the risks of a breach [47,48], we found evidence that not all physicians had their smartphones encrypted or password protected, and others were unsure whether their smartphones were encrypted [37].

Physicians are increasingly using instant messaging tools, such as WhatsApp, Facebook, and Google Hangout, for physician-physician and physician-patient communications. However, using social media at work may result in the mingling of personal and hospital data. Most social media tools mentioned in our review are not Health Insurance Portability and Accountability Act compliant, which aims to protect patient privacy and ensure the integrity of sensitive medical information [49]. Despite the absence of Health Insurance Portability and Accountability Act–specific regulations for smartphones and apps, some organizations have developed recommendations and guidelines for mobile security measures [49-53]. A previous study [47] suggested that educating health care professionals about the available hospital policy on the use of smartphones at work could be useful in implementing the policy. However, our review revealed a lack of direction for ideal smartphone use at work. Consequently, it might be helpful to have a policy or legislation that provides comprehensive guidance on authentication, access control, chain of responsibility, data ownership, allowed devices, acceptable use, training, and noncompliance with the use of smartphones and mobile apps [47,54]. Compliance with the legislation of smartphone use at work should be considered in the future during the appraisal process of health care professionals.

This review found that physicians use evidence-based medical apps because they provide instant access to evidence. One example of such an app is the evidence-based point-of-care information summaries [5,34,40]. Point-of-care information summaries are defined as medical compendia specifically designed to deliver predigested, rapidly accessible, comprehensive, periodically updated, and evidence-based information (and possibly guidance) to clinicians [55]. Our review found that Medscape and UpToDate were the most commonly reported evidence-based point-of-care information summaries apps. However, health care organizations lack information on the use of evidence-based medical apps [5]. They were unaware of the reliability of evidence-based information provided by medical apps [5]. To ensure quality and safety, the use of medical apps must undergo rigorous evaluation, validation, and development of best practice standards [40]. Therefore, as a means of mitigating the use of non-evidence-based information in clinical practice, future research should assess the quality of evidence within medical apps to support health care professionals to be more confident when using such apps for practice. In addition, the findings from such research may inform policy on the audit and regulation of medical apps.

There were some limitations when conducting this scoping review. As 8 (80%) of the 10 studies used quantitative methods such as surveys to gather data, deep descriptions and examples to provide an in-depth understanding of smartphones and mobile app use were limited [5,22,33-38]. In addition, only English-language studies were included in this narrative synthesis. Although our classification of data was determined through detailed analysis, team discussions, and consensus, there may be themes that we have overlooked. However, as our comprehensive analysis was based on a commonly used framework on smartphone use by health care professionals, missing out on themes may have been minimized [41].

Implication of the Findings

Physicians use smartphones and mobile apps for communication, clinical decision-making, drug compendium, medical education and training, maintaining health records, managing time, and monitoring patients in clinical practice. However, we found several gaps related to the use of smartphones and mobile apps by physicians at work. These gaps are the lack of regulatory oversight either at a hospital or at a government level, that is, the need to address concerns about the risks of infringement of patient privacy and confidentiality when using smartphones and mobile apps for communication of patient information. There is a need to identify medical apps that provide reliable clinical information and nonmedical apps that can be used for communication by physicians at work. We also found that the use of smartphones differs in different subgroups, such as participants of different ages, sexes, and work experience. Therefore, there may be possible implications on the association of the characteristics of participants with the use of smartphones and mobile apps. Future studies should explore the associations between smartphone use with clinical practice. Future research should also provide more information about smartphone use in clinical practice, including whether smartphones were used for work-related or personal purposes, how smartphone features and apps were used, and how health care professionals communicate using smartphones.

Conclusions

Our review found literature reporting on the use of smartphones and mobile apps for communication, medical education and training, clinical decision-making, and drug compendia. Challenges related to the use of smartphones and mobile apps include the lack of patient privacy and confidentiality and regulatory oversight. The benefits of smartphones and mobile apps for physicians at work include the availability of having flexible communication methods and mobile app choices to accomplish many different purposes at work, easy access to evidence-based medicine and clinical decision-making support, and portability. Physicians commonly use Medscape and WhatsApp mobile apps. Future research should address patient privacy issues, as well as legislation related to smartphone and mobile apps in clinical practice.
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Authors’ Contributions
LTC conceived the idea of the review. ML and ABSBM screened the studies and extracted data. ML synthesized the findings and wrote the manuscript. LTC, HES, ESL, and ABSBM provided insightful feedback on the manuscript.

Conflicts of Interest
None declared.

Multimedia Appendix 1
Search strategy.

Multimedia Appendix 2
Characteristics of the included studies on the use of smartphones and mobile apps for physicians.

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Abbreviations
GP: general practitioner
PRISMA-ScR: Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews
Re

iew

Health Monitoring Using Smart Home Technologies: Scoping Review

Plinio P Morita1,2,3,4,5*, PEng, PhD; Kirti Sundar Sahu1*, MPH, PhD; Arlene Oetomo1*, BSc

1School of Public Health Sciences, University of Waterloo, Waterloo, ON, Canada
2Institute of Health Policy, Management, and Evaluation, University of Toronto, Toronto, ON, Canada
3Research Institute of Aging, University of Waterloo, Waterloo, ON, Canada
4Department of Systems Design Engineering, University of Waterloo, Waterloo, ON, Canada
5Centre for Digital Therapeutics, University Health Network, Toronto, ON, Canada

*all authors contributed equally

Abstract

Background: The Internet of Things (IoT) has become integrated into everyday life, with devices becoming permanent fixtures in many homes. As countries face increasing pressure on their health care systems, smart home technologies have the potential to support population health through continuous behavioral monitoring.

Objective: This scoping review aims to provide insight into this evolving field of research by surveying the current technologies and applications for in-home health monitoring.

Methods: Peer-reviewed papers from 2008 to 2021 related to smart home technologies for health care were extracted from 4 databases (PubMed, Scopus, ScienceDirect, and CINAHL); 49 papers met the inclusion criteria and were analyzed.

Results: Most of the studies were from Europe and North America. The largest proportion of the studies were proof of concept or pilot studies. Approximately 78% (38/49) of the studies used real human participants, most of whom were older females. Demographic data were often missing. Nearly 60% (29/49) of the studies reported on the health status of the participants. Results were primarily reported in engineering and technology journals. Almost 62% (30/49) of the studies used passive infrared sensors to report on motion detection where data were primarily binary. There were numerous data analysis, management, and machine learning techniques employed. The primary challenges reported by authors were differentiating between multiple participants in a single space, technology interoperability, and data security and privacy.

Conclusions: This scoping review synthesizes the current state of research on smart home technologies for health care. We were able to identify multiple trends and knowledge gaps—in particular, the lack of collaboration across disciplines. Technological development dominates over the human-centric part of the equation. During the preparation of this scoping review, we noted that the health care research papers lacked a concrete definition of a smart home, and based on the available evidence and the identified gaps, we propose a new definition for a smart home for health care. Smart home technology is growing rapidly, and interdisciplinary approaches will be needed to ensure integration into the health sector.

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KEYWORDS

monitor; smart home; ambient assisted living; active assisted living; AAL; assisted living; review; internet of things; aging; gerontology; elder; older adult; older people; geriatric; digital health; eHealth; smart technology; older population; independent living; big data; machine learning; algorithm; deep learning
Introduction

Smart home technology is rapidly becoming a permanent fixture in our everyday lives. Globally, there are 175 million connected smart homes—a number projected to continue rising. Smart home technology employs the Internet of Things (IoT) concept to interconnect and share data among household devices across a Wi-Fi–based wireless network [1]. Through connection and automated action, smart homes provide convenience and comfort to homeowners [2-4]. Smart devices can include video monitors, motion sensors, alarms, smart planners or calendars, and thermostats. Data can be leveraged for a variety of purposes, including energy saving [5], security and safety [6], fall detection [7], light management [8], and fire detection [7]. However, the benefits of smart home technology run deeper than the superficial hype of comfort and convenience. These may be the solutions to our health care crisis.

The COVID-19 pandemic revealed what many health professionals already suspected: our health care system is overburdened. Our aging population places increased demand on the health care system. Many services are inaccessible to remote communities. Long-term care homes face high mortality and morbidity. To relieve an overwhelmed system, health care is turning to technology [9]—specifically, the application of smart home devices to support independent living. Through continuous behavioral monitoring, IoT devices can be harnessed to detect, diagnose, and monitor health conditions. At the community level, the collection and analysis of sensor data could inform public health initiatives. Interdisciplinary research teams are already working on the application of smart devices in health care. For example, smart wearable trackers, passive infrared sensors, and chair occupancy sensors deliver daily insights into the physical activity levels. Smart thermostats and bed occupancy sensors have been used to track sleep patterns. As physical activity and sleep are good overall health predictors, these can be powerful tools for motivating healthy behavioral changes [10]. The application of machine learning to these systems can be used for behavior change detection [11,12]. Applications can include monitoring the onset and progression of age-related diseases [10], detection of hazardous events (such as falls), and analyzing behavioral impacts following health interventions such as cancer treatments or physical therapy [12]. Information exchange with primary health care providers and caregivers will strengthen health care delivery. Public health authorities could also assess, in real time, the implications of COVID-19 lockdown policies at the population level. These data can be used to inform care delivery, support evidence-based policy making, and enhance care strategies in real time.

The main advantage of using IoT technologies is that they provide objective data in real time. Sensor data are collected passively without human effort; one can go about their day, forgetting about the device. The data are therefore less prone to performance and recall biases compared to the traditional data collection methods. As data are collected continuously and uploaded to the cloud storage, they are immediately available for analysis. The analysis can be conducted automatically, and the resulting insights can be shared immediately with users. The development and deployment of smart home technology for health care will require the concerted effort of an interdisciplinary research team: combining expertise in technology, engineering, and health care. Despite the potential of smart home solutions to health challenges, their real-world implementation continues to be scarce. There is a need to understand the current state of research in smart home technology for health care. Existing reviews on the application of smart home technology in health care are limited [2,3]. Here, we present a scoping review to address this need. The goal was to synthesize the literature on how smart home technologies are being used for health care within the home and community. This study also aims to identify gaps or opportunities in smart home technology to inform practice, policy making, and research. Our review was guided by the following research questions:

1. What smart home technologies are currently being used to monitor health care indicators in vulnerable populations at home or in the community?
2. What types of information are these sensors gathering?
3. What insights can be generated from these data sets?

Our extensive database search led to the identification of 49 peer-reviewed publications on smart home technology for health care, which met our inclusion criteria. We were able to identify multiple research trends and knowledge gaps and provide insight into the next steps needed to propel the field forward.

Methods

Data Sources and Search Strategy

This scoping review is based on the widely accepted framework by Arksey and O’Malley [13]. This framework was selected because it allows for the inclusion of various methodological designs across an interdisciplinary field. We searched for papers across 4 databases: PubMed, Scopus, ScienceDirect, and CINAHL. The search terms utilized are presented in Table S1 of Multimedia Appendix 1; they briefly encompassed the following search terms: health, monitor, smart home, ambient assisted living, active assisted living, and AAL. We limited our search to papers published between January 2008 and August 2021. Only peer-reviewed papers published in English were included. Of note, the term “surveillance” was not used in the search query, as its inclusion returned hundreds of results outside of the scope of this research project. A total of 5995 potential papers were identified using the search queries.

Paper Selection Process

Papers were organized into Mendeley and Zotero reference managers. Following the removal of 2159 duplicate papers, 3836 papers remained for title screening (Figure 1). Paper selection was further refined by ensuring that paper titles contained one of our keywords as mentioned above. AO and KSS each reviewed half of the papers. Papers not in English and those not related to humans were excluded; papers related to animal, agricultural, or biology research were excluded. Further, conference papers, book chapters, white papers, reviews, and theses were removed. Following title screening, 1743 papers were selected for abstract review by AO and KSS in Mendeley. AO and KSS screened the abstracts to ensure that
the papers focused on remote sensor technology and its application in a home setting. Papers that used synthetic data or described infrastructure architecture or were in hospital or laboratory settings were excluded. The remaining 538 papers proceeded to full-text screening and were transitioned to Zotero for file management due to software issues in Mendeley. Studies using wearables or video-based technologies, theoretical or conceptual papers, and algorithm-based technologies were removed. Both authors independently and unanimously agreed on the inclusion of 29 papers with an additional 97 papers with conflicting votes. These papers were discussed on a case-by-case basis until a unanimous decision was reached. Of the 97 papers that had conflicting votes, 20 papers were included in this review. Thus, 49 papers were found to be eligible for the final scoping review. The selected papers were saved in a database, and a master chart was built by AO and KSS to summarize the key information for subsequent analysis.

**Figure 1.** Systematic study selection using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart.

### Results

**Selection and Characterization of Studies on Smart Home Technologies**

To gain an understanding of the types of smart home technologies being used and the information collected, we conducted a literature search across 4 databases (PubMed, Scopus, ScienceDirect, and CINAHL) between January 2008 and August 2021 by using the queries outlined in Table S1 of Multimedia Appendix 1. A total of 49 papers met the inclusion criteria for this scoping review (Table 1). Among the types of studies conducted, 31% (13/49) were pilot studies, 14% (7/49) were proof of concept, 12% (6/49) were algorithm evaluations, 10% (5/49) were proposals, 8% (4/49) were technical validations, 8% (4/49) were case studies, 6% (3/49) were method evaluations, 6% (3/49) were longitudinal studies, 4% (2/49) were platform evaluations, 2% (1/49) were randomized controlled trials, and 2% (1/49) were qualitative studies. When we examined the country of origin for each paper, we found that most of the studies were conducted in western societies, with 47% (23/49) of the papers originating from Europe and 35% (17/49) from North America. Few studies were conducted in Asia (6/49, 12%), Africa (2/49, 4%), and Oceania (1/49, 2%).

We observed an increase in the number of publications in recent years: 71% (35/49) of the papers were published within the last 5 years (2015-2020), while only 29% (14/49) of the papers were published before 2015. All the studies were either directly or indirectly associated with academic institutions. When classified based on a publication’s domain, 64% (31/49) of the selected papers were published primarily in the fields of engineering and computer science, 18% (9/49) of the selected papers were published primarily in the fields of biomedical engineering and health informatics journals, and 18% (9/49) were published in health-related journals (Figure 2 and Table S2 of Multimedia Appendix 1).
Table 1. Profile of the selected studies by type and human participation.

<table>
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<th>Type of study, reference</th>
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<th>Participant health profile</th>
</tr>
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</tr>
<tr>
<td>Chen et al [14]</td>
<td>5</td>
<td>&gt;45, 2 males, 3 females</td>
<td>Spinal cord injury, muscular dystrophy, multiple sclerosis, polio</td>
</tr>
<tr>
<td>Bock et al [15]</td>
<td>11</td>
<td>&gt;18</td>
<td>Healthy</td>
</tr>
<tr>
<td>Fritz and Dermody [16]</td>
<td>10</td>
<td>&gt;55</td>
<td>Chronic diseases</td>
</tr>
<tr>
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<td>34</td>
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<td>263</td>
<td>&gt;18, 72 males, 191 females</td>
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<tr>
<td>Choi et al [19]</td>
<td>37</td>
<td>&gt;65, 7 males, 30 females</td>
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</tr>
<tr>
<td>Clemente et al [20]</td>
<td>6</td>
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<td>No data</td>
</tr>
<tr>
<td>Pigini et al [21]</td>
<td>32</td>
<td>No data</td>
<td>Healthy and cardiac conditions</td>
</tr>
<tr>
<td>Monteriù et al [22]</td>
<td>13</td>
<td>&gt;65</td>
<td>Healthy</td>
</tr>
<tr>
<td>Grgurić et al [23]</td>
<td>13</td>
<td>&gt;65</td>
<td>No data</td>
</tr>
<tr>
<td>Dasios et al [24]</td>
<td>2</td>
<td>&gt;70, 1 male, 1 female</td>
<td>Healthy</td>
</tr>
<tr>
<td>Marcelino et al [25]</td>
<td>23</td>
<td>&gt;30, 11 males, 12 females</td>
<td>Healthy</td>
</tr>
<tr>
<td>Yu et al [26]</td>
<td>1</td>
<td>&gt;65, 1 female</td>
<td>Chronic diseases</td>
</tr>
<tr>
<td><strong>Proof of concept (n=7)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kim et al [27]</td>
<td>20</td>
<td>&gt;65</td>
<td>Depression</td>
</tr>
<tr>
<td>Alberdi Aramendi et al [10]</td>
<td>29</td>
<td>&gt;18</td>
<td>Healthy</td>
</tr>
<tr>
<td>Hassan et al [28]</td>
<td>0</td>
<td>N/A^a</td>
<td>N/A</td>
</tr>
<tr>
<td>Shirali et al [29]</td>
<td>1</td>
<td>&gt;65</td>
<td>No data</td>
</tr>
<tr>
<td>Jung [30]</td>
<td>22</td>
<td>&gt;60, 10 males, 12 females</td>
<td>No data</td>
</tr>
<tr>
<td>Alsina-Pagès et al [31]</td>
<td>0</td>
<td>No data</td>
<td>N/A</td>
</tr>
<tr>
<td>Mahmoud et al [32]</td>
<td>1</td>
<td>No data</td>
<td>Healthy</td>
</tr>
<tr>
<td><strong>Algorithm evaluation (n=6)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jakkula and Cook [33]</td>
<td>1</td>
<td>&gt;18</td>
<td>Healthy</td>
</tr>
<tr>
<td>Rashidi et al [34]</td>
<td>40</td>
<td>&gt;18</td>
<td>Healthy</td>
</tr>
<tr>
<td>Singla et al [35]</td>
<td>40</td>
<td>No data</td>
<td>Healthy</td>
</tr>
<tr>
<td>Damodaran et al [36]</td>
<td>0</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Hamad et al [37]</td>
<td>19</td>
<td>No data</td>
<td>No data</td>
</tr>
<tr>
<td>Enshaeifar et al [38]</td>
<td>12</td>
<td>No data</td>
<td>Healthy</td>
</tr>
<tr>
<td><strong>Proposals (n=5)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ros et al [39]</td>
<td>0</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Navarro et al [40]</td>
<td>0</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Gayathri et al [41]</td>
<td>0</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Kwon et al [42]</td>
<td>150</td>
<td>&gt;60, 23 males, 127 females</td>
<td>Healthy</td>
</tr>
<tr>
<td>Taiwo and Ezugwo [43]</td>
<td>0</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Technical validation (n=4)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mora et al [44]</td>
<td>0</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Bassoli et al [45]</td>
<td>0</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Schlebusch [46]</td>
<td>10</td>
<td>&gt;18, 7 males, 3 females</td>
<td>Healthy</td>
</tr>
<tr>
<td>Virone et al [47]</td>
<td>22</td>
<td>&gt;45, 7 males, 15 females</td>
<td>Healthy</td>
</tr>
<tr>
<td>Type of study, reference</td>
<td>Sample size</td>
<td>Demographic profile of the participants (age [years], male/female)</td>
<td>Participant health profile</td>
</tr>
<tr>
<td>-------------------------</td>
<td>-------------</td>
<td>---------------------------------------------------------------</td>
<td>---------------------------</td>
</tr>
<tr>
<td><strong>Case studies (n=4)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sprint et al [12]</td>
<td>3</td>
<td>&gt;70, 3 females</td>
<td>Lung cancer, insomnia, leg pain</td>
</tr>
<tr>
<td>Lazarou et al [48]</td>
<td>4</td>
<td>&gt;70, 1 male, 3 females</td>
<td>Amnestic, mild cognitive impairment, dementia</td>
</tr>
<tr>
<td>Hercog et al [49]</td>
<td>1</td>
<td>&gt;60, 1 female</td>
<td>Healthy</td>
</tr>
<tr>
<td>Yang and Hsu [50]</td>
<td>0</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Method evaluation (n=3)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yao et al [51]</td>
<td>0</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Fleury et al [52]</td>
<td>13</td>
<td>&gt;18</td>
<td>Healthy</td>
</tr>
<tr>
<td>Fiorini et al [53]</td>
<td>17</td>
<td>&gt;18</td>
<td>Healthy</td>
</tr>
<tr>
<td><strong>Longitudinal studies (n=3)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fritz et al [54]</td>
<td>11</td>
<td>&gt;65</td>
<td>No data</td>
</tr>
<tr>
<td>Austin et al [55]</td>
<td>16</td>
<td>&gt;70, 3 males, 13 females</td>
<td>Healthy</td>
</tr>
<tr>
<td>Lyons et al [56]</td>
<td>480</td>
<td>&gt;70</td>
<td>No data</td>
</tr>
<tr>
<td><strong>Platform evaluation (n=2)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Junnila et al [57]</td>
<td>2</td>
<td>&gt;70, 1 male, 1 female</td>
<td>Healthy and hip surgery rehabilitation</td>
</tr>
<tr>
<td>Lamprinakos et al [58]</td>
<td>207</td>
<td>&gt;65</td>
<td>Frailty</td>
</tr>
<tr>
<td><strong>Randomized controlled trial (n=1)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mora et al [1]</td>
<td>78</td>
<td>&gt;18, 69 males, 9 females</td>
<td>Healthy</td>
</tr>
<tr>
<td><strong>Qualitative study (n=1)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cahill et al [59]</td>
<td>200</td>
<td>No data</td>
<td>No data</td>
</tr>
</tbody>
</table>

* N/A: not applicable.

**Figure 2.** Journals of the published papers reviewed in this study.
Population Demographics

As it is common practice in computer science or engineering research to use simulated data for platform or algorithm evaluation, we first categorized the studies based on the source of their data. Approximately 78% (38/49) of the papers used data collected from human participants, and the remaining 22% (11/49) of the studies used simulated data (Table 1). The age of the participants ranged from 18 to 93 years. Of the 38 studies that utilized human participants, 63% (31/49) reported participant age, but only 33% (16/49) indicated the gender of the participants. Of those that did report gender, female participants were nearly 3 times more prevalent than male participants (425 females vs 145 males). Volunteer participants were typically students recruited from the researcher’s institution or patients from memory care units and assisted-living residents. Of the papers on human participants, 79% (30/49) reported the health status of the participants.

Study Settings and Parameters

The 49 papers included in this review can be broadly divided into 2 groups: 41% (20/49) approached the use of IoT for health purposes and 59% (29/49) used IoT for technological validations. The primary research focus was recognizing human mobility patterns (Table 2; complete data in Table S3 of Multimedia Appendix 1). Study length ranged from a single day of data collection to 8 years. Data were collected primarily in real-world settings, including smart apartments or smart workplaces. One of the studies used simulated home environments [39]. If the study took place in an apartment, the number of rooms typically used was between 2 and 3. Typically, there was only a single occupant in the study location.
<table>
<thead>
<tr>
<th>Type of study, reference</th>
<th>Primary focus</th>
<th>Outcome measure</th>
<th>Algorithm</th>
<th>Type of data</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Pilot study</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chen et al [14], Dasios et al [24], Yu et al [26]</td>
<td>Independent living for the older population who may or may not have chronic diseases</td>
<td>Activity, fall detection, indoor motion</td>
<td>Statistical analysis of the machine learning algorithm</td>
<td>Binary sensors: motion, light, temperature, humidity,</td>
</tr>
<tr>
<td>Marcelino et al [25]</td>
<td>e-Service provision</td>
<td>Physical, medical, social interaction by audio-visual communication with service providers</td>
<td>Qualitative and quantitative data analysis</td>
<td>Interview questionnaire</td>
</tr>
<tr>
<td><strong>Proof of concept</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alberdi Aramendi et al [10], Kim et al [27], Hassan et al [28], Shirali et al [29], Jung [30], Alsina-Pagés et al [31], Mahmoud et al [32]</td>
<td>From 2013 to 2020, the proof of concept improved from synthetic data to real-world data, single individual to multi-individual, but the objectives more or less—the same activity recognition, anomaly detection, pattern recognition to improve the quality of life of older individuals</td>
<td>Motion or presence data</td>
<td>Binary sensor data, machine learning algorithm-support vector machine as the typical model with many of the studies; the recent study used the parallel activity log inference algorithm</td>
<td>Sensor data</td>
</tr>
<tr>
<td><strong>Algorithm evaluation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jakkula and Cook [33], Rashidi et al [34], Singla et al [35], Damodaran et al [36], Hamad et al [37], Enshaeifar et al [38]</td>
<td>All the studies tried to recognize normal activity patterns and anomaly detection</td>
<td>Motion or presence data, device-free solutions based on radio signals like home Wi-Fi, 802.11 channel state information</td>
<td>Machine learning and deep learning algorithms</td>
<td>Passive infrared sensors</td>
</tr>
<tr>
<td><strong>Proposal</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ros et al [39], Navarro et al [40], Gayathri et al [41], Kwon et al [42], Taiwo and Ezugwo [43]</td>
<td>Activity recognition of the individual</td>
<td>Mobility pattern recognition</td>
<td>Machine learning, deep learning algorithms</td>
<td>Binary sensor and acoustic sensor data</td>
</tr>
<tr>
<td><strong>Technical validation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mora et al [44], Bassoli et al [45], Schlebusch [46], Virone et al [47]</td>
<td>Active assisted living monitoring, intelligent toilet seat, differentiate regular patterns, and identify abnormalities in household activities</td>
<td>Passive infrared sensors, magnetic contact, bed occupancy, chair occupancy, toilet presence, fridge sensor, electrocardiogram and bioimpedance spectroscopy measurements, behavioral monitoring by presence data</td>
<td>Behavior explanatory models, sensor profiles, multivariate habits clusters, R-peak detection, software for automatic measurement of circadian activity deviation/circadian activity rhythms</td>
<td>Motion sensor data, electrocardiogram, bioimpedance spectroscopy, passive infrared sensors</td>
</tr>
<tr>
<td><strong>Case studies</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sprint et al [12], Lazarou et al [48], Hercog et al [49], Yang and Hsu [50]</td>
<td>Behavior change detection, home monitoring system, activity recognition, effective active home automation solution based on open-source home automation software, and wireless, custom-developed, Wi-Fi–based hardware</td>
<td>Activity change, sleep, physical activity, and activities of daily living, automatic classification of activities of daily living, system functionality</td>
<td>CASAS middleware</td>
<td>Motion, light, temperature, door, motion, presence, utility usage sensors, passive infrared/current sensors</td>
</tr>
</tbody>
</table>
Data Collection and Analysis

To determine which smart home technologies were being used, sensors were grouped into 16 main categories (Table 3): utilization of space (bed and chair occupancy, toilet, fridge, kitchen, or GPS), human vitals (blood pressure, electrocardiography, blood glucose, heart rate, or respiratory rate), and environmental sensors (light, air temperature, humidity, sound, airflow, smoke, carbon monoxide, gas, or flooding). Nearly 62\% (30/49) of the studies used passive infrared sensors to report on motion detection. As motion detectors and object presence sensors primarily record binary (yes/no) data, it was unsurprising that this data type was the most reported in the studies examined. Quantitative data were reported in many papers. Audiovisual (sound, light), vital indicators (heart rate, respiratory, blood glucose, body temperature), and environmental conditions (room temperature, humidity) typically record quantitative data. Finally, several papers reported spatiotemporal data typical of GPS sensors.

As smart home data collection produces large quantities of data, data management software is frequently employed. Examining the papers, we found SQL [34,35,56,57] and MYSQL [24,25,55] were frequently used to organize the data. MATLAB and Python were used for data analysis and visualization by nearly all the studies. Various statistical methods were used for data analysis, including descriptive statistics, model building, machine learning, and deep learning. Descriptive statistics were primarily used to describe the demographic characteristics of the study participants, whereas multidomain approaches [52], longitudinal linear mixed-effect regression [55], and out-of-sample cross-validation methods [55] were used for statistical models.

As 41\% (20/49) of the papers reported the use of machine learning algorithms, we sought to determine which algorithms were more commonly employed. Clustering in 5 studies [1,28,30,34,53] and Hidden Markov Model in 4 studies [23,30,34,39] were the most used in data analysis to identify a regular pattern and predict future patterns. The other algorithms used in the studies were decision tree emerging pattern [11,25,27], clustering conditional random field [37,51], context-aware reasoning [28,42], fuzzy logic [41,49], k-nearest neighbors [10,51], logistic regression classifier [51,55], AdaBoost [10], Bayes network [27], boosting model using ensemble [42], circadian activity rhythms [47], multi-Hidden Markov Model [34], multiple regression model [42], multivariate habits cluster [44], ontological modelling [41], software for automatic measurement of circadian activity deviation [47], and support vector machines [52].

<table>
<thead>
<tr>
<th>Type of study, reference</th>
<th>Primary focus</th>
<th>Outcome measure</th>
<th>Algorithm</th>
<th>Type of data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yao et al [51], Fleury et al [52], Fiorini et al [53]</td>
<td>Activity recognition</td>
<td>Automatic classification of activities of daily living</td>
<td>Support vector machine, unsupervised machine learning, rule-based reasoning method for activity recognition</td>
<td>Location, temperature, sound, postural transitions and walk periods, motion sensor, location, activity, motion</td>
</tr>
<tr>
<td>Fritz et al [54], Austin et al [55], Lyons et al [56]</td>
<td>Remote monitoring of pain, loneliness</td>
<td>Recognize pain-associated behaviors</td>
<td>Machine learning algorithm, isolation forest (forest) anomaly detection algorithm, decision tree classifier, logistic regression classifier</td>
<td>Passive infrared-based sensor data, light, temperature, humidity</td>
</tr>
<tr>
<td>Junnila et al [57], Lampri-nakos et al [58]</td>
<td>Remote patient monitoring using home health or telehealth</td>
<td>Interoperability/ adaptability, which can accommodate different types of sensors</td>
<td>Rule-based ontological framework, partial human monitoring is required</td>
<td>Passive infrared-based sensor data</td>
</tr>
<tr>
<td>Cahill et al [59]</td>
<td>Identify and validate the requirements for new technology enabling resident wellness and person-centered care delivery in a residential care environment</td>
<td>State of environment and state of care delivery, state of resident</td>
<td>Qualitative data analysis and machine learning algorithm</td>
<td>Sensor and interview data</td>
</tr>
<tr>
<td>Mora et al [1]</td>
<td>Internet of Things–based home monitoring for older patients with stroke</td>
<td>Behavioral aspects: bed/rest patterns, toilet usage, room presence, and many others</td>
<td>Regression framework and anomaly detection, unsupervised clustering techniques</td>
<td>Sensor data</td>
</tr>
</tbody>
</table>

\textsuperscript{a}CASAS: Center for Advanced Studies in Adaptive Systems
Nearly 14% (7/49) of the papers used deep learning methods, which included artificial neural networks [40], activity recognition using the discontinuous varied-order sequential model [34], latent trajectory models [56], longitudinal linear mixed-effect regression recurrent neural networks [55], open pass neural networks [60], recurrent neural networks [32], and multilayer perceptron [10]. One study used mixed methods and included a thematic analysis of the quantitative data [25]. Another study used the activity discovery method [34], and yet another conducted qualitative data analysis by using a mixed methods approach [25]. Some studies used induction algorithms, behavioral monitoring systems, rapid iterative testing and evaluation [15], or QRS recognition [57] for electrocardiography.

**Table 3.** Types of sensors, data characteristics, and their association with health.

<table>
<thead>
<tr>
<th>Sensor type</th>
<th>Data type</th>
<th>Health indicator/proxy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motion: passive infrared sensors, radiofrequency identification, magnetic switches</td>
<td>Any movement within the room, door movement</td>
<td>Physical activity/speed/quality of physical health/sleep</td>
</tr>
<tr>
<td>Presence</td>
<td>Any movement within the room, indoor movement</td>
<td>Physical activity/gait speed/quality of physical health/sleep</td>
</tr>
<tr>
<td>Temperature</td>
<td>Temperature of room, temperature of stove/oven</td>
<td>Body temperature, health quality/activity-sleep/awake/sedentary</td>
</tr>
<tr>
<td>Light</td>
<td>Luminosity (lux)</td>
<td>Sleep/active</td>
</tr>
<tr>
<td>Sound/microphone</td>
<td>Noise</td>
<td>Sleep/active</td>
</tr>
<tr>
<td>Humidity</td>
<td>Indoor environment</td>
<td>Indoor environment</td>
</tr>
<tr>
<td>Biosensors</td>
<td>Fall detection</td>
<td>Activity/alert</td>
</tr>
<tr>
<td>Plug sensors</td>
<td>Appliance use: television, fridge, kitchen appliance, medicine dispenser</td>
<td>Activity</td>
</tr>
<tr>
<td>Body position sensors</td>
<td>Activity</td>
<td>Activity</td>
</tr>
<tr>
<td>Carbon monoxide</td>
<td>Indoor environment</td>
<td>Indoor environment</td>
</tr>
<tr>
<td>Flooding sensors</td>
<td>Water use/consumption</td>
<td>Indoor environment</td>
</tr>
<tr>
<td>Gas sensors</td>
<td>Use of gas in the kitchen</td>
<td>Indoor environment</td>
</tr>
<tr>
<td>Smoke detector</td>
<td>Indoor environment</td>
<td>Indoor environment</td>
</tr>
<tr>
<td>Pressure sensor/smart tiles/pressure pad</td>
<td>Bed movement, gait speed, chair movement</td>
<td>Sleep time/quality</td>
</tr>
<tr>
<td>Electrocardiogram patch</td>
<td>Heart health</td>
<td>Heart health</td>
</tr>
<tr>
<td>Airflow sensors</td>
<td>Room environment</td>
<td>Indoor environment</td>
</tr>
<tr>
<td>SpO2</td>
<td>Oxygen saturation of blood</td>
<td>Heart health/fung health</td>
</tr>
<tr>
<td>Blood pressure</td>
<td>Heart health</td>
<td>Heart health</td>
</tr>
<tr>
<td>Heart rate</td>
<td>Heart health</td>
<td>Heart health</td>
</tr>
<tr>
<td>Respiratory rate</td>
<td>Lung health</td>
<td>Lung health</td>
</tr>
<tr>
<td>Blood glucose sensors</td>
<td>General health</td>
<td>Diabetes</td>
</tr>
<tr>
<td>Smart weighing scale</td>
<td>Body weight</td>
<td>Weight</td>
</tr>
<tr>
<td>Pedometer</td>
<td>Walking</td>
<td>Physical activity</td>
</tr>
<tr>
<td>Contact sensors</td>
<td>Usage of a phone book, cooking pot, medicine container</td>
<td>Activity analysis</td>
</tr>
<tr>
<td>GPS</td>
<td>Location</td>
<td>Location</td>
</tr>
<tr>
<td>Wi-Fi signal</td>
<td>Indoor activity</td>
<td>Location</td>
</tr>
<tr>
<td>Smart seismic sensor</td>
<td>Floor vibration</td>
<td>Activity analysis, including fall</td>
</tr>
</tbody>
</table>

**Outcome Measures**

All the studies reported that IoT improved the quality of care, increased participants’ sense of comfort, enabled early detection, and increased participants’ understanding of the impact of health events on overall health. The health indicators specifically measured through smart home technologies included fall detection [24], functional health decline/improvement [10], high-level activities of daily living/instrumental activities of daily living [34,35,48,50,59,61-63], leisure services [59], loneliness [55], medical services [17,21,30,64], patient health status [17,21,30,64], perception [58], physical activity [48], sedentary behaviors [24,62], medication adherence [62], movement patterns [29], sequence of gestures [61], sleep
Review, database searches were conducted in August 2021. Due to the constraints in our search queries and inclusion criteria, it is possible that potentially relevant publications may have been overlooked. We recognize that there are several limitations to our study and that potentially relevant publications may have been overlooked due to the constraints in our search queries and inclusion criteria. As smart home technologies are often developed by the technology industry, not all work is likely published in peer-reviewed journals. Furthermore, our use of the query term “smart home” may have excluded relevant research settings in a community or an institution. For the purposes of this scoping review, database searches were conducted in August 2021. Due to the rapid nature of this field of research, new insights may have emerged since the initial search.

Limitations and Challenges in the Studies

To gain insight into future research needs in the field of smart home technologies, we extracted information pertaining to the challenges and limitations self-reported by researchers. In the 49 studies, the biggest challenge faced by the researchers was differentiating between multiple participants in a single space. The second challenge identified was the lack of technology interoperability and the ability to scale up. The third challenge identified was linked to data security and privacy. The additional challenges identified by the researchers included calibration of the sensors, cost of technology and data management, data streaming and integration, data velocity, data volume, difficulty differentiating activities, generalization of activities, and demographic discrepancies (data collected from young volunteers, while algorithms were designed for the older population). Heterogeneity, installation of the sensors, lack of patient motivation, large numbers of nodes, limited data bandwidth, limited indoor activities, malfunctioning sensors, privacy, sample size, security, service quality, user acceptance, and varying levels of data accuracy were also noted as challenges.

Discussion

Key Findings

Existing reviews on the application of smart home technology for health care are limited [2,3]. At present, they focus on a very specific specialty within health care, such as geriatric care [65], dementia [66,67], fall prevention [68], or pregnancy [69]. This scoping review aims to address this knowledge gap by elucidating how smart home technologies are being used for health care within the home and community. An extensive database search revealed 49 peer-reviewed publications, which met our inclusion criteria. A wide variety of sensors were used to meet the differing needs in each study. Passive infrared sensors, which report on motion detection, were the most studied technology, not restricted to IoT, to automate, regulate, and monitor home occupants' physical health, mental health, and environments within the home. The focus must be on convenience, safety, and improvement of one's quality of life, to address the needs of the individual, caregivers, and health professionals.

Sociodemographic Inequalities

The studies included in this review were predominantly performed in western societies. This bias could be due to our requirement that studies should be published in English. However, it is known that high-income nations dominate the field of smart home technology. This could be due to several factors. First, western countries are trending toward an aging population, and thus, the interest in assisted living technologies is higher [71]. Second, low- and middle-income countries are focused on reducing mortality and morbidity related to infectious diseases; therefore, their resources are not focused on the needs of an aging population [72-74]. To address global health and knowledge inequalities, researchers and funding bodies must ensure that low- and middle-income countries have the resources to benefit from health technologies. Future research should prioritize including study participants in nonwestern societies.

Computer science or engineering research often use simulated data due to budget, staffing, and time constraints. Traditional technical training does not consider health outcomes and overlooks the social determinants of health. Without health care experts as part of the research team, many are unaware of the importance of reporting the demographic characteristics of human study participants. This was reflected in our scoping review, as many of the included studies failed to report this information. Of those that did report demographics, we found that female participants were more prevalent, being nearly 3 times more likely to have been studied than male participants. This was unexpected, given that research is typically dominated by male participants [75,76]. Some potential reasons for this variance could be that women live longer [77], are more likely to live in assisted care units [78], are more likely to participate in studies [79], or have altruistic considerations [80]. Moreover, the use of simulated data despite the availability of actual data highlights the need for better access to high-quality data.

The Intersection of Health and Technology

Smart home technology is a rapidly growing interdisciplinary field at the intersection of health, information technology, and engineering [81]. Yet, our scoping review highlighted a strong bias toward publication within primarily engineering and...
information technology journals. Many of the papers included in this scoping review contained highly technical language, tools, and databases. However, the primary audience is the health care field. Although we acknowledge that much of the technology is in its early stages, with research focused on technical challenges (data handling, analysis, storage, security, and privacy), this finding highlights a lack of collaboration between health and technical fields. Future work must address this gap—fostering interdisciplinary research teams with a broad spectrum of skills and domain knowledge experts. The involvement of health professionals in smart home technology research will ensure that these tools are relevant and bolster their successful implementation.

Technological Challenges
Interoperability was a commonly noted challenge faced by researchers. Technology is constantly being upgraded and improved with new products continually hitting the market. As diverse companies compete to create the latest technology, interoperability becomes an issue. Because there are no standardized guidelines, companies develop their own unique protocols and architectures for handling data, which contribute to incompatibility across the IoT landscape. The result is a jungle of systems that are confusing and intimidating to navigate for many non–tech-savvy individuals. One must subscribe to a single system that may not meet all their needs, grapple with the inconvenience of systems that do not communicate seamlessly, or implement third-party software or hardware to bridge the gap. There is a need to continue to develop solutions that allow these systems to integrate and communicate with one another. Similarly, the other 2 challenges faced by the researchers were differentiating individuals within a multipartisan household and data security and privacy. Health care technology brings a new layer of complexity due to risks associated with personally identified data, health data, privacy, data rights, and ethical considerations [82].

Data Quality
Some of the studies [18,27,55] examined here had insufficient data quality to make their research findings relevant in the health care field. In many cases, the number of study participants was minimal and lacked demographic information. The quality of many of the sensors used in a home setting is lesser than that of the instruments used in a clinical setting, often diminishing the value of the data. Additionally, some of the technologies were not diagnostic tools at all because the health indicators were not quantifiable (video or audio). Other health conditions such as loneliness or mental health cannot be quantified and thus must be measured through the integration of multiple proxy indicators. The challenges of data integration will likely be addressed with continued improvements in artificial intelligence. Here, we have highlighted the existing research on the application of smart home technology to improve health and revealed multiple gaps in our knowledge. The IoT has ushered in a period of ultracoviability [83], converting commercial, off-the-shelf sensors like smart Wi-Fi thermostats and wearable devices into vital sources of health data. With the collaborative efforts of technology experts and health care professionals, we have the potential to leverage these data to improve physical and mental health.

Conclusion
Smart home technology has the potential to improve the quality of life by monitoring health indicators in vulnerable persons. Despite their potential, there is still a lack of large-scale utilization of these technologies for health care. A scoping review of the existing literature enabled us to identify the types of sensors and the data being explored. The trends and knowledge gaps identified here will invite new progress in remote patient monitoring in public health. This kind of a care system can support and complement medical interventions to improve population health.

Acknowledgments
We would like to thank Adson Rocha for helping with screening, charting, and providing input throughout the process and the Ubiquitous Health Technology Lab (UbiLab) volunteers, namely, Clarisse Misola, Nadia Somani, Arjun Mehta, Chaeyoon Jeong, Thianna Edwards, Kunal Karhanis, and Harneet Dhillon, for their timely help whenever and wherever required. We would like to thank the Natural Sciences and Energy Research Council, ecobee, and The Mathematics of Information Technology and Complex Systems (MITACS) for supporting this work.

Conflicts of Interest
None declared.

Multimedia Appendix 1
Supplementary data.

References


4. Vaidya V, Vishwakarma P. A comparative analysis on smart home system to control, monitorsecure home, based on technologies like GSM, IOT. Bluetooth and PIC microcontroller with zigbee modulation. 2018 Presented at: International Conference on Smart City and Emerging Technology (ICSCET); January 5; Mumbai, India URL: https://ieeexplore.ieee.org/document/8537381 [doi: 10.1109/icscet.2018.8537381]


Abbreviations

IoT: Internet of Things
Mobile Health Self-management Support for Spinal Cord Injury: Systematic Literature Review

Renaldo M Bernard¹, PhD; Vanessa Seijas¹,²,³, MD; Micheal Davis¹,², MSc; Anel Volkova¹,², BSc; Nicola Diviani¹,², PhD; Janina Lüscher¹, PhD; Carla Sabariego¹,²,³, PhD

¹Swiss Paraplegic Research, Nottwil, Switzerland
²Faculty of Health Sciences and Medicine, University of Lucerne, Lucerne, Switzerland
³Center for Rehabilitation in Global Health Systems, World Health Organization Collaborating Center, University of Lucerne, Lucerne, Switzerland

Corresponding Author:
Renaldo M Bernard, PhD
Swiss Paraplegic Research
Guido A. Zäch-Strasse 4
Nottwil, 6207
Switzerland
Phone: 41 419396654
Email: renaldo.bernard@paraplegie.ch

Abstract

Background: Self-management plays a critical role in maintaining and improving the health of persons with spinal cord injury (SCI). Despite their potential, existing mobile health (mHealth) self-management support (SMS) tools for SCI have not been comprehensively described in terms of their characteristics and approaches. It is important to have an overview of these tools to know how best to select, further develop, and improve them.

Objective: The objective of this systematic literature review was to identify mHealth SMS tools for SCI and summarize their characteristics and approaches to offering SMS.

Methods: A systematic review of the literature published between January 2010 and March 2022 was conducted across 8 bibliographic databases. The data synthesis was guided by the self-management task taxonomy by Corbin and Strauss, the self-management skill taxonomy by Lorig and Holman, and the Practical Reviews in Self-Management Support taxonomy. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) standards guided the reporting.

Results: A total of 24 publications reporting on 19 mHealth SMS tools for SCI were included. These tools were introduced from 2015 onward and used various mHealth technologies and multimedia formats to provide SMS using 9 methods identified by the Practical Reviews in Self-Management Support taxonomy (eg, social support and lifestyle advice and support). The identified tools focused on common SCI self-management areas (eg, bowel, bladder, and pain management) and overlooked areas such as sexual dysfunction problems and environmental problems, including barriers in the built environment. Most tools (12/19, 63%) unexpectedly supported a single self-management task instead of all 3 tasks (ie, medical, role, and emotional management), and emotional management tasks had very little support. All self-management skills (eg, problem-solving, decision-making, and action planning) had coverage, but a single tool addressed resource use. The identified mHealth SMS tools were similar in terms of number, introduction period, geographical distribution, and technical sophistication compared with SMS tools for other chronic conditions.

Conclusions: This systematic literature review provides one of the first descriptions of mHealth SMS tools for SCI in terms of their characteristics and approaches to offering SMS. This study’s findings highlight a need for increased coverage of key SMS for SCI components; adopting comparable usability, user experience, and accessibility evaluation methods; and related research to provide more detailed reporting. Future research should consider other data sources such as app stores and technology-centric bibliographic databases to complement this compilation by identifying other possibly overlooked mHealth SMS tools. A consideration of this study’s findings is expected to support the selection, development, and improvement of mHealth SMS tools for SCI.

(JMIR Mhealth Uhealth 2023;11:e42679) doi:10.2196/42679
Introduction

Background

Spinal cord injury (SCI) is a complex chronic health condition that carries a high health, economic, and social burden for those affected and their families. SCI can be traumatic or nontraumatic in nature and is characterized by the loss or impairment of motor, sensory, or autonomic functions below the level of the injury [1]. Frequent health complications include pressure injury, urinary tract infections, bowel dysfunction, mental health conditions, pulmonary complications, pain, and sexual dysfunction [2,3]. The limitations in functioning caused by SCIs are largely dependent on the neurological level and severity of the injury, associated comorbidities and complications, the age of onset, available health and social care resources, and the presence of barriers or facilitators in the person’s environment [1]. Similarly, wider participation in society is also made difficult without a concerted effort to pursue further education or sustainable employment, sufficient financial support, and the alleviation of comorbidities [4].

Self-management plays a critical role in maintaining and improving the health of persons with SCI [5]. It is widely understood as the ability of an individual to manage the symptoms, treatment, biopsychosocial consequences, and lifestyle changes inherent to living with a chronic health condition [6]. Corbin and Strauss [7] introduced 3 tasks, namely, medical, role, and emotional management, that describe how people with chronic health conditions manage their health. Lorig and Holman [8] described 6 key skills that support the execution of these tasks: problem-solving, decision-making, resource use, forming patient-provider partnerships, action planning, and self-tailoring. Pearce et al [9] argued that self-management is nonetheless not the sole responsibility of persons affected by chronic health conditions and proposed the Practical Reviews in Self-Management Support (PRISMS) taxonomy to highlight 14 self-management support (SMS) activities such as the provision of social support and equipment. SMS is often provided in the form of traditional institutional and paper-based options [6]. However, technology-based SMS options help overcome traditional barriers of distance, time, and high economic costs and are increasingly becoming available for SCI [10,11].

The use of technology-based SMS for chronic conditions has expanded with the widespread adoption of mobile health (mHealth) technology [10]. Compared with early desktop computer–based technologies, mHealth provides more person-centered, available, accessible, and scalable tools [12]. It introduces the use of mobile and wireless information and communications technologies, including geospatial services, movement, light and proximity sensors, and Bluetooth technology, bundled into mobile devices, apps, and wearable technologies, among other similar products, to support meeting health needs [13]. In the context of SMS, this could involve using a mobile device to receive visual, auditory, and tactile-based reminders to perform a health behavior (eg, taking medication), self-monitor health status (eg, recording vital signs), learn from web-based informational resources, and secure social support from online peer groups [9,14]. mHealth is well positioned to benefit from the high adoption rates among persons with SCI. Over 87% of participants with traumatic SCI in a 2018 study indicated that they were mobile internet users, which represented a 35% increase from 2012 [15] and a 12% higher rate than the global mobile internet subscription rate in 2019 [16]. An increase in the global user base has also been attributed to the recent pandemic [17], which is also expected to have a similar impact among persons with SCI in the last 2 years.

Nonetheless, to the best of our knowledge, the available mHealth SMS for SCI has not been comprehensively compiled. Reviews on the closest related topics have focused on accessing telerehabilitation [10], telehealth care [18], and telecounseling [19-21] outside clinical settings but have not adequately considered SMS and, with the exception of one study [10], mHealth. The latest review was also completed in early 2016, which does not account for the expected rapid increase in the development of mHealth options over the last 6 years. Therefore, it is important to have an overview of available mHealth SMS options for SCI.

Objectives

The objective of this systematic literature review was to identify and summarize the mHealth SMS tools developed for SCI. It aimed to describe their volume, features, evidence base, and reporting and recommend future directions for the development, evaluation, and reporting of these tools. Articulating data on effectiveness, gaps in coverage, usability shortcomings, and impact is expected to help patients and clinicians with selecting tools and support researchers and developers in optimizing existing tools or deciding and planning the development of new ones.

Methods

Overview

A systematic review was conducted to identify and summarize the mHealth SMS tools developed for SCI. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [22] and the extension for searching [23] were used to guide reporting (Multimedia Appendix 1). The inclusion of an assessment of methodological quality for other types of observational studies overlooked by the study protocol [24] was the single protocol deviation observed.

Search Strategy

MEDLINE, Academic Search Premier, LISTA, Business Source Premier, Scopus, CINAHL Complete, PsycINFO, and Web of Science Core Collection were searched using keywords for SCI and mHealth (Multimedia Appendix 2). The reference lists of included articles were also hand searched.
Eligibility Criteria
Publications were eligible for inclusion if they described an mHealth [13] SMS tool [6] for SCI. Eligible mHealth SMS tools were optimized for access from mobile devices to help accommodate the accessibility needs of people with SCI and were intended for use outside a clinical setting or not dependent on assistance from others to obtain benefits. Publications including primary research studies, books, and gray literature (eg, conference proceedings, theses, government documents, and professional publications) made available in the English language between January 2010 and March 2022 were considered. Gray literature such as commentaries and letters to the editor that were unlikely to discuss mHealth SMS tools for SCI in sufficient detail were not considered.

Eligibility Assessment
In total, 3 researchers (AV, MD, and RMB), including a health scientist, psychologist, and health technologist, were involved in screening. They attended a training workshop to help ensure consistency in screening using the web-based service Rayyan (Rayyan Systems Inc) [25] without its artificial intelligence–based features. The screeners completed a training set of 100 publications. Conflicting screening decisions (ie, include, maybe, or exclude) were discussed to clarify any misunderstandings. A total of 2 screeners were then randomly assigned a screening set of titles and abstracts. A third screener afterward performed a second screening of 29% (29/100) of the publications. In total, 2 screeners (AV and RMB) conducted eligibility checks on the full texts. Screening was independently conducted to reduce the risk of reviewer bias [26], and conflicting screening decisions were resolved collaboratively.

Risk-of-Bias Assessment
The same researchers who conducted the screening (RMB and AV), along with a rehabilitation physician (VS), independently evaluated the risk of bias for the included studies based on recommendations from Ma et al [27] and according to the assessment strategy shown in Textbox 1. Disagreements in evaluations were resolved collaboratively.


<table>
<thead>
<tr>
<th>Experimental studies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Revised version of the Cochrane Collaboration tool for assessing risk of bias in randomized trials [28]</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Mixed methods studies</th>
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<tbody>
<tr>
<td>Mixed Methods Appraisal Tool for systematic mixed studies reviews [29]</td>
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<table>
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<tr>
<th>Other observational studies</th>
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</thead>
<tbody>
<tr>
<td>Joanna Briggs Institute Checklist for Analytical Cross-Sectional Studies [30]</td>
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</table>

<table>
<thead>
<tr>
<th>Qualitative studies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Joanna Briggs Institute Checklist for Qualitative Research [31]</td>
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<table>
<thead>
<tr>
<th>Quasi-experimental studies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Joanna Briggs Institute Checklist for Quasi-Experimental Studies [32]</td>
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</tbody>
</table>

Data Extraction and Synthesis
MD and RMB completed the data extraction. These researchers attended a training workshop to help ensure consistency and reliability using a web-based data extraction form. This form was discussed and modified for increased clarity. One researcher extracted data from the included publications, another reviewed and verified the extracted data, and discrepancies were resolved collaboratively. The extracted data were collated and summarized by 2 researchers (RMB and AV) using a descriptive synthesis. The analysis of frequencies, except for publication characteristics, only considered unique data extracted from publications focusing on the same mHealth option. The synthesis of evaluative information considered usability [33] and user experience [34]. Data extraction and synthesis were also guided by frameworks for self-management tasks [7] and skills [8], as detailed in Textbox 2, and support activities [9]. Aspects of SMS for SCI that were targeted by the included mHealth tools [35] were described using emergent themes.
### Results

#### Overview

A total of 24 publications [36-59] were included, and Figure 1 details the methodological process.

<table>
<thead>
<tr>
<th>Textbox 2. Self-management task and skill frameworks.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Self-management tasks [7]</strong></td>
</tr>
<tr>
<td>- Medical management</td>
</tr>
<tr>
<td>- Making health-related appointments, following treatment plans, tracking symptoms, and taking medication as directed</td>
</tr>
<tr>
<td>- Role management</td>
</tr>
<tr>
<td>- Organizing and coordinating the various everyday roles and responsibilities related to work, family, community, and self-care and adapting these roles as needed</td>
</tr>
<tr>
<td>- Emotional management</td>
</tr>
<tr>
<td>- Regulating and coping with emotions resulting from living with a condition in a healthy and effective manner</td>
</tr>
<tr>
<td><strong>Self-management skills [8]</strong></td>
</tr>
<tr>
<td>- Problem-solving</td>
</tr>
<tr>
<td>- Identifying problems and finding, implementing, and evaluating solutions</td>
</tr>
<tr>
<td>- Decision-making</td>
</tr>
<tr>
<td>- Weighing options and choosing the best course of action in response to changes in their condition</td>
</tr>
<tr>
<td>- Resource use</td>
</tr>
<tr>
<td>- Finding and effectively using resources</td>
</tr>
<tr>
<td>- Forming patient-provider partnerships</td>
</tr>
<tr>
<td>- Learning from and partnering with health care professionals to understand the patterns experienced with a condition, make informed decisions, and discuss related issues</td>
</tr>
<tr>
<td>- Action planning</td>
</tr>
<tr>
<td>- Developing a realistic action plan that can be confidently used to achieve a set goal</td>
</tr>
<tr>
<td>- Self-tailoring</td>
</tr>
<tr>
<td>- Developing and implementing personalized self-management strategies as needed</td>
</tr>
</tbody>
</table>
Characteristics of the Included Publications

The 24 included publications comprised 20 (83%) studies [36,37,40,42-57,59], 3 (12%) reports [38,39,58], and 1 (4%) protocol paper [41] (Table S1 Multimedia Appendix 3). The included publications primarily aimed to describe and develop mHealth tools (10/24, 42%) [38,39,43,45,46,48,54,56-58], evaluate implementation factors (9/24, 38%) [37,40,45,46,49,50,54,55,57], evaluate usability and user experience (7/24, 29%) [45-48,52-54] and effectiveness (6/24, 25%) [36,41,42,44,51,54], and describe stakeholder perspectives (1/24, 4%). The included publications were published between 2015 and 2022, and most (18/24, 75%) were published from 2018 onward [41-57,59]. The research teams were mainly based in North America (15/24, 62%) [38,40-42,44-47,50,52,53,55,56,58,59], followed by Europe (6/24, 25%) [36,37,48,49,54,57], Asia (2/24, 8%) [43,51], and describe stakeholder perspectives (1/24, 4%) [39].

Of the 20 included studies, 7 (35%) were quasi-experimental [37,42,43,50,51,53,57], 5 (25%) were mixed methods [46-48,54], 4 (20%) were qualitative [49,52,56,59], 2 (10%) were observational [45,55], and 2 (10%) were experimental [36,44]. The risk of bias was deemed low in just over half (11/20, 55%) of the included studies [44,45,47,49,51,52,55-57,59] (Multimedia Appendix 4 [36-59]). No studies were excluded based on the risk assessment. Study participants experienced various limitations in body functions, including musculoskeletal and movement-related functions [37,39,43], sensory functions and pain [36,47,51,59], urination and defecation [40,45,47,50,58,59], skin [38,45-50,52,53,59], sleep [54], and functions that help manage the psychological and social demands of daily life [44,45,47,54,59]. The sample sizes of the 20 included studies ranged from 4 to 75 participants where reported [36,37,40,42-57,59]. The age range of the study participants was 18 to 81 years, and most study participants were male (232/396, 59%) where reported (19/20, 95%) [36,37,40,42,44-57,59].

Characteristics of the Underlying mHealth Technology

A total of 19 mHealth tools were identified (Table 1 and Table S2 Multimedia Appendix 3). In total, 4% (1/24) of the publications focused on 2 tools [37], 12% (3/24) focused on 1 tool [41,47,50], and 2 sets of 2 focused on 1 tool equally (2/24, 8%) [40,48,49,58]. In total, 4 tools were unnamed (4/24, 17%) [38,40,43,48,49]. The included publications documented mHealth tools mainly at their testing stage (10/19, 53%) [36,40,43-45,47,50-52,54,55,58], followed by the developmental (6/19, 32%) [38,39,41,46,48,56,59], proof-of-concept (3/19, 6%) [37,42,49], proposal (1/19, 5%) [57], and launch (1/19, 5%) [53] stages.

The design and development of the included mHealth tools followed phases largely characteristic of user-centered design

Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart of the review search, selection, and inclusion process.
as the process was iterative and sought to understand users, the relevant tasks they needed to perform, and the environment of use (10/19, 53%) [36,39,40,44,46,47,50-52,54,57,59]. Participatory design, in which stakeholders are encouraged to make substantial contributions to design decisions, was used to a lesser extent (3/19, 16%) [45,48,49]. A total of 32% (6/19) of the publications [37,38,42,43,53,55] did not describe the design process adopted.

The primary technologies used were apps (16/19, 84%) [37-39,41-55,57,59], mobile-optimized websites (2/19, 11%) [40,56], and a glove (ie, wearable; 1/19, 5%) [36]. These technologies were mainly connected to mobile phones (10/19, 53%) [39,42-44,46,48,49,51,53,54,57], followed by tablets (7/19, 37%) [37,39,41,45,47,50,52,54,55], unspecified mobile devices (4/19, 21%) [36,38,40,56,58], pressure mats (2/19, 11%) [46,53], smartwatches (ie, wearable; 2/19, 11%) [42,52], smart garments (ie, wearable; 1/19, 5%) [39], and Raspberry Pi (1/19, 5%) [46].

The Android mobile operating system was the most frequently chosen (8/19, 42%) [39,41-44,48,50,53,57], closely followed by iOS (7/19, 37%) [37,38,45-47,52,53]. A total of 11% (2/19) of the tools used both operating systems [41,47,50,53], 11% (2/19) were operating system–agnostic [40,56,58], and 21% (4/19) did not report this information [36,51,54,55]. Further requirements regarding the device and operating system version and full language and country availability were largely vague or absent and could not be extracted.

When reported, devices required a display (18/19, 95%) [37-48,50-57,59], internet connectivity (12/19, 63%) [38,40-43,46,48,51,53-56], audio (6/19, 32%) [36,39,45-48,55,57], camera (5/19, 26%) [37,39,43-45,48], Bluetooth (5/19, 26%) [36,39,42,46,53], reminder features (5/19, 26%) [38,43,44,48,54], accelerometer sensor (4/19, 21%) [38,42,43,57], notification features (4/19, 21%) [38,39,42,46], messaging (3/19, 16%) [44,45,48], and cloud storage (1/19, 5%) [38]. Table 2 summarizes each requirement of the included mHealth tools. Multimedia Appendix 5 [36-59] organizes each requirement by self-management tasks, skills, and support components and tasks.

### Table 1. Number of mobile health (mHealth) tools introduced per year (n=19).

<table>
<thead>
<tr>
<th>Year of introduction</th>
<th>mHealth tools, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015</td>
<td>3 (16)</td>
</tr>
<tr>
<td>2016</td>
<td>2 (11)</td>
</tr>
<tr>
<td>2017</td>
<td>0 (0)</td>
</tr>
<tr>
<td>2018</td>
<td>0 (0)</td>
</tr>
<tr>
<td>2019</td>
<td>7 (37)</td>
</tr>
<tr>
<td>2020</td>
<td>3 (16)</td>
</tr>
<tr>
<td>2021</td>
<td>3 (16)</td>
</tr>
<tr>
<td>2022</td>
<td>1 (5)</td>
</tr>
</tbody>
</table>

### Table 2. Device requirements of the included mobile health tools (n=19).

<table>
<thead>
<tr>
<th>Device requirement and citation</th>
<th>Description of use</th>
<th>Frequency, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Display [37-59]</td>
<td>Used for presenting the mobile device’s user interface in visual and tactile form</td>
<td>18 (95)</td>
</tr>
<tr>
<td>Internet connectivity [38,40,43-46,48,49,51,53-56,58]</td>
<td>Used for accessing web-based information, having voice and video calls, and sending and storing information via the web</td>
<td>12 (63)</td>
</tr>
<tr>
<td>Audio [36,39,45,48,59,55,57]</td>
<td>Used for listening to multimedia content with sound, creating audio messages, and having voice calls</td>
<td>6 (32)</td>
</tr>
<tr>
<td>Bluetooth [36,39,42,46,53]</td>
<td>Used for exchanging data over short distances between mobile devices and paired technologies</td>
<td>5 (26)</td>
</tr>
<tr>
<td>Camera [37,43-45,48,49]</td>
<td>Used for having video calls and capturing still images</td>
<td>5 (26)</td>
</tr>
<tr>
<td>Reminders [38,43,44,48,49,54]</td>
<td>Used for alerting users to participate in a planned activity</td>
<td>5 (26)</td>
</tr>
<tr>
<td>Accelerometer [38,42,43,57]</td>
<td>Embedded in a smartphone or wearable (eg, smartwatch) and used for motion sensing</td>
<td>4 (21)</td>
</tr>
<tr>
<td>Notifications [38,39,42,46]</td>
<td>Used for informing users of available mobile technology information updates via audio, visual, and tactile indicators</td>
<td>4 (21)</td>
</tr>
<tr>
<td>Messaging [44,45,48,49]</td>
<td>Used for multimedia communication via the internet</td>
<td>3 (16)</td>
</tr>
<tr>
<td>Cloud storage [38]</td>
<td>Used for data storage</td>
<td>1 (5)</td>
</tr>
</tbody>
</table>
Characteristics of Approaches Providing SMS for SCI

The mHealth tools supported the completion of all self-management tasks (Table 3). Emotional management had little support (3/19, 16%) [44,47,54,59] compared with medical (14/19, 74%) [36-39,41,43,44,46,50,53-56,58,59] and role (12/19, 63%) [38,40-42,45,47-52,54,56-59] management tasks. Most mHealth tools supported 1 self-management task (12/19, 63%) [36,37,39,42,43,45,46,51-53,55,57], followed by 26% (5/19) supporting 2 self-management tasks [38,40,44,48,49,56,58] and 11% (2/19) supporting 3 self-management tasks [41,47,50,54,59].

The mHealth tools supported the practice of all self-management skills (Table 4). The top 4 self-management skills were supported more than the average number of times. These 4 represented 84% (31/37) of the total number of times that self-management skills were supported. Most mHealth tools (7/19, 37%) supported 1 self-management skill [41,44,47-51,56,57,59], followed by 32% (6/19) supporting 2 self-management tasks [38,40,43,45,54,55,58] and 3 self-management tasks [36,37,39,42,46,52,53].

The mHealth tools incorporated 64% (9/14) of the PRISMS support components (Table 5). The top 4 components were incorporated more than the average number of times. These 4 represented 74% (35/47) of the total number of times that the components were incorporated. Most mHealth tools (8/19, 42%) incorporated 1 support component [36,37,39,42,46,52,53,55], followed by 21% (4/19) incorporating 4 support components [40,44,51,54,58], 16% (3/19) incorporating 3 support components [38,45,48,49], and 11% (2/19) incorporating 2 support components [43,57] and 5 support components [41,47,50,56,59]. These 10 components largely focused on supporting pressure injury prevention, physical activity promotion, and bladder management (Table 3). The lowest focus was placed on spasticity management, autonomic dysreflexia management, sleep management, and shoulder posture monitoring (Table 6).

The adopted self-management approaches were individualized only or combined with a group-based approach. Individualized approaches included multimedia educational content (eg, audio, text, images, and video), real-time behavioral visualizations or illustrations, textual or haptic feedback, personalized physical movement plans, games, 2-way messaging with health care professionals, content requiring active end-user engagement (eg, diary), and progress-tracking features (16/19, 84%) [36-39,41-53,55,57,59]. Combined approaches included forums and progress-tracking leaderboards (3/19, 16%) [40,54,56,58].

The included mHealth tools were intended mostly for use in nonclinical (ie, home and community environment) settings (17/19, 89%) [37-39,42-46,48,51-58], and only 11% (2/19) were also intended for use in clinical settings [36,41,47,50,59]. The adopted approaches largely relied on research (14/19, 74%) [36,42,44-48,51,52,54,55,58], followed by theory (5/19, 26%) [38,39,41,43,56] and expertise (1/19, 5%) [57]. Approaches targeting therapeutic exercise for legs [43] and shoulder posture monitoring [39] solely relied on theory. The provision of training and practice for everyday activities that targeted therapeutic exercise for the hands was the only approach that was without an app [36].
<table>
<thead>
<tr>
<th>mHealth tool name, citation, and country availability</th>
<th>Self-management focus areas</th>
<th>Relevant self-management tasks</th>
<th>Relevant self-management skills</th>
<th>Relevant self-management support components</th>
</tr>
</thead>
<tbody>
<tr>
<td>AW-Shift [53], United States</td>
<td>Pressure injury management</td>
<td>Medical management</td>
<td>Decision-making</td>
<td>Monitoring of the condition with feedback</td>
</tr>
<tr>
<td>Ball Strike, Pop Flux [37], Italy</td>
<td>Therapeutic exercise for hands, legs, or trunk</td>
<td>Medical management</td>
<td>Action planning</td>
<td>Training and rehearsal for practical self-management activities</td>
</tr>
<tr>
<td>CMAP [46], United States</td>
<td>Pressure injury management</td>
<td>Medical management</td>
<td>Problem-solving</td>
<td>Monitoring of the condition with feedback</td>
</tr>
<tr>
<td>Fisiofriend [57], Italy</td>
<td>Physical activity promotion</td>
<td>Role management</td>
<td>Maintaining patient-provider partnership, action planning, and self-tailoring</td>
<td>Training and rehearsal for practical self-management activities and monitoring of the condition with feedback</td>
</tr>
<tr>
<td>iMHere [44], United States</td>
<td>Bladder management, pressure injury management, and psychosocial support</td>
<td>Medical and emotional management</td>
<td>Maintaining patient-provider partnership, self-tailoring, and decision-making</td>
<td>Practical support with adherence (medication or behavioral), information about the condition or its management, provision of easy access to advice or support when needed, and monitoring of the condition with feedback</td>
</tr>
<tr>
<td>MMT [36], Turkey</td>
<td>Therapeutic exercise for hands, legs, or trunk</td>
<td>Medical management</td>
<td>Problem-solving</td>
<td>Training and rehearsal for everyday activities</td>
</tr>
<tr>
<td>M2M [55], United States</td>
<td>Physical activity promotion</td>
<td>Medical management</td>
<td>Self-tailoring and problem-solving</td>
<td>Information about the condition or its management</td>
</tr>
<tr>
<td>NR [38], United States</td>
<td>Pressure injury management</td>
<td>Medical and role management</td>
<td>Decision-making and resource use</td>
<td>Practical support with adherence (medication or behavioral), information about the condition or its management, and monitoring of the condition with feedback</td>
</tr>
<tr>
<td>NR [40,58], United States</td>
<td>Bladder management</td>
<td>Role and medical management</td>
<td>Maintaining patient-provider partnership and problem-solving</td>
<td>Practical support with adherence (medication or behavioral) and training and rehearsal for practical self-management activities</td>
</tr>
<tr>
<td>NR [43], Thailand</td>
<td>Therapeutic exercise for hands, legs, or trunk</td>
<td>Medical management</td>
<td>Self-tailoring and decision-making</td>
<td>Practical support with adherence (medication or behavioral) and training and rehearsal for practical self-management activities</td>
</tr>
<tr>
<td>NR [48,49], Switzerland</td>
<td>Pressure injury management</td>
<td>Medical and role management</td>
<td>Maintaining patient-provider partnership, self-tailoring, and problem-solving</td>
<td>Practical support with adherence (medication or behavioral), information about the condition or its management, and provision of easy access to advice or support when needed</td>
</tr>
<tr>
<td>PHOENIX [45], United States</td>
<td>Pressure injury, bladder, and bowel management</td>
<td>Role management</td>
<td>Action planning and problem-solving</td>
<td>Information about the condition or its management, lifestyle advice and support, and social support</td>
</tr>
<tr>
<td>PHIRE [42], United States</td>
<td>Physical activity promotion</td>
<td>Role management</td>
<td>Self-tailoring</td>
<td>Monitoring of the condition with feedback</td>
</tr>
<tr>
<td>mHealth tool name, citation, and country availability</td>
<td>Self-management focus areas</td>
<td>Relevant self-management tasks</td>
<td>Relevant self-management skills</td>
<td>Relevant self-management support components</td>
</tr>
<tr>
<td>-----------------------------------------------------</td>
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<td>-------------------------------</td>
<td>--------------------------------</td>
<td>------------------------------------------</td>
</tr>
<tr>
<td>PUT[^52], Canada</td>
<td>Pressure injury management</td>
<td>Role management</td>
<td>Problem-solving</td>
<td>Information about the condition or its management</td>
</tr>
<tr>
<td>Punsook [^51], Thailand</td>
<td>Bladder and pain management</td>
<td>Role management</td>
<td>Maintaining patient-provider partnership, action planning, and problem-solving</td>
<td>Practical support with adherence (medication or behavioral), information about the condition or its management, monitoring of the condition with feedback, and provision of easy access to advice or support when needed</td>
</tr>
<tr>
<td>SCI Health Storylines [^41,47,50,59], Canada</td>
<td>Bladder management, bowel management, pressure injury management, spasticity management, autonomic dysreflexia management, physical activity promotion, pain management, psychosocial support, medicating and dieting, sensation of pain, handling stress and other psychological demands, and looking after one’s health</td>
<td>Medical, role, and emotional management</td>
<td>Action planning, decision-making, and self-tailoring</td>
<td>Practical support with adherence (medication or behavioral), information about the condition or its management, training and rehearsal for practical self-management activities, monitoring of the condition with feedback, and training and rehearsal for psychological strategies</td>
</tr>
<tr>
<td>WHEELS[^54], the Netherlands</td>
<td>Physical activity promotion, psychosocial support, sleep management, and medicating and dieting</td>
<td>Medical, role, and emotional management</td>
<td>Problem-solving and action planning</td>
<td>Practical support with adherence (medication or behavioral), information about the condition or its management, social support, and training and rehearsal for practical self-management activities</td>
</tr>
<tr>
<td>WOWii[^56], United States</td>
<td>Physical activity promotion</td>
<td>Medical and role management</td>
<td>Problem-solving, action planning, and decision-making</td>
<td>Practical support with adherence (medication or behavioral), information about the condition or its management, social support, lifestyle advice and support, and training and rehearsal for practical self-management activities</td>
</tr>
</tbody>
</table>

[^mHealth]: mobile health.
[^AW-Shift]: Assisted Weight Shift.
[^CMAP]: Comprehensive Mobile Assessment of Pressure.
[^iMHere]: Interactive Mobile Health and Rehabilitation.
[^MMT]: Mobile Music Touch.
[^M2M]: Movement-to-Music.
[^NR]: not reported.
[^PHOENIX]: Peer-Supported Health Outreach, Education, and Information Exchange.
[^PHIRE]: Personal Health Informatics and Rehabilitation Engineering.
[^PUT]: Pressure Ulcer Target.
[^WHEELS]: Wheelchair Exercise and Lifestyle Study.
[^WOWii]: Workout on Wheels internet intervention.
Table 4. Supported self-management skills (n=19).

<table>
<thead>
<tr>
<th>Self-management skills</th>
<th>Frequency, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Problem-solving [36,40,45, 46, 48, 49, 51, 52, 54-56, 58]</td>
<td>10 (53)</td>
</tr>
<tr>
<td>Decision-making [38,39,41, 43, 44, 50, 53, 56, 59]</td>
<td>7 (37)</td>
</tr>
<tr>
<td>Self-tailoring [42-44,47-49, 55, 57]</td>
<td>7 (37)</td>
</tr>
<tr>
<td>Action planning [37,41,45,47,50, 51, 54, 56, 57, 59]</td>
<td>7 (37)</td>
</tr>
<tr>
<td>Maintaining patient-provider partnership [40,44,48,49,51, 57, 58]</td>
<td>5 (26)</td>
</tr>
<tr>
<td>Resource use [38]</td>
<td>1 (5)</td>
</tr>
</tbody>
</table>

Table 5. Incorporated self-management support components (n=19).

<table>
<thead>
<tr>
<th>Self-management support components</th>
<th>Frequency, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information about the condition, its management, or both [38,40,41,44,45,47-49,51,52,54-56,58,59]</td>
<td>11 (58)</td>
</tr>
<tr>
<td>Practical support with adherence (medication or behavioral) [38-41,44,47-49,51,54,56,58,59]</td>
<td>10 (53)</td>
</tr>
<tr>
<td>Monitoring of the condition with feedback [38,41,42,44,46,47,51,53,57,59]</td>
<td>8 (42)</td>
</tr>
<tr>
<td>Training or rehearsal for practical self-management activities [37,41,43,47,50,54,56,57,59]</td>
<td>6 (32)</td>
</tr>
<tr>
<td>Provision of easy access to advice or support when needed [40,44,48,49,51,58]</td>
<td>4 (21)</td>
</tr>
<tr>
<td>Social support [40,45,54,56,58]</td>
<td>4 (21)</td>
</tr>
<tr>
<td>Lifestyle advice and support [45,56]</td>
<td>2 (11)</td>
</tr>
<tr>
<td>Training or rehearsal for everyday activities [36]</td>
<td>1 (5)</td>
</tr>
<tr>
<td>Training or rehearsal for psychological strategies [47,59]</td>
<td>1 (5)</td>
</tr>
</tbody>
</table>

Table 6. Targeted self-management focus areas (n=19).

<table>
<thead>
<tr>
<th>Self-management focus areas</th>
<th>Frequency, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pressure injury management [38,41,44-50,52,53,59]</td>
<td>8 (42)</td>
</tr>
<tr>
<td>Physical activity promotion [41,42,50,54-57]</td>
<td>6 (32)</td>
</tr>
<tr>
<td>Bladder management [40,41,44,45,47,50,51,58,59]</td>
<td>5 (26)</td>
</tr>
<tr>
<td>Psychosocial support [44,47,54,59]</td>
<td>3 (16)</td>
</tr>
<tr>
<td>Therapeutic exercise for hands, legs, or trunk [36,37,43]</td>
<td>3 (16)</td>
</tr>
<tr>
<td>Bowel management [41,45,47,50,59]</td>
<td>2 (11)</td>
</tr>
<tr>
<td>Pain management [47,50,51,59]</td>
<td>2 (11)</td>
</tr>
<tr>
<td>Medicating and dieting [47,54,59]</td>
<td>2 (11)</td>
</tr>
<tr>
<td>Spasticity management [41,47]</td>
<td>1 (5)</td>
</tr>
<tr>
<td>Autonomic dysreflexia management [41]</td>
<td>1 (5)</td>
</tr>
<tr>
<td>Sleep management [54]</td>
<td>1 (5)</td>
</tr>
<tr>
<td>Shoulder posture monitoring [39]</td>
<td>1 (5)</td>
</tr>
</tbody>
</table>

Evaluation of mHealth SMS for SCI

The included studies reported a significant change in trunk control [37], urinary tract infections [44], hand sensory functions [36], self-management for neurogenic bladder dysfunction [40], and bowel management confidence [50] (Table 1). No significant changes in urinary tract leakage and infections or pain [51] and psychosocial-related outcomes [44] were observed. None of the included studies published before 2019 (6/20, 30%) had the primary aim of evaluating usability or user experience. The included studies that conducted these evaluations increased 4-fold during the last 4 years (15/18, 83%) [45-48,51,54,56] compared with the previous period (3/18, 17%) [37,39,40] (Figure 2). When evaluated by 58% (14/24) of the included publications [37,40,43,45-49,51,52,54,56,57,59], interviews, focus groups, surveys, and field studies were used. A widely adopted instrument (eg, the System Usability Scale; 4/14, 29%) [46-48,54] was seldom used for evaluating usability or user experience (Table 3). All evaluations relied on empirical methods involving participants with SCI. The results from the usability evaluations were largely very good (6/12, 50%) [37,40,45-48,51], followed by those indicating good (3/12, 25%)
and poor (1/12, 8%) [54] usability. The user experience evaluations were mostly good (3/4, 75%) [43,46,57] and very good (1/4, 25%) [51]. Other evaluations of usability [56,59] and user experience [49,52] generated 12 change requests from study participants regarding design, content, and functionality. No accessibility evaluations were reported.

Figure 2. Temporal distribution of mobile health tool evaluation.

Discussion

Principal Findings and Comparison With Prior Work
The 24 included publications introduced 19 mHealth SMS tools for SCI since 2015 using various mHealth technologies and multimedia formats. The findings support the notion that the adoption of mHealth SMS tools for SCI is a growing area of interest [10]. The findings are similar to those of studies of a comparable period identifying 23 heart failure– [60]; 21 cardiovascular disease– [61]; 23 HIV-, AIDS-, or HIV and AIDS– [62]; and 17 Parkinson disease–related [63] mHealth SMS tools that were introduced from 2012 onward. The geographical distribution of the tools in the included publications is also similar to that in these reviews, with the large majority of tools being introduced in North America and Europe except in the case of HIV or AIDS [62], where no tools introduced in Europe were reported.

mHealth Technologies Underlying SMS for SCI
A review of mHealth SMS tools for heart failure [60] reported that 48% of the identified tools benefited from a participatory design approach compared with 16% (3/19) in this review. However, as evidenced in the study by Allin et al [64], adopting participatory design for the development of mHealth SMS tools for SCI is instrumental in highlighting accessibility, design, and information quality concerns and developing potential solutions in response. Nonetheless, research also highlights that a participatory design approach does not guarantee sustained engagement [64]. The remaining reviews did not report the approach adopted for designing the identified tools, which is similar to 32% (6/19) of the tools identified in this review. Unlike comparable reviews [61,62], our review found a nearly equal operating system share between Android and iOS despite the former being the most used by a large margin [65]. Unlike comparable reviews [61,63] except for that by Mehraeen et al [62], widely used wearable devices (eg, smartwatches) were not identified in this review despite their demonstrated potential for health self-management. This likely results partially from the difficulty to accurately measure physical activity in persons with SCI using wearables [66]. The identified device requirements are also common features found in many mobile devices, which allowed for the easy adoption of these tools and which were also present in and similarly used by the tools identified in comparable reviews.

Approaches to SMS for SCI
The lack of support for all 3 self-management tasks (ie, medical, role, and emotional) was unexpected as SMS tools should aim to include content that addresses all of them [8]. The lack of support for emotional management was unexpectedly pronounced given that managing the psychological demands of SCI and other chronic conditions is a core task for those affected [67]. Compared with the 10 most common problems reported by persons with SCI [68,69], the included mHealth tools largely addressed similar problems but prioritized them differently. For example, pressure injury was ranked much lower by people with SCI than the high level of coverage this complication had in the included mHealth tools. Moreover, the included mHealth tools did not address environmental problems such as barriers in the built environment and sexual dysfunction problems. Compared with non–mHealth-based self-management interventions identified in a recent scoping review [70], the identified mHealth tools reflected a very similar level of focus on SCI symptoms. Except for sexual functions, the identified mHealth tools considered many additional symptoms and health self-management options in comparison. The interventions and mHealth tools identified in this review similarly ascertained the provision of information about the condition and/or its management as being the most common PRISMS support component offered. However, the findings from the recent scoping review and this review differ in their coverage of the remaining PRISMS components and self-management skills. This is likely partially due to mHealth being more suited for...
offering practical support with adherence, monitoring of the condition with feedback, and provision of easy access to advice or support when needed, for example, compared with alternative methods (eg, paper- and desktop computer–based options). The recent scoping review [70] also found that most self-management interventions following an SCI were individualized or combined with a group-based approach. The identified mHealth tools used more sophisticated but comparable formats with alternative self-management interventions [70].

Evaluation of mHealth SMS Tools for SCI

mHealth tools require a high level of usability to ensure that they can be easily used over time without expending unwarranted effort. Comparable reviews have reported a lower percentage of usability evaluations for hypertension (2/21, 10%) [71], diabetes (14/31, 45%) [72], and heart failure (9/18, 50%) [73] than that reported by the included studies. Although the usability of the included tools was generally ranked positively, the failure to use standardized measurement instruments makes it difficult to ascertain what exactly was measured and compare with findings from similar studies. Comparable reviews have reported a slightly higher adoption of standardized instruments for usability evaluations for diabetes (6/31, 19%) [72] and heart failure (4/18, 22%) [73]. Comparable studies investigating user experience of self-management tools were few [74,75], similarly revealed positive results [74], did not adopt widely used assessment instruments [74], and benefited from qualitative methods to gain insights into improvements [74,75].

Implications for Future Practice and Research

More effort is needed to develop mHealth SMS tools for SCI with consideration for incorporating all self-management tasks and undersupported self-management skills and support components. New approaches that can bridge the observed fragmentation of SMS provided by mHealth tools for SCI should be pursued. For example, mHealth SMS tools for chronic health conditions share several common features, and a reference architecture could be of benefit for the efficient and cost-effective development of mHealth SMS tools for SCI, other chronic health conditions, or a combination of these. These technologies are shaped by their underlying technical frameworks as much as by their features. Decisions regarding the design, development, and implementation of mHealth tools need to be reported in detail and investigated to inform future decision-making regarding mHealth tools. Usability and user experience evaluations should use commonly adopted instruments, including the System Usability Scale [76]; the Usefulness, Satisfaction, and Ease of Use Questionnaire [77]; and the Post-Study System Usability Questionnaire [78], to enhance the validity of evaluations and comparability of findings. Furthermore, empirical methods such as usability testing with users should be complemented by other methods [79], including expert inspections and automated evaluations, to improve the validity of these evaluations. Considering and reporting the supported level of functioning by an mHealth tool is essential given the considerable accessibility needs of people with SCI (eg, difficulties associated with sensory and motor impairments). Similar reviews should include more technology-centric databases, for example, the one from the Institute of Electrical and Electronics Engineers, in their search strategy. A systematic search of the most used app stores can complement this review’s findings by identifying and evaluating SMS apps for SCI that are available to the public.

Limitations

The included publications were unlikely to account for all available mHealth SMS tools for SCI. Furthermore, one of the identified apps was retired from the Apple App Store (ie, Assisted Weight Shift) [53], another was retired from the Google Play Store (ie, Pop Flux) [37], and a single app was available from both digital distribution platforms (eg, Interactive Mobile Health and Rehabilitation) [44]. Nonetheless, this systematic literature review is necessary to comprehensively account for these tools. The mHealth tools were also insufficiently described by the included studies, and this prevented a deeper evaluation. For example, despite notable differences in the cost and features of mobile devices using the Android and iOS operating systems, it was difficult to understand how the operating system was chosen without a rationale being provided, especially when their adoption rates were almost the same. Information about the intervention, such as its name; details about primary and secondary users, including lesion type and injury etiology; the design process followed; and minimum hardware and software requirements, was vaguely reported or absent and could have provided valuable insight. For example, it might have indicated a fuller coverage of self-management tasks. This inadequate reporting might also reflect publication restrictions regarding word limits and alternative focus topics where authors instead strategically prioritize other details. Despite these shortcomings in reporting, the included studies still provided more relevant details than tools identified via other means, such as app store descriptions. The publication year restriction could have excluded otherwise eligible mHealth tools, but the findings from this study and the latest review on a related topic [10] strongly suggest that very few or no tools would have been missed as a result. Only considering mobile-optimized web-based services for inclusion likely reduced the number of web-based mHealth tools included, but it is an essential feature given the accessibility needs of people with SCIs. Usability and user experience evaluations were limited as they relied on empirical evaluations, which typically focus on testing select system tasks with users instead of all possible tasks. However, the focus is often on essential tasks, and the practice reduces costs such as time, money, and effort to conduct the evaluation [79].

Conclusions

This systematic literature review provides one of the first overviews of mHealth SMS tools for SCI and represents one of the first steps in a wider research agenda aiming to comprehensively account for these tools. This review identified 19 mHealth tools reported across the 24 included publications and an increasing development trend. A synthesis of these findings highlighted the need for mHealth to support key underserved SMS components for SCI, more standardized or commonly used evaluation methods for usability and user experience, and more detailed reporting that includes key technical details and decisions that shape the mHealth tool. Future research is encouraged to consider other sources for the
identification of mHealth SMS tools for SCI, such as app stores and more technology-centric bibliographic databases, to complement this compilation.

Conflicts of Interest
None declared.

Multimedia Appendix 1
PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist.
[DOCX File, 26 KB - mhealth_v11i1e42679_app1.docx ]

Multimedia Appendix 2
Search concepts and terms and search strategies for the queried bibliographic databases.
[DOCX File, 55 KB - mhealth_v11i1e42679_app2.docx ]

Multimedia Appendix 3
Characteristics of the included publications (N=24) and included mobile health (mHealth) tools (n=19).
[DOCX File, 40 KB - mhealth_v11i1e42679_app3.docx ]

Multimedia Appendix 4
Risk-of-bias assessment of the included studies.
[XLSX File (Microsoft Excel File), 102 KB - mhealth_v11i1e42679_app4.xlsx ]

Multimedia Appendix 5
Device requirements by self-management area, skills, and support methods.
[DOCX File, 358 KB - mhealth_v11i1e42679_app5.docx ]

References


Abbreviations

**mHealth**: mobile health
**PRISMA**: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
**PRISMS**: Practical Reviews in Self-Management Support
**SCI**: spinal cord injury
**SMS**: self-management support
Assessing the Pragmatic Nature of Mobile Health Interventions Promoting Physical Activity: Systematic Review and Meta-analysis

Chad Stecher¹, PhD; Bjorn Pfisterer², MSc; Samantha M Harden³, PhD; Dana Epstein¹, PhD; Jakob M Hirschmann⁴, MA; Kathrin Wunsch², PhD; Matthew P Buman¹, PhD

¹College of Health Solutions, Arizona State University, Phoenix, AZ, United States
²Institute of Sports and Sports Science, Karlsruhe Institute of Technology, Karlsruhe, Germany
³Department of Human Nutrition, Foods, and Exercise, Virginia Tech, Blacksburg, VA, United States
⁴Institute of Sport Sciences, Goethe University, Frankfurt, Germany

Corresponding Author:
Chad Stecher, PhD
College of Health Solutions
Arizona State University
500 N 3rd Street
Room 438
Phoenix, AZ, 85004
United States
Phone: 1 6024960957
Email: chad.stecher@asu.edu

Abstract

Background: Mobile health (mHealth) apps can promote physical activity; however, the pragmatic nature (ie, how well research translates into real-world settings) of these studies is unknown. The impact of study design choices, for example, intervention duration, on intervention effect sizes is also understudied.

Objective: This review and meta-analysis aims to describe the pragmatic nature of recent mHealth interventions for promoting physical activity and examine the associations between study effect size and pragmatic study design choices.

Methods: The PubMed, Scopus, Web of Science, and PsycINFO databases were searched until April 2020. Studies were eligible if they incorporated apps as the primary intervention, were conducted in health promotion or preventive care settings, included a device-based physical activity outcome, and used randomized study designs. Studies were assessed using the Reach, Effectiveness, Adoption, Implementation, Maintenance (RE-AIM) and Pragmatic-Explanatory Continuum Indicator Summary-2 (PRECIS-2) frameworks. Study effect sizes were summarized using random effect models, and meta-regression was used to examine treatment effect heterogeneity by study characteristics.

Results: Overall, 3555 participants were included across 22 interventions, with sample sizes ranging from 27 to 833 (mean 161.6, SD 193.9, median 93) participants. The study populations' mean age ranged from 10.6 to 61.5 (mean 39.6, SD 6.5) years, and the proportion of males included across all studies was 42.8% (1521/3555). Additionally, intervention lengths varied from 2 weeks to 6 months (mean 60.9, SD 34.9 days). The primary app- or device-based physical activity outcome differed among interventions: most interventions (17/22, 77%) used activity monitors or fitness trackers, whereas the rest (5/22, 23%) used app-based accelerometry measures. Data reporting across the RE-AIM framework was low (5.64/31, 18%) and varied within specific dimensions (Reach=44%; Effectiveness=52%; Adoption=3%; Implementation=10%; Maintenance=12.4%). PRECIS-2 results indicated that most study designs (14/22, 63%) were equally explanatory and pragmatic, with an overall PRECIS-2 score across all interventions of 2.93/5 (SD 0.54). The most pragmatic dimension was flexibility (adherence), with an average score of 3.73 (SD 0.92), whereas follow-up, organization, and flexibility (delivery) appeared more explanatory with means of 2.18 (SD 0.75), 2.36 (SD 1.07), and 2.41 (SD 0.72), respectively. An overall positive treatment effect was observed (Cohen $d=0.29$, 95% CI 0.13-0.46). Meta-regression analyses revealed that more pragmatic studies (−0.81, 95% CI −1.36 to −0.25) were associated with smaller increases in physical activity. Treatment effect sizes were homogenous across study duration, participants’ age and gender, and RE-AIM scores.

Conclusions: App-based mHealth physical activity studies continue to underreport several key study characteristics and have limited pragmatic use and generalizability. In addition, more pragmatic interventions observe smaller treatment effects, whereas...
study duration appears to be unrelated to the effect size. Future app-based studies should more comprehensively report real-world applicability, and more pragmatic approaches are needed for maximal population health impacts.

**Trial Registration:** PROSPERO CRD42020169102; https://www.crd.york.ac.uk/prospero/display_record.php?RecordID=169102

**KEYWORDS**
physical activity; mobile health; mHealth; Reach, Effectiveness, Adoption, Implementation, Maintenance; RE-AIM; Pragmatic-Explanatory Continuum Indicator Summary-2; PRECIS-2; systematic review; meta-analysis; digital health; mobile phone

**Introduction**

**Background**
Regular physical activity can combat numerous chronic conditions and is associated with reduced premature mortality [1,2]. Despite these benefits, behavioral interventions and public policy have been largely unsuccessful in promoting higher physical activity among the general population. Worldwide, 28% of individuals are currently classified as insufficiently active [3], and physical inactivity has an estimated annual health care cost of >US $50 billion globally [4]. Thus, increasing physical activity across the world is an important economic and public health objective that requires scalable and pragmatic strategies [5].

Mobile health (mHealth) tools are one promising approach for improving health care delivery and scaling behavioral interventions worldwide [6,7]. Mobile app–based platforms can be particularly effective at increasing intervention accessibility and cost-effectiveness, and they offer the ability to tailor intervention methods to individuals’ unique needs [8-10]. Accordingly, the use of app-based mHealth tools in health care has rapidly increased since 2008 [10,11], and several review papers have recently highlighted the important potential role of app-based interventions for improving global physical activity levels [12-14]. In addition, app-based interventions saw a large relative increase in publications compared with SMS text messaging, telehealth, or web-based interventions [14], making app-based interventions one of the most popular new clinical tools [15] and an important intervention approach to review to inform current and future researchers, as well as health care providers (eg, general practitioners).

Despite the growth of research using app-based tools to promote physical activity, there is limited evidence that app-based interventions for increasing physical activity have been widely adopted by policy makers or integrated into clinical or other practice settings [16,17]. One potential explanation for this lack of real-world application is that this research has generally centered on internal validity (ie, reliability or accuracy of the outcomes) over external validity (ie, generalizability or applicability of results) [18,19]. In other words, the existing research has emphasized explanatory approaches rather than more pragmatic study designs [20]. Explanatory studies measure whether an intervention has a beneficial effect under ideal and thoroughly controlled circumstances and, therefore, substantially differ from real-world conditions (eg, restrictive selection of study sample and control of intervention delivery). Pragmatic study designs can determine the effect of an intervention under more realistic conditions by maximizing external validity (eg, broad and inclusive eligibility criteria and flexibility in intervention delivery) [20-23]. Studies are not strictly dichotomous in their design; instead, they are situated along the explanatory-pragmatic continuum [21,22,24]. Essentially, the challenge is to strike a balance between a highly effective program and whether it can be integrated into practice settings. mHealth interventions have the unique advantages of leveraging automation, data-informed decision-making, and other technological components that might aid in adherence to the core elements (eg, key ingredients or mechanism of change) while scaling out [25].

Existing systematic reviews of mHealth studies have broadly called for increased pragmatism [18,26,27]; however, only one research review has specifically explored the generalizability and applicability of app-based physical activity interventions [16]. However, the results were limited by the insufficient reporting of external validity factors within the included studies. Thus, the review authors were not able to determine the generalizability of the findings and recommended that future mHealth researchers better report all study characteristics [16]. Specific study design characteristics, such as the study sample’s demographics (eg, average age and gender) and the duration of the intervention, are important dimensions to evaluate when determining the generalizability of a study’s findings to the full population.

Given the continued growth of app-based physical activity interventions [14] and the lack of clarity surrounding the pragmatic nature of these approaches, we conducted a systematic review and meta-analysis of mHealth apps for physical activity promotion.

**Objective**
Our primary aim was to analyze the degree to which these interventions reported the study characteristics necessary to inform generalizability and applicability and to assess the explanatory versus pragmatic nature of these studies. Our secondary aim was to explore the association between study design characteristics (eg, explanatory vs pragmatic, intervention duration, and participant demographics) and the observed effect sizes on participants’ physical activity.
Methods

Protocol and Registration
This review followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Multimedia Appendix 1) [28,29].

Search Strategy and Study Selection
We conducted a systematic search in 4 electronic databases on April 4, 2020: PubMed, Scopus, Web of Science, and PsycINFO. The search combined synonyms and keywords related to an app-based mHealth intervention for promoting physical activity (Table 1; Multimedia Appendix 2). We attempted to control for language bias by using a search strategy without language restriction (ie, no selective inclusion of trials published in English) [30]. In addition to these databases, the list of papers discussed by relevant systematic reviews [8,31-40] was examined to identify any further eligible studies.

Table 1. Search strategy used in PubMed on April 4, 2020.

<table>
<thead>
<tr>
<th>Search category</th>
<th>Search term</th>
</tr>
</thead>
<tbody>
<tr>
<td>mHealth</td>
<td>mHealth OR mobile health OR m-health OR activity tracker OR fitness tracker OR wearable OR tablet OR personal digital assistant OR pda OR short message service OR sms OR text message OR android OR iphone OR iOS OR mobile phone OR cellphone OR cell phone OR cellular phone OR cellular telephone OR mobile telephone OR smart-phone OR smartphone OR mobile application OR mobile app</td>
</tr>
<tr>
<td>Physical activity</td>
<td>physical activity OR leisure activity OR active living OR exercise OR sport OR fitness OR motor activity OR sedentary behavior OR sedentary lifestyle OR sitting OR physical inactivity</td>
</tr>
<tr>
<td>Intervention</td>
<td>Intervention OR trial OR program</td>
</tr>
<tr>
<td>Study design</td>
<td>clinical trial OR controlled trial OR controlled study OR double blind OR RCT OR pragmatic trial OR practical trial OR PCT OR ecological trial OR dynamic trial OR real-world OR real world</td>
</tr>
<tr>
<td>Combined</td>
<td>mHealth AND Physical activity AND Intervention AND Study design</td>
</tr>
</tbody>
</table>

a mHealth: mobile health.
b RCT: randomized controlled trial.
c PCT: practical clinical trial.

The included studies were limited to app-based physical activity interventions that were published in a peer-reviewed journal between January 2012 and April 2020 that primarily targeted physical activity and at most one other behavioral outcome and that presented quantitative outcome data. We further restricted our review to studies that collected device-based physical activity measures, as opposed to self-reported measures because device-based measures are frequently observed to be more reliable [41,42] and the use of physical activity–monitoring devices has become more commonplace in the real world [43], demonstrating the feasibility, acceptability, and pragmatism of these intervention tools. A complete list of the eligibility criteria is presented in Table 2. We obtained additional data sources (when available) such as the study protocol, the CONSORT (Consolidated Standards of Reporting Trials) checklist, or any other publicly available information from the corresponding authors provided via an email invitation to assess the Reach, Effectiveness, Adoption, Implementation, Maintenance (RE-AIM) framework for internal and external validity factors [44,45] and the Pragmatic-Explanatory Continuum Indicator Summary-2 (PRECIS-2) tool for evaluating interventions’ pragmatism [24]. Specifically, this email contained a brief description of our study, and then asked, “In order to comprehensively evaluate the reporting of RE-AIM and PRECIS-2 criteria, we are also extracting data from study protocols and companion articles (eg, qualitative or quantitative methods measuring implementation). Would you be willing to help us by providing these additional resources?”

All records from the databases and supplementary searches were managed using the Microsoft EndNote X9 (Clarivate) reference manager software. After removing duplicates, we exported the records to Abstrackr (Brown University) for semiautomatic citation screening [46]. The relevance of the titles and abstracts was independently assessed by 2 authors (BP and JMH). Each eligible full text was independently reviewed by 2 researchers (SMH and MPB). Discrepancies were resolved through discussion between the screening authors. Any remaining conflicts were discussed among the other authors (CS, DE, KW, and BP) until consensus was reached.
RE-AIM and PRECIS-2 coding sheets recommended for a given setting. Thus, we adapted the study setting, additional modifications to these frameworks are considered primarily pragmatic with previous research. Mean scores of >3.5 were deemed equally pragmatic and explanatory, and scores <2.5 were rated as primarily explanatory. Although both frameworks can be applied regardless of the study setting, additional modifications to these frameworks are recommended for a given setting. Thus, we adapted the RE-AIM and PRECIS-2 coding sheets for our setting (Multimedia Appendix 4 presents these adapted coding sheets).

The final scoring by the study is presented in Multimedia Appendix 5.

Quality Assessment
For each study, we also assessed quality of the study using the revised Cochrane risk-of-bias (RoB 2.0) tool for randomized controlled trials. Two authors (BP and JMH) independently performed these assessments, and any disagreements were resolved through discussion with a third author (SMH, DE, and MPB). The studies were classified as having a low risk of bias if all 5 assessment domains were considered low risk. Otherwise, the studies were classified as having some concerns when concerns were raised in at least 1 of the 5 domains, or they were classified as having high risk of bias when at least one of the domains was judged to be at high risk. These categories were drawn from the original Cochrane RoB 2.0 tool.

Statistical Analyses
We used counts and percentages to summarize the general study characteristics and RE-AIM and PRECIS-2 scores for each study.

Meta-analyses were performed by using meta commands in Stata 16 (StataCorp). We used the standardized average treatment effect in each study’s primary app- or device-based physical activity outcome (ie, minutes of moderate to vigorous physical activity or step count) to compare treatment effects across studies with different outcomes. The standardized average treatment effect (or Cohen d) was calculated as the difference in the mean change in primary physical activity outcome between the intervention group and the control group divided by the pooled SD of the physical activity outcome in both the intervention and control groups, with a priori interpretations of trivial (<0.2), small (0.2-0.5), moderate (0.5-0.8), and large (>0.8) effects.

In addition, we tested for heterogeneous treatment effects using random-effects models estimated through restricted maximum likelihood. All the following moderating variables were log

### Table 2. Eligibility criteria.

<table>
<thead>
<tr>
<th>Data type</th>
<th>Eligibility criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population</td>
<td>Participants of any age participating in physical activity programs in the context of health promotion or preventive care settings were included. Studies focusing on special populations (eg, pregnant women) or studies including participants with physical or psychological morbidities preventing them from participating in physical activity were excluded.</td>
</tr>
<tr>
<td>Intervention</td>
<td>Stand-alone mobile apps and web apps exclusively designed for mobile devices; multicomponent interventions (eg, supported through brief counseling sessions or paired with other mHealth technologies) were included as long as the app was the primary component to the intervention; interventions that targeted ≥2 health behaviors in addition to physical activity (eg, diet, sleep, and SB) were excluded; apps solely used for data collection purposes or as an appointment reminder service only were not eligible.</td>
</tr>
<tr>
<td>Comparator</td>
<td>Active or inactive comparator arms were included; single-subject design trials were excluded.</td>
</tr>
<tr>
<td>Outcome</td>
<td>Device-based measures of physical activity.</td>
</tr>
<tr>
<td>Study design</td>
<td>RCTs and randomized ecologically valid research designs (ie, practical clinical trials, RCTs); randomized pilot and feasibility studies were included.</td>
</tr>
</tbody>
</table>

### Data Collection Process

**General Study Characteristics**

We adapted an existing extraction template to collect and summarize the general study characteristics. Specifically, we collected information about the study setting and design, study population, intervention components, outcome measures, key findings, and statistical analyses performed (Multimedia Appendix 3). Two authors (BP and JMH) separately extracted additional quantitative data for the meta-analyses; discrepancies were resolved through discussion and consultation with a third author (SMH).

**RE-AIM Evaluation and PRECIS-2 Assessment**

We used the RE-AIM framework to describe the degree of reporting of study characteristics across 5 dimensions (ie, reach, effectiveness, adoption, implementation, and maintenance). The evaluation was assisted by a 31-item RE-AIM coding system used in a previous study. We then applied the PRECIS-2 tool to compare the interventions with usual care and to identify the pragmatic versus explanatory nature of each study. Following the guidance of Loudon et al and the PRECIS-2 toolkit published on the web, usual care was defined as the primary care that patients usually received for medical advice and treatment. The PRECIS-2 tool comprises 9 domains (ie, eligibility criteria, recruitment, setting, flexibility [delivery], flexibility [adherence], follow-up, primary outcome, and primary analysis), each of which is assigned a score from 1 to 5 (1 is very explanatory and 5 is very pragmatic) [24]. In accordance with previous research, mean scores of >3.5 were deemed primarily pragmatic. Values between 2.5 and 3.5 were considered equally pragmatic and explanatory, and scores <2.5 were rated as primarily explanatory.

Although both frameworks can be applied regardless of the study setting, additional modifications to these frameworks are recommended for a given setting. Thus, we adapted the RE-AIM and PRECIS-2 coding sheets for our setting (Multimedia Appendix 4 presents these adapted coding sheets).
transformed to better compare the effect sizes: baseline physical activity, sample size, participants’ age, participants’ gender, intervention duration, RoB score, RE-AIM score, and PRECIS-2 score. Bubble plots were used to graphically examine the relationships between treatment effect size and the continuous moderating variables.

We assessed the statistical significance of treatment effect heterogeneity by using Cochran Q test and calculating the Higgins $I^2$ statistic [53]. The following thresholds for the interpretation of the $I^2$ statistic were used: 0%-40%, 30%-60%, 50%-90%, or 75%-100%; these were interpreted as not likely important, moderate, substantial, and considerable heterogeneity, respectively [53].

Finally, the combined impact of small-study effects and publication bias was assessed by using the trim-and-fill method and performing the Egger test using the metafor package [54] in R (version 3.6.3; R Foundation for Statistical Computing) [55]. The results are reported with 95% CI, and a $P$ value of <.05 was considered statistically significant.

Results

Study Selection

The search yielded 3308 unique studies after duplicates were removed. Of the 3308 studies, we screened 3207 (96.95%) studies based on title and abstract, leaving 101 (3.05%) potentially relevant studies. After additional content reviews, 23 studies reporting 22 unique interventions met the eligibility criteria for inclusion in the RE-AIM and PRECIS-2 analyses. We emailed the corresponding authors of all 23 studies to request additional study information. We received responses from 52% (12/23) of the studies, and these responses either contained more information on the study (7/12, 58%) or simply stated that there was no additional information available (5/12, 42%). In total, only 74% (17/23) of these studies presented sufficient quantitative detail for inclusion in the meta-analyses. The detailed study selection process is visualized in the PRISMA flowchart (Figure 1).

Figure 1. Flowchart of study selection. PA: physical activity.

Study Characteristics

All interventions were published in English between 2012 and 2020 and were conducted in 10 countries, with most interventions (10/22, 45%) having based in the United States [56-65]. Of the 22 interventions, 21 (95%) used a randomized controlled trial design, of which 19 (90%) interventions randomized participants on an individual level and 3 (14%) interventions were randomized in clusters [66-68]. One study explicitly used a pragmatic study design [69]; 6 studies identified their trials as pilot studies [56,61,62,64,70,71], and 1 was classified as a feasibility study [72]. One study used a factorial design between multiple intervention components as part of a multiphase optimization strategy [57]. An overview of these study characteristics for each study is presented in detail in Multimedia Appendix 6.

A total of 3555 participants were included across all 22 interventions, with sample sizes ranging from 27 to 833 (mean 161.6, SD 193.9, median 93) participants. All studies were
conducted in a health promotion or preventive care setting, and the most common study settings were the local community (10/22, 45%), a university or other type of school (7/22, 32%), or a clinical care setting (3/22, 14%). In addition, 10 interventions exclusively targeted insufficiently active individuals. Study populations varied in age and gender, with mean ages ranging from 10.6 to 61.5 (mean 39.6, SD 6.5) years, and the proportion of males included across all studies was 42.8% (1521/3555). Moreover, 2 studies exclusively targeted men, and 2 studies included women only.

Intervention length varied from 2 weeks to 6 months (mean 60.9, SD 34.9 days). The primary app- or device-based physical activity outcomes differed between interventions, with most interventions (17/22, 77%) using activity monitors or fitness trackers and the rest (5/22, 23%) using app-based accelerometry measures. All studies reported either moderate to vigorous physical activity, daily steps, or both measures. The comparator groups received either no intervention (10/22, 45%); a minimal intervention such as generic physical activity information (6/22, 27%); a basic app version targeting physical activity (3/22, 14%); a control app unrelated to physical activity (1/22, 5%); or a wearable activity monitor with access to its corresponding generic tracking app (2/22, 9%).

A total of 27% (6/22) of studies targeted physical activity, and 5% (1/22) of studies targeted additional health behavior outcome (ie, diet or sedentary behavior). With regard to the physical activity intervention strategies used in all studies, 27% (6/22) of studies provided brief in-person expert consultations (eg, goal setting or generic physical activity information), and 5% (1/22) of interventions included weekly telephone counseling. Most studies (19/22, 83%) also used emails and text messages as physical activity reminders or to provide participants with an activity summary.

The interventions’ apps varied greatly between the studies and consisted of both commercial products and apps designed solely for research purposes. The apps included features such as physical activity tracking and self-monitoring, feedback, goal setting, social interaction, and gamification features (Multimedia Appendix 6 provides the full list of app features by intervention).

RoB Assessment

Table 3 shows the RoB in the included studies. Overall, 17% (4/23) of studies showed a low risk; 43% (10/23) of studies raised some concerns; and 39% (9/23) of studies were rated high risk. A lack of balance across randomized study groups in terms of baseline physical activity and gender contributed to a high risk of bias classification for 3 studies, and 2 other studies were considered to have a high risk of bias for deviating from their intended intervention design, which the authors attributed to a lack of participant engagement with the intervention’s physical activity app and the intended intervention. In addition, most studies (14/22, 64%) did not provide enough information to determine whether the data were analyzed according to their prespecified data analysis plan, which resulted in them being classified as having some concerns.
Table 3. Risk-of-bias (RoB) assessment based on the revised Cochrane RoB tool for randomized trials (RoB 2.0).a

<table>
<thead>
<tr>
<th>Study, year</th>
<th>Randomization biasb</th>
<th>Deviation biasc</th>
<th>Missing data biasd</th>
<th>Measurement biasd</th>
<th>Selection biasf</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direito et al [69], 2015</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Edney et al [66], 2020</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Fukuoka et al [58], 2019</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
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<tr>
<td>Garcia-Ortiz et al [73], 2018</td>
<td>+</td>
<td>?</td>
<td>?</td>
<td>+</td>
<td>+</td>
<td>?</td>
</tr>
<tr>
<td>Garde et al [74], 2018</td>
<td>+</td>
<td>?</td>
<td>?</td>
<td>+</td>
<td>?</td>
<td>–</td>
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<tr>
<td>Glynn et al [75], 2014</td>
<td>?</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Gremaud et al [59], 2018</td>
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<td>?</td>
<td>+</td>
<td>?</td>
<td>–</td>
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<tr>
<td>Harries et al [76], 2016</td>
<td>?</td>
<td>?</td>
<td>+</td>
<td>+</td>
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<tr>
<td>Hurkmans et al [77], 2018</td>
<td>–</td>
<td>?</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>King et al [60], 2016</td>
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<td>+</td>
<td>+</td>
<td>+</td>
<td>?</td>
<td>–</td>
</tr>
<tr>
<td>Kitagawa et al [70], 2020</td>
<td>?</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>?</td>
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</tr>
<tr>
<td>Leinonen et al [72], 2017</td>
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<td>–</td>
<td>+</td>
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<tr>
<td>Lyons et al [61], 2017</td>
<td>+</td>
<td>+</td>
<td>+</td>
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<tr>
<td>Martin et al [56], 2015</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
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</tr>
<tr>
<td>Recio-Rodriguez et al [78], 2016</td>
<td>+</td>
<td>?</td>
<td>?</td>
<td>+</td>
<td>+</td>
<td>+</td>
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<tr>
<td>Robertson et al [67], 2018</td>
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<td>–</td>
<td>–</td>
<td>+</td>
<td>?</td>
<td>–</td>
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<td>?</td>
<td>+</td>
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<tr>
<td>Walsh et al [71], 2016</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>?</td>
<td>–</td>
</tr>
<tr>
<td>Zhang, and Jemmott [64], 2019</td>
<td>+</td>
<td>?</td>
<td>+</td>
<td>+</td>
<td>?</td>
<td>–</td>
</tr>
<tr>
<td>Zhou et al [65], 2018</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>?</td>
<td>–</td>
</tr>
</tbody>
</table>

a+ = low risk of bias; ?=some concerns; −=high risk of bias.
bBias arising from the randomization process.
cBias because of deviations from the intended intervention.
dBias because of missing outcome data.
eBias because of measurement tools used to collect outcome data.
fBias in selection of the reported result.

RE-AIM Evaluation

Overview

The overall rating of sufficiently reported individual RE-AIM items across all interventions was 18% (5.64/31, SD 2.30%; Table 4). Reporting ranged from 2 to 11 of the 31 RE-AIM items. The most commonly reported items were those in the Effectiveness (2.6/5, 52%) and Reach (1.8/4, 45%) dimensions. Reported data within the Maintenance categories were observed in only 12% (1.1/9) of the interventions, and the reporting of items in the Adoption and the Implementation dimensions were found in 4% (0.3/8) and 10% (0.5/5) of the interventions, respectively. A summary of the key findings of the factors within each dimension is presented in the subsequent section.
Table 4. Inclusion of Reach, Effectiveness, Adoption, Implementation, Maintenance (RE-AIM) items across all interventions (N=22).\textsuperscript{a,b}

<table>
<thead>
<tr>
<th>RE-AIM dimension and items</th>
<th>Values, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Reach (44.3%)</strong></td>
<td></td>
</tr>
<tr>
<td>Exclusion criteria</td>
<td>17 (77)</td>
</tr>
<tr>
<td>Participation rate</td>
<td>16 (73)</td>
</tr>
<tr>
<td>Representativeness</td>
<td>6 (27)</td>
</tr>
<tr>
<td>Use of qualitative methods to understand reach and recruitment</td>
<td>0 (0)</td>
</tr>
<tr>
<td><strong>Effectiveness (52.7%)</strong></td>
<td></td>
</tr>
<tr>
<td>Measure of primary outcome</td>
<td>22 (100)</td>
</tr>
<tr>
<td>Measure of broader outcomes (ie, QoL\textsuperscript{c}, negative outcomes)</td>
<td>11 (50)</td>
</tr>
<tr>
<td>Measure of robustness across subgroups</td>
<td>4 (18)</td>
</tr>
<tr>
<td>Measure of short-term attrition</td>
<td>14 (64)</td>
</tr>
<tr>
<td>Use of qualitative methods or data to understand outcomes</td>
<td>7 (32)</td>
</tr>
<tr>
<td><strong>Adoption-setting (3.4%)</strong></td>
<td></td>
</tr>
<tr>
<td>Setting exclusions</td>
<td>2 (9)</td>
</tr>
<tr>
<td>Setting adoption rate</td>
<td>1 (4)</td>
</tr>
<tr>
<td>Setting representativeness</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Use of qualitative methods to understand adoption at setting level</td>
<td>0 (0)</td>
</tr>
<tr>
<td><strong>Adoption-staff (0%)</strong></td>
<td></td>
</tr>
<tr>
<td>Staff exclusions</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Staff participation rate</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Staff representativeness</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Use of qualitative methods to understand staff participation</td>
<td>0 (0)</td>
</tr>
<tr>
<td><strong>Implementation (10%)</strong></td>
<td></td>
</tr>
<tr>
<td>Delivered as intended</td>
<td>5 (23)</td>
</tr>
<tr>
<td>Adaptations to intervention</td>
<td>4 (18)</td>
</tr>
<tr>
<td>Cost of intervention (time or money)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Consistency of implementation across staff or time or settings subgroups</td>
<td>2 (9)</td>
</tr>
<tr>
<td>Use of qualitative methods to understand implementation</td>
<td>0 (0)</td>
</tr>
<tr>
<td><strong>Maintenance-individual (9%)</strong></td>
<td></td>
</tr>
<tr>
<td>Measure of primary outcome at ≥6-mo follow-up</td>
<td>3 (14)</td>
</tr>
<tr>
<td>Measure of broader outcomes (ie, QoL, negative outcomes) at follow-up</td>
<td>2 (9)</td>
</tr>
<tr>
<td>Measure of long-term robustness across subgroups</td>
<td>2 (9)</td>
</tr>
<tr>
<td>Measure of long-term attrition</td>
<td>3 (14)</td>
</tr>
<tr>
<td>Use of qualitative methods to understand long-term effects</td>
<td>0 (0)</td>
</tr>
<tr>
<td><strong>Maintenance-setting (3.4%)</strong></td>
<td></td>
</tr>
<tr>
<td>Program ongoing (≥6-mo poststudy funding)</td>
<td>1 (4)</td>
</tr>
<tr>
<td>Long-term program adaptations</td>
<td>2 (9.1)</td>
</tr>
<tr>
<td>Some discussion of sustainability of business model</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Use of qualitative methods to understand setting-level institutionalization</td>
<td>0 (0)</td>
</tr>
</tbody>
</table>

\textsuperscript{a}The table formatting was adapted from Burke et al \textsuperscript{[47]}.  
\textsuperscript{b}Overall RE-AIM was 18.2\%.  
\textsuperscript{c}QoL: quality of life.
Reach

Exclusion criteria commonly included health contraindications for participating in physical activity or comprised mHealth-specific requirements (eg, specifications around technical devices). Most studies provided accurate information (ie, either n and valid denominator or percentage) on the participation rate (16/22, 73%) [56-60,62-66,68,69,71,72,75,78]; however, only a few (3/22, 14%) reported the sample size in relation to the total number exposed to recruitment [65,68,72], and the remaining trials reported only on the relation of the sample size to potentially eligible participants [56-60,62-64,66,69,71,75,78]. A few interventions (6/22, 27%) adequately reported the representativeness of the study sample. One intervention compared their sample to eligible individuals who declined participation [72], and 5 compared their sample and their target audience [58,62,66,70,71]. Comparisons were made on physical activity variables and anthropometry and fitness measures.

Effectiveness

All studies (23/23, 100%) reported a measure of primary outcome related to physical activity (per review eligibility criteria), and half of the interventions (11/22, 50%) addressed a measure of broader outcomes [56,57,60,61,65-67,69,70,72,75]. Moreover, 45% (10/22) of studies compared their physical activity–related findings to a public health goal (ie, physical activity guidelines) [56,58,62-64,71,74-76]; however, only a few studies (4/22, 18%) analyzed the robustness across study subgroups (eg, gender and age groups) [56,58,64,76]. Potential explanations for physical activity–related findings were explored using qualitative research methods in several interventions (7/22, 32%) [57,62,67-69,72,76].

Adoption

Both nonresearch and research staff participation were considered, and more participation of either nonresearch or research staff would result in a study being less pragmatic if it exceeded the usual standard of care. However, no items were reported within the dimension “Adoption-staff.” Regarding “Adoption-setting,” 2 studies specified setting exclusions (eg, unqualified staff and irregular physical education classes) [67,68]. One intervention presented a valid setting adoption rate [68].

Implementation

The delivered as intended and the adaptations to intervention items were infrequently addressed and were mainly of technical nature (eg, app bug or app appearance). None of the studies sufficiently reported the cost of intervention, meaning that costs were not addressed across all levels of the intervention or were not detailed enough (eg, app development, technical equipment, and support). The consistency of implementation was outlined in 2 trials (eg, fidelity checks) [58,78].

Maintenance

A few interventions (3/22, 14%) assessed a ≥6-month follow-up measure; 2 studies reported a 6-month follow-up phase [58,66]; 1 implemented a 9-month follow-up measure [73]; and all these studies reported an accurate long-term attrition rate. Two studies analyzed the long-term robustness (eg, age and weight status) [58,73]. A measure of broader outcomes was reported in 2 interventions, assessing the quality of life using the 12-Item Short-Form Health Survey [58,66].

Items within the Maintenance-Setting dimension were only addressed by 3 interventions, including potential long-term adaptations (eg, implementing an educational app component) [56,72,74]. The sustainability of the program in the RE-AIM context was not discussed at all.

PRECIS-2 Assessment

The overall PRECIS-2 score across all interventions was 2.93/5 (SD 0.54). Of the 22 assessed interventions, 14 (64%) interventions were categorized as equally pragmatic and explanatory (range 2.56-3.44) [57,59,62-67,69–71,73,74,76]; 5 (23%) studies were identified as being primarily explanatory (range 2.00-2.44) [58,60,61,68,77]; and 3 (14%) studies were primarily pragmatic (range 3.56-4.44) [56,72,74].

The most pragmatic dimension across all interventions was flexibility (adherence), with an average score of 3.73 (SD 0.92), as demonstrated by letting the participants use the app at their convenience or lacking any measures to improve adherence. Follow-up, organization, and flexibility (delivery) appeared to be more explanatory, with means of 2.18 (SD 0.75), 2.36 (SD 1.07), and 2.41 (SD 0.72), respectively. For example, delivery flexibility was considered more explanatory based on in-person requirements, clinician oversight, or specific app use or compliance requirements. Domains considered equally explanatory and pragmatic were eligibility criteria, recruitment, setting, primary outcome, and primary analysis (range 2.95-3.45). Overall, the studies in this review were equally pragmatic and explanatory in terms of the eligibility criteria.

Meta-analysis

Overall Treatment Effect

Data from only 17 interventions were extracted for this meta-analysis because 5 interventions did not present complete outcome data (ie, they did not report SE or 95% CI). Overall, these 17 mHealth interventions significantly improved the participants’ physical activity (Cohen d=0.29, 95% CI 0.13-0.46; Figure 2).
Figure 2. Forest plot of standardized treatment effects on physical activity with studies weighted by the inverse of the SE of the estimated treatment effect. REML: restricted maximum likelihood.

<table>
<thead>
<tr>
<th>Study</th>
<th>Standard Mean Difference (95% CI)</th>
<th>Weight (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direito et al, 2015</td>
<td>0.09 [-0.58, 0.75]</td>
<td>3.91</td>
</tr>
<tr>
<td>Edney et al, 2020</td>
<td>0.03 [-0.20, 0.26]</td>
<td>8.86</td>
</tr>
<tr>
<td>Fanning et al, 2017</td>
<td>-0.13 [-0.67, 0.41]</td>
<td>4.98</td>
</tr>
<tr>
<td>Fukuoka et al, 2019</td>
<td>0.58 [0.35, 0.80]</td>
<td>8.88</td>
</tr>
<tr>
<td>Garde et al, 2018</td>
<td>0.58 [0.05, 1.10]</td>
<td>5.12</td>
</tr>
<tr>
<td>Glynn et al, 2014</td>
<td>0.31 [0.06, 0.55]</td>
<td>8.69</td>
</tr>
<tr>
<td>Gremaud et al, 2018</td>
<td>2.32 [0.88, 3.77]</td>
<td>1.15</td>
</tr>
<tr>
<td>Harries et al, 2016</td>
<td>0.42 [0.02, 0.82]</td>
<td>6.54</td>
</tr>
<tr>
<td>King et al, 2016</td>
<td>1.65 [0.43, 1.67]</td>
<td>4.25</td>
</tr>
<tr>
<td>Kitagawa et al, 2020</td>
<td>0.07 [-0.02, 0.17]</td>
<td>10.35</td>
</tr>
<tr>
<td>Leinonen et al, 2017</td>
<td>0.79 [-1.00, 2.58]</td>
<td>0.78</td>
</tr>
<tr>
<td>Lyons et al, 2017</td>
<td>0.26 [-0.07, 0.59]</td>
<td>7.49</td>
</tr>
<tr>
<td>Martin et al, 2015</td>
<td>0.47 [-0.07, 1.00]</td>
<td>5.04</td>
</tr>
<tr>
<td>Recio-Rodriguez et al, 2016</td>
<td>-0.07 [-0.19, 0.05]</td>
<td>10.12</td>
</tr>
<tr>
<td>Robertson et al, 2018</td>
<td>-0.52 [-1.28, 0.24]</td>
<td>3.27</td>
</tr>
<tr>
<td>Walsh et al, 2016</td>
<td>0.97 [0.10, 1.84]</td>
<td>2.67</td>
</tr>
<tr>
<td>Zhou et al, 2018</td>
<td>0.33 [0.03, 0.63]</td>
<td>7.90</td>
</tr>
<tr>
<td>Overall</td>
<td>0.29 [0.13, 0.46]</td>
<td></td>
</tr>
</tbody>
</table>

Heterogeneity: $t^2=0.07$, $I^2=77.27\%$, $H^2=4.4$
0 Test of $\theta=0$: $Q(16)=62.91$, $P<0.01$
Test of $\theta=0$: $z=3.47$, $P<0.01$

Random-effects REML model

**Meta-regression Analyses**

Meta-regression analyses revealed a statistically significant negative association between the standardized treatment effect and the study’s sample size ($P=.01$), PRECIS-2 score ($P<.001$), and study participants’ baseline physical activity ($P<.001$; Table 5), that is, a larger sample size, higher PRECIS-2 score (ie, more pragmatic), and higher observed baseline physical activity levels were all associated with smaller treatment effect sizes on participants’ physical activity. None of the other covariate measures (ie, intervention duration, participants’ age, participants’ gender, and RE-AIM score) were significantly related to changes in participants’ physical activity.

To graphically depict the interaction between the treatment effect size and the continuous measure of a study’s PRECIS-2 score, we created a bubble plot with studies represented by circles sized by the inverse of the SE of the estimated treatment effect (Figure 3). The plot also shows the weighted linear relationship between these study characteristics and the 95% CI for this estimated relationship.
Table 5. Meta-regression results showing the interaction between study characteristics and the standardized treatment effect on physical activity.\(^a\)

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Standardized mean difference (95% CI)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log (intervention duration [days])</td>
<td>0.0171 (−0.0338 to 0.0680)</td>
<td>.51</td>
</tr>
<tr>
<td>Log (participant mean age [years])</td>
<td>−0.00296 (−0.224 to 0.218)</td>
<td>.98</td>
</tr>
<tr>
<td>Log (sample size)</td>
<td>−0.0616(^b) (−0.111 to −0.0123)</td>
<td>.01</td>
</tr>
<tr>
<td>Log (percentage male)</td>
<td>−0.0615 (−0.266 to 0.143)</td>
<td>.56</td>
</tr>
<tr>
<td>Log (baseline step count)</td>
<td>−0.420(^c) (−0.637 to −0.202)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Log (baseline MVPA(^d) [minutes])</td>
<td>−0.199(^f) (−0.288 to −0.109)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Log (PRECIS-2(^e) score)</td>
<td>−0.805(^f) (−1.361 to −0.249)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Log (RE-AIM(^g) score)</td>
<td>−0.0277 (−0.177 to 0.122)</td>
<td>.72</td>
</tr>
<tr>
<td>Log (risk-of-bias score)</td>
<td>−0.199 (−0.406 to 0.0690)</td>
<td>.06</td>
</tr>
</tbody>
</table>

\(^a\)All covariates were log transformed; therefore, the coefficients measure the associated change in the standardized treatment effect size from a 1% increase in the indicated variable.

\(^b\)P<.05.

\(^c\)P<.001.

\(^d\)MVPA: moderate to vigorous physical activity.

\(^e\)RE-AIM: Reach, Effectiveness, Adoption, Implementation, Maintenance.

\(^f\)P<.01.

\(^g\)PRECIS-2: Pragmatic-Explanatory Continuum Indicator Summary-2.

Figure 3. Bubble plot of standardized treatment effect on Pragmatic-Explanatory Continuum Indicator Summary-2 (PRECIS-2) score (a single outlier was removed).
Overall Treatment Effect Heterogeneity

The meta-analysis showed considerable heterogeneity between the studies, with an \( I^2 \) value of 77.27%. The \( I^2 \) value represents the estimated percentage of variability in the results because of heterogeneity rather than chance [53]. Cochran Q test for treatment effect heterogeneity across these studies was \( Q_{16} = 62.91 \), which demonstrates a statistically significant degree of heterogeneity (\( P < .001 \)).

Analysis of Publication Bias and Small-Study Effects

We used the trim-and-fill method to explore the potential impact of publication bias in this literature, which estimated the number of studies missing from this literature to be 4 (SE 2.80; Figure 4). After imputing these missing studies, the overall standardized treatment effect size was slightly reduced from 0.29 (95% CI 0.13-0.46) to 0.20 (95% CI 0.01-0.40) but remained statistically significant. A high \( I^2 \) value of 83.8% indicated that the heterogeneity between studies remained at a considerable level after imputing these potentially missing studies. We then carried out the Egger test for small-study effects, which reached statistical significance under most specifications (Multimedia Appendix 7).

Discussion

Principal Findings

Among recent studies using app-based interventions to promote physical activity, we observed a significant degree of underreporting on several RE-AIM dimensions, which limits researchers’ and policy makers’ ability to assess the generalizability of the research results. In addition, the interventions in this literature, in general, had more explanatory rather than pragmatic designs, which further limits our ability to forecast how successful these interventions would be in promoting physical activity if implemented among the general population. Finally, the aggregate study results showed a small but significant improvement in participants’ physical activity. Taken
together, these findings suggest that app-based physical activity interventions would have limited efficacy in promoting physical activity if more widely scaled and adopted among the general population, suggesting that more pragmatic study designs are needed to increase the transferability from research to practice. The recommendations provided by Blackman et al [16] should be used more widely by researchers in this literature when designing and reporting study findings.

RE-AIM Evaluation and PRECIS-2 Assessment

RE-AIM Evaluation

Our findings build on a prior review of mHealth physical activity interventions that also observed a lack of reporting on study characteristics and research findings in this literature [16]. Without sufficient information on these important study dimensions, the previous review was unable to determine the generalizability of the research findings at that time. Our more detailed and updated review demonstrates that only small improvements in transparency and the reporting of study characteristics have been achieved in mHealth physical activity research since then.

Our finding that recent mHealth physical activity studies lack transparency builds on similar observations reported in reviews of physical activity interventions using both mHealth and other intervention tools [47,49,79]. Specifically, the review by Blackman et al [16] on the mHealth physical activity literature found that few studies reported on the maintenance of intervention effects and the degree of implementation fidelity. In addition, the review by Harden et al [49] on group-based physical activity interventions showed that external validity factors were consistently underreported, and the review by Burke et al [47] on physical activity interventions for adults with spinal cord injuries found that several items within the Adoption and Maintenance dimensions of RE-AIM were not reported in any study, limiting the generalizability of these studies.

Two specific areas of underreporting in the mHealth physical activity studies that we reviewed were in the Adoption and Maintenance dimensions. The lack of reported information on the ability of health care providers to adopt these app-based physical activity intervention tool or tools significantly limits the willingness of clinicians and organizations to implement these new intervention approaches [16,47,49]. More pragmatic study designs with greater reporting of the Adoption and Maintenance dimensions are needed to increase the implementation of these mHealth tools in real-world settings. In addition, none of the studies reported sufficiently the cost of the intervention (in terms of either time or money), making it difficult to assess the benefit versus cost of these tools. Rubin et al [80] noted that prior complications experienced when integrating mHealth technologies into clinical practice have likely increased providers’ hesitancy to adopt new mHealth strategies. Therefore, we believe that increased reporting of interventions’ organizational requirements and costs (eg, required staff qualifications, equipment for delivery and analysis, cost of acquiring the intervention tools, and maintenance) would increase the applicability of this research.

PRECIS-2 Assessment

With regard to the PRECIS-2 results, our domain-specific assessments suggest that these recent studies testing app-based physical activity interventions tend to be primarily explanatory in nature. To combat a lack of app engagement, many studies used additional text messages or email reminders to reengage participants with the interventions’ app. These additional intervention components lowered our assessment of pragmatism, as it is not clear how well these methods can be widely implemented in usual care practices. Although the apps were considered relatively pragmatic in terms of their ease of accessibility, many studies also used frequent assessments and in-person intervention components or brought participants into research-specific facilities, limiting their overall level of pragmatism. Importantly, the use of device-based physical activity measures did not influence PRECIS-2 scores, as these devices are increasingly available and integrated into usual care.

Challenges and Adaptations of RE-AIM and PRECIS-2

To address the underreporting of study characteristics, we combined the main intervention report with additional documents available on the web but found few additional study details through these additional sources; thus, we want to emphasize that a greater “consensus around the use of frameworks and checklists across scientific fields and journals” is still needed [47]. We also expanded the original RE-AIM framework to include a third scoring category (inadequately/insufficiently reported) but found that assessing this added nuance in reporting adds substantially more work to the review process. Therefore, we refer readers and future reviewers to the ongoing creation of domain-specific review tools [81], which will hopefully be able to strike a better balance between researcher burden and improved accuracy.

Meta-analysis

Overall, these recent app-based physical activity interventions produced small but significant increases in participants’ physical activity. This finding is in line with the results of previous reviews that also found a small and significant effect of app-based interventions on promoting physical activity [31-33,82]. In addition, our meta-analysis found that study effect sizes were not significantly different between interventions with durations longer than 8 weeks compared with those with shorter durations (Multimedia Appendix 7), which suggests that duration alone is not a predictor of a successful physical activity intervention and that additional approaches and intervention tools are still needed to change and maintain physical activity increases. Finally, a few of these studies were able to demonstrate, or even assess, the maintenance of physical activity after the interventions were withdrawn. This finding emphasizes the need for an improved understanding of physical activity habits and the maintenance of initial behavioral change.

The lack of evidence for an optimal physical activity intervention duration and for the maintenance of physical activity increases has been noted in previous reviews of the mHealth literature. Contrary to our findings, Romeo et al [32] found that the most effective physical activity interventions had durations longer than 8 weeks. In addition, the review by
Schoeppe et al [33] on app-based health interventions showed the greatest effects among interventions for up to 3 months in duration. The discrepancy between our results and those of previous studies demonstrates the need for more evidence on the optimal intervention duration. With regard to the maintenance of intervention effects, a recent systematic review by Pradal-Cano et al [82] described the need for longer-term studies to observe the maintenance of intervention effects after the intervention components are withdrawn. Among the studies reviewed by Pradal-Cano et al [58,66,73], only 3 reported on the maintenance of intervention effects at least 6 months after the intervention was withdrawn, and there were fixed findings on maintenance among these studies.

**Strengths and Limitations**

Adapting 2 complementary implementation science tools to better understand the generalizability and applicability of app-based physical activity intervention findings is a key strength of this review; however, this review is not without limitations. First, our literature search identified a relatively small number of unique interventions, which limited the power of our statistical methods. Second, the included studies significantly varied in terms of design parameters (eg, sampling frame and intervention components) and methodological parameters (eg, outcome measures). This considerable heterogeneity was identified in the meta-analyses and indicated the difficulties in synthesizing this literature. Although we focused only on app-based physical activity interventions, most interventions incorporated additional intervention components, precluding us from isolating the individual effect of the app on physical activity. Third, our literature search was performed in 2020, and more studies using mobile apps to increase physical activity have been published since then [83-85]. Although it is beyond the scope of this paper to incorporate these studies into our complete analyses, they all provide additional evidence that mobile apps can improve physical activity. In addition, one of these recent studies reported long-term behavioral maintenance outcomes [85], which is an important step in the mHealth app literature. Another important limitation is that most included studies targeted adults (19/22, 86%), which limits the generalizability of our findings to physical activity interventions among younger and older populations. Fourth, the significant degree of underreporting of study characteristics limited our ability to assess treatment moderation by individual RE-AIM dimensions, which is an important area for future research. Finally, our statistical analyses indicated the presence of a publication bias, potentially compromising the robustness of our findings. However, subsequent trim-and-fill analyses suggested that the overall treatment effect was only slightly reduced when attempting to account for these missing studies.

**Conclusions**

This review highlights important limitations in the mHealth literature that uses app-based interventions to promote physical activity. Specifically, studies continue to underreport several key study characteristics that are necessary to determine the generalizability and scalability of these intervention approaches. Importantly, more pragmatic study designs are needed to help researchers and policy makers confidently implement app-based tools in standard care practice. In addition, studies with different intervention durations were equally effective in increasing physical activity, suggesting that additional intervention methods and approaches are necessary to improve the maintenance and growth of initial physical activity improvements.

**Conflicts of Interest**

None declared.

Multimedia Appendix 1

PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines.

[DOC File, 68 KB - mhealth_v11i1e43162_app1.doc ]

Multimedia Appendix 2

Search strategy for all electronic databases.

[PDF File (Adobe PDF File), 108 KB - mhealth_v11i1e43162_app2.pdf ]

Multimedia Appendix 3

Data extraction form (general study characteristics).

[PDF File (Adobe PDF File), 76 KB - mhealth_v11i1e43162_app3.pdf ]

Multimedia Appendix 4

Combined coding sheet (adapted Reach, Effectiveness, Adoption, Implementation, Maintenance [RE-AIM] and Pragmatic-Explanatory Continuum Indicator Summary-2 [PRECIS-2]).

[PDF File (Adobe PDF File), 158 KB - mhealth_v11i1e43162_app4.pdf ]

Multimedia Appendix 5

Reach, Effectiveness, Adoption, Implementation, Maintenance (RE-AIM) and Pragmatic-Explanatory Continuum Indicator Summary-2 (PRECIS-2) scoring.
References


52. Fukuoka Y, Haskell W, Lin F, Vittinghoff E. Short- and long-term effects of a mobile phone app in conjunction with brief counseling for sedentary behavior change in midlife and older adults: a randomized controlled trial. JMIR Mhealth Uhealth 2017 Mar 6;4(3):e28 [FREE Full text] [doi: 10.2196/mhealth.6967] [Medline: 28264796]


Abbreviations

CONSORT: Consolidated Standards of Reporting Trials
mHealth: mobile health
PRECIS-2: Pragmatic-Explanatory Continuum Indicator Summary-2
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RE-AIM: Reach, Effectiveness, Adoption, Implementation, Maintenance
RoB: risk-of-bias
Review

Participant Engagement in Microrandomized Trials of mHealth Interventions: Scoping Review

Utek Leong¹, BSocSci; Bibhas Chakraborty²,³,⁴, PhD

¹Department of Psychology, National University of Singapore, Singapore, Singapore
²Centre for Quantitative Medicine and Program in Health Services and Systems Research, Duke-NUS Medical School, National University of Singapore, Singapore, Singapore
³Department of Statistics and Data Science, National University of Singapore, Singapore, Singapore
⁴Department of Biostatistics and Bioinformatics, Duke University, Durham, NC, United States

Corresponding Author:
Bibhas Chakraborty, PhD
Centre for Quantitative Medicine and Program in Health Services and Systems Research
Duke-NUS Medical School
National University of Singapore
8 College Road, #06-31
Singapore, 169857
Singapore
Phone: 65 66016502
Email: bibhas.chakraborty@duke-nus.edu.sg

Abstract

Background: Microrandomized trials (MRTs) have emerged as the gold standard for the development and evaluation of multicomponent, adaptive mobile health (mHealth) interventions. However, not much is known about the state of participant engagement measurement in MRTs of mHealth interventions.

Objective: In this scoping review, we aimed to quantify the proportion of existing or planned MRTs of mHealth interventions to date that have assessed (or have planned to assess) engagement. In addition, for the trials that have explicitly assessed (or have planned to assess) engagement, we aimed to investigate how engagement has been operationalized and to identify the factors that have been studied as determinants of engagement in MRTs of mHealth interventions.

Methods: We conducted a broad search for MRTs of mHealth interventions in 5 databases and manually searched preprint servers and trial registries. Study characteristics of each included evidence source were extracted. We coded and categorized these data to identify how engagement has been operationalized and which determinants, moderators, and covariates have been assessed in existing MRTs.

Results: Our database and manual search yielded 22 eligible evidence sources. Most of these studies (14/22, 64%) were designed to evaluate the effects of intervention components. The median sample size of the included MRTs was 110.5. At least 1 explicit measure of engagement was included in 91% (20/22) of the included MRTs. We found that objective measures such as system usage data (16/20, 80%) and sensor data (7/20, 35%) are the most common methods of measuring engagement. All studies included at least 1 measure of the physical facet of engagement, but the affective and cognitive facets of engagement have largely been neglected (only measured by 1 study each). Most studies measured engagement with the mHealth intervention (Little e) and not with the health behavior of interest (Big E). Only 6 (30%) of the 20 studies that measured engagement assessed the determinants of engagement in MRTs of mHealth interventions; notification-related variables were the most common determinants of engagement assessed (4/6, 67% studies). Of the 6 studies, 3 (50%) examined the moderators of participant engagement—2 studies investigated time-related moderators exclusively, and 1 study planned to investigate a comprehensive set of physiological and psychosocial moderators in addition to time-related moderators.

Conclusions: Although the measurement of participant engagement in MRTs of mHealth interventions is prevalent, there is a need for future trials to diversify the measurement of engagement. There is also a need for researchers to address the lack of attention to how engagement is determined and moderated. We hope that by mapping the state of engagement measurement in existing MRTs of mHealth interventions, this review will encourage researchers to pay more attention to these issues when planning for engagement measurement in future trials.
Introduction

Background

In the past decade, digital solutions that leverage mobile technologies to improve health and well-being have become increasingly popular and have emerged as promising adjuncts to traditional health care provision [1]. These so-called mobile health (mHealth) interventions generally involve the use of mobile technologies such as mobile apps, SMS text messaging, and wearable devices to improve patient health outcomes by delivering health-related intervention content. Mounting evidence suggests that mHealth interventions are largely effective for treating chronic health conditions [2,3] and for preventing unhealthy behaviors [4]. Effectiveness aside, it is not difficult to see why mHealth interventions are so popular; mHealth interventions are highly scalable and cost-efficient [1]. High rates of mobile ownership worldwide also signal the potential for mHealth interventions to reach a diverse audience, including the underserved; however, we must acknowledge that there are barriers to access (such as the lack of internet access) that prevent mHealth interventions from being truly equitable [5].

Recently, more sophisticated mHealth interventions have been proposed to take advantage of the technological advances in mobile technology. These novel interventions (such as just-in-time adaptive interventions) tend to be multicomponent, that is, they tend to involve the manipulation of ≥2 components hypothesized to have a treatment effect. They also tend to be adaptive, in the sense that components of the intervention (eg, its content and timing of delivery) can change in response to some input data provided by the user (tailoring data collected from surveys or sensors). To make this concrete, let us consider a hypothetical mHealth intervention designed to reduce the severity of depression symptoms by sending daily motivational messages via SMS text messaging. The intervention is said to be multicomponent if both message content and timing of SMS delivery are thought to be active ingredients that can influence depression symptom severity. Such an intervention could be made adaptive if daily message content is tailored to the participant’s mood the night before such that if a given participant had high negative mood the night before, a more strongly worded motivational message would be sent the next day. Unfortunately, conventional randomized controlled trials (RCTs) cannot be used to develop and optimize these interventions because they do not allow researchers to separate the treatment effect of individual treatment components from the overall treatment effect. In addition, RCTs do not allow researchers to investigate time-varying effects, which is of interest when the goal is to identify the optimal time to administer an intervention component [6]. Therefore, if the RCT design is used to study the aforementioned hypothetical mHealth intervention, we will only be able to estimate the overall treatment effect of sending motivational messages on depression symptom severity and not the specific treatment effect of message content and timing of SMS delivery on the severity of depressive symptoms.

To address these limitations of the RCT design, several cutting-edge trial designs have been proposed in recent years. The microrandomized trial (MRT) design in particular has gained considerable traction as a way to optimize multicomponent and adaptive mHealth interventions (including but not limited to just-in-time adaptive interventions) [6-9]. Essentially, the MRT design involves the repeated random assignment of participants to different intervention options of a single or multiple intervention components; therefore, an MRT of our hypothetical multicomponent motivational SMS text messaging intervention would entail repeatedly randomizing participants to receive different types of motivational messages at different times daily. This repeated random assignment then facilitates the estimation of the time-varying causal effects of each specific treatment component [6], that is, we can estimate the treatment effect of message content and timing of SMS text message delivery on the severity of depressive symptoms. Therefore, unlike RCTs, MRTs allow researchers to investigate the effectiveness of specific components of mHealth interventions, which could be informative for theory, future research, and intervention optimization. Notably, RCTs and MRTs are not mutually exclusive. One additional benefit of the MRT design is that it can be easily embedded within the treatment arm of a conventional RCT; therefore, the overall treatment effect and the effect of specific intervention components can be tested simultaneously.

Regardless of the trial design used, the measurement of participant engagement is integral to understanding the feasibility of mHealth interventions. This is because engagement with the constituent digital or nondigital intervention stimuli and tasks of an mHealth intervention is necessary for the individual to experience the intended distal health outcomes of the intervention [10,11]. The measurement of engagement, however, is not straightforward. Engagement, like many other psychological constructs, is an abstract and fuzzy concept that is not directly measurable (unlike, for example, the measurement of height). To measure engagement, researchers must first operationalize engagement, that is, define engagement in measurable terms [12]. To unpack how exactly engagement with mHealth interventions can be operationalized, it is instructive to consider how engagement can be measured, which kinds of engagement can be measured, and what levels of engagement can be measured.

Measures of Engagement

According to Yardley et al [13] and then Short et al [14], there are 7 methods of engagement measurement that researchers can use to obtain a sense of participant engagement in their digital interventions: self-report questionnaires, ecological momentary assessments (EMAs), qualitative methods, system usage data,
sensor data, social media data, and psychophysiological measures. The measurement of engagement via self-report questionnaires and EMAs involves directly asking participants to report (via single items or questionnaires) their subjective experience of using the digital intervention or their use of the intervention. Qualitative methods of engagement, by contrast, involve the inference of engagement from qualitative sources (such as written responses and semistructured interviews). Measuring engagement via system usage data involves the quantification of how the digital intervention is used through metrics including, but not limited to, the number of log-ins, time spent on the intervention, and number of modules viewed. Engagement can also be measured by analyzing passively collected social media and sensor data if social media and sensors (eg, pedometers and heart rate sensors) are a feature of the intervention. Finally, psychophysiological measures of engagement involve the use of measures such as electroencephalography, eye tracking, or functional magnetic resonance imaging to infer engagement from neural and physiological activity.

Facets of Engagement

Engagement is thought to be a multifaceted construct composed of 3 distinct facets—physical, affective, and cognitive [11,14]. The physical facet of engagement refers to the “actual performance of an activity or task” [11]. The affective facet by contrast is thought to capture “a wide range of positive affective reactions to a task or activity, from feeling pride, enthusiasm, and satisfaction, to affective states that may underlie more enduring experiences of attachment, identification, and commitment” [11]. Finally, the cognitive facet of engagement is thought to refer to “selective attention and processing of information related to a task or activity” [11]. These facets represent distinct kinds of engagement that can be measured in mHealth interventions.

Levels of Engagement

When discussing the measurement of engagement in digital interventions, it is crucial to ask the question, “engagement with what?” [11]. This is because engagement measures can either be measures of engagement with the features and the active ingredients of the intervention or engagement with the health behavior of interest. Formally, Cole-Lewis et al [15] termed engagement with the mHealth intervention as “Little e” and engagement with the health behavior of interest as “Big E”; elsewhere, the terms microengagement and macroengagement are used instead [13]. In essence, Little e and Big E represent 2 distinct levels of engagement, where the 7 methods of engagement outlined in the Measures of Engagement section can be applied to measure participant engagement in the mHealth intervention context.

This Study

Given the importance of engagement to mHealth interventions, researchers have endeavored to understand how engagement has been conceptualized and operationalized in studies evaluating mHealth interventions. For instance, Pham et al [16] recently reviewed how engagement has been defined and measured in mHealth apps for chronic conditions. Perski et al [10], by contrast, reviewed how engagement was conceptualized in digital behavior change interventions (their review was not limited to mHealth interventions; it included other digital interventions). Other recent reviews evaluated the measurement of engagement in mHealth interventions designed for specific health conditions [17,18]. However, none of these reviews examined mHealth interventions evaluated by MRTs, perhaps owing to the relative infancy of the trial design. Thus, not much is known about the state of participant engagement measurement in MRTs of mHealth interventions. Furthermore, it is not yet known what kinds of factors have been studied as determinants of engagement in these MRTs.

Therefore, we conducted a scoping review to map this relatively new research area. We chose to conduct a scoping review as we expected that only a handful of mHealth intervention MRTs have been conducted to date—too few to be meaningfully synthesized with a systematic review. This scoping review aimed to address 3 review questions:

1. What proportion of existing (or planned) MRTs of mHealth interventions to date have assessed (or have planned to assess) engagement?
2. How has engagement been operationalized in existing (or planned) MRTs of mHealth interventions that have assessed (or have planned to assess) engagement?
3. In existing (or planned) MRTs of mHealth interventions that have assessed (or have planned to assess) engagement, what kind of factors have been studied as determinants of engagement?

Methods

Protocol and Registration

The protocol for this scoping review was developed using the Joanna Briggs Institute Manual for Evidence Synthesis [19] and was designed to ensure adherence to the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analysis extension for Scoping Reviews) guidelines [20]. The protocol and its appendices were prospectively registered with the Open Science Framework (OSF) on June 30, 2022 [21].

Eligibility Criteria

We prioritized the inclusion of papers published in peer-reviewed journals. We included preprints, trial protocols, and dissertations (this was mistakenly left out of the “Types of Sources” section of our protocol [21]) only if no corresponding peer-reviewed journal articles were available. Conference abstracts were excluded from this scoping review. All papers fulfilling these criteria to date were considered for inclusion if they were written in English and if they reported MRTs of mHealth interventions. We also included any secondary analyses of mHealth intervention engagement data collected from an MRT if the primary analysis (if available) did not report the assessment of engagement in detail. We defined mHealth interventions as any intervention designed to improve health outcomes through (though not limited to) the modification of health behavior (such as physical activity or treatment adherence), the improvement of patient knowledge,
health monitoring, and the reduction of psychological distress via mobile technology such as SMS text messaging; mobile phone apps; or devices (including but not limited to smartwatches, wearables, and sensors) [1].

As the review’s objectives concerned the assessment of engagement in MRTs of mHealth interventions, we included all studies in which authors explicitly attempted or claimed to quantitatively or qualitatively measure the participation in or use of mHealth interventions directly (by measuring participation in or performance of mHealth intervention activities or components) or indirectly (using measurements derived from non–intervention-related activities or components as a proxy), regardless of how they actually defined and measured engagement (eg, if they use alternative terms like adherence).

Information Sources and Search Strategy

We conducted a broad search for all published MRTs of mHealth interventions to date (the search was initially conducted on July 13, 2022, and again on September 28, 2022) by searching the following 5 bibliographic databases: MEDLINE (via PubMed), Embase, PsycINFO, CINAHL, and Cochrane Library. The search strategy was originally developed for MEDLINE, and we consulted an academic librarian from the National University of Singapore to ensure that the search strategy was comprehensive and sound. This search strategy was then translated for the other 4 databases (only syntax was changed to accommodate differences in search engines; keywords remained the same). Although only 1 broad search was eventually performed, it must be noted that we registered 2 separate searches in our protocol—1 for all published MRTs of mHealth interventions to date and 1 fine-grained search for MRTs of mHealth interventions that have assessed (or have planned to assess) engagement. During our search process, we realized that the latter search was redundant as it was nested within the former (because we used the Boolean operator AND between the mHealth intervention search terms and the engagement-related search terms). Therefore, we condensed the 2 planned searches into 1 by using the Boolean operator OR instead, such that our database searches indexed any MRTs that mentioned mHealth interventions or engagement-related terms. The comprehensive search strategies for all 5 databases (and their respective previous iterations) can be found on OSF [21].

To search for gray literature and unpublished studies, we searched the reference lists of included studies for any additional sources not indexed by our database search. We also posted an open call for unpublished MRTs of mHealth interventions on Twitter and contacted known experts of the MRT design to request unpublished and file-drawer studies. Finally, we performed a search (similarly, this search was initially conducted on July 13, 2022, and again on September 28, 2022) of MRTs of mHealth intervention on 2 preprint servers (PsyArXiv and medRxiv; we added this search during our search process to ensure the comprehensiveness of our gray literature search) and on 2 clinical trial registries, ClinicalTrials.gov (as detailed in our protocol) and the International Clinical Trials Registry Platform (this was added during the search process as well). The following search terms were used: “microrandomised,” “microrandomized,” “micro-randomised,” and “micro-randomized.”

Selection of Sources of Evidence

The results of the searches described in the previous section were imported into EndNote (version 20; Clarivate; we did not use Zotero as planned because of technical difficulties) for source selection and screening. The titles and abstracts of all potential evidence sources were first screened for eligibility. Eligible sources were then subjected to a full-text screening. Before the 2 screening stages, both authors discussed a subset of the search results (5 titles and abstracts and 4 full-text articles) to calibrate the selection of evidence sources. UL performed the screening using the eligibility criteria, and BC verified the screening at both stages. Any disagreements were resolved by consensus.

Data Charting Process and Data Items

As described in our protocol [21], we developed an initial data extraction form (a Microsoft Excel [Microsoft Corporation] spreadsheet) to chart the data from eligible evidence sources to obtain the information necessary to answer our review questions. Both authors (UL and BC) piloted this initial data extraction form with 4 included articles to calibrate the charting process and to ensure that relevant data items were captured by the form. This form was continuously updated during the charting process through the discussion of the extracted results. UL performed data charting, and BC verified the charted data for all eligible evidence sources. Any disagreements were resolved by consensus.

The initial data collection form was designed to abstract the following information from each paper: whether the paper described a primary or secondary analysis of MRT data, type of paper, sample size of the MRT, sample characteristics, purpose of the study, type of mHealth intervention assessed, mode of delivery for the mHealth intervention, if engagement was or will be assessed, how engagement was operationalized (if assessed), if determinants of engagement were or will be assessed, and (if any) what determinants of engagement were or will be assessed; for comprehensiveness, we also charted any moderating variables and control variables (covariates) assessed. After piloting the form and during the charting process, we included additional data items to capture the following information: primary and secondary (if any) outcomes of the study, randomization design of the MRT, frequency of microrandomization, and the overall duration of the MRT. The final version of the data extraction form is available on OSF [21].

Synthesis of Results

To quantify the proportion of existing and planned MRTs of mHealth interventions to date that have assessed (or have planned to assess) engagement, we tabulated the number of evidence sources charted to have assessed or planned to assess engagement. The included evidence sources were grouped by their purpose and presented in a tabular format. The mHealth interventions of each included evidence source were categorized based on their target. We used the following categories: mental...
health promotion, smoking cessation, physical activity promotion, sleep improvement, dietary lapse prevention or weight management behavior promotion, gambling reduction, and alcohol use reduction.

To understand how engagement has been operationalized in MRTs of mHealth interventions, we sought to determine how included evidence sources measured engagement, which kinds of engagement they measured, and what levels of engagement they measured. To determine how engagement has been measured, we classified explicit measures of engagement from each included source according to the methods of engagement measurement outlined by Short et al [14] described in the Introduction section. We combined the self-report questionnaires and EMA categories for parsimony, as they are largely similar methods of measuring engagement. To determine which kinds of engagement have been measured, we classified explicit measures of engagement by the facets (physical, affective, or cognitive) of engagement they appear to measure [11]. Finally, to determine what levels of engagement have been measured, we classified the explicit measures of engagement from each included source as Little e or Big E measures [15].

To identify the factors that have been studied as determinants of engagement in MRTs of mHealth interventions, we extracted the variables of interest, moderators, and covariates from each model (with a measure of engagement as the dependent variable) tested in each included source. We then organized these variables into the following categories: notification related (eg, type of prompt sent), time related (eg, days since the start of the intervention or day of the week), psychological, societal, health behavior related (eg, alcohol use), contextual (eg, location data), physiological (heart rate), demographic, anthropometric (eg, weight change), or task related (eg, intervention-related activities).

**Results**

**Selection of Sources of Evidence**

A total of 165 evidence sources were retrieved by our database search. After removing duplicates, 91 evidence sources were retained for further screening. During the title and abstract screening, 41 sources were excluded. Of the remaining 50 evidence sources, 28 were excluded at the full-text screening (Figure 1).

Notably, 17 of these sources excluded at full-text screening were trial registrations (a total of 19 trial registrations were retrieved by our database search of the Cochrane Library). A total of 15 (88%) of these 17 sources had no published protocol, journal article, or preprint; we performed a manual Google search of their respective trial identification numbers to confirm this. In total, 2 (12%) of these 17 sources were duplicate trial registrations, that is, a corresponding protocol, journal, article, or preprint for each registration was already indexed by our database search. Therefore, only 22 evidence sources identified by our database search were considered eligible for this scoping review. No additional studies were identified and included from our planned searches of gray literature and unpublished studies.

**Figure 1.** Evidence source selection flow diagram.
Characteristics of Sources of Evidence

All charted data described in the preceding section are available on OSF [21] and Multimedia Appendix 1 [22-43]. We present a subset of the charted data that are pertinent to our review questions.

Table 1 details the characteristics of each included evidence source. Of the 22 included sources, 12 (54%) were published journal articles, 8 (36%) were trial protocols, 1 (5%) was a preprint, and 1 (5%) was a dissertation. Only 1 evidence source was a secondary analysis of MRT data [22]. All included sources were published between 2018 and 2022. More than half of the included sources (14/22, 64%) were designed to evaluate the effect of intervention components. Physical activity promotion was the most common target of the mHealth interventions (8/22, 36%). Interventions were largely delivered via smartphone apps. The median sample size of the included MRTs was 110.5.

Table 1. Characteristics of included evidence sources.

<table>
<thead>
<tr>
<th>Source and intervention type</th>
<th>Mode of delivery</th>
<th>Engagement assessed?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evaluate effect of intervention components</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aguilera et al [23], 2021</td>
<td>Mental health promotion</td>
<td>SMS</td>
</tr>
<tr>
<td>Battalio et al [24], 2021</td>
<td>Smoking cessation</td>
<td>App</td>
</tr>
<tr>
<td>Figueroa et al [25], 2022</td>
<td>Physical activity promotion</td>
<td>SMS, app</td>
</tr>
<tr>
<td>Goldstein et al [26], 2021</td>
<td>Dietary lapse prevention or weight management behavior promotion</td>
<td>App</td>
</tr>
<tr>
<td>Klasnja et al [27], 2021</td>
<td>Physical activity promotion</td>
<td>SMS</td>
</tr>
<tr>
<td>Klasnja et al [28], 2019</td>
<td>Physical activity promotion</td>
<td>App</td>
</tr>
<tr>
<td>Kramer et al [29], 2020</td>
<td>Physical activity promotion</td>
<td>App</td>
</tr>
<tr>
<td>Latham [30], 2021</td>
<td>Sleep improvement</td>
<td>App</td>
</tr>
<tr>
<td>Jeganathan et al [31], 2022</td>
<td>Physical activity promotion</td>
<td>SMS</td>
</tr>
<tr>
<td>NeCamp et al [32], 2020</td>
<td>Physical activity promotion, mental health promotion, and sleep improvement</td>
<td>App</td>
</tr>
<tr>
<td>Spruijt-Metz et al [33], 2022</td>
<td>Physical activity promotion</td>
<td>App</td>
</tr>
<tr>
<td>Wang et al [34], 2022</td>
<td>Physical activity promotion and sleep improvement</td>
<td>App</td>
</tr>
<tr>
<td>Dowling et al [35], 2022</td>
<td>Gambling reduction</td>
<td>App</td>
</tr>
<tr>
<td>Rodda et al [36], 2022</td>
<td>Gambling reduction</td>
<td>App</td>
</tr>
<tr>
<td>Evaluate strategies to improve engagement</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bell et al [22], 2020</td>
<td>Alcohol use reduction</td>
<td>App</td>
</tr>
<tr>
<td>Bidargaddi et al [37], 2018</td>
<td>Mental health promotion</td>
<td>App</td>
</tr>
<tr>
<td>Nahum-Shani et al [38], 2021</td>
<td>Smoking cessation</td>
<td>App</td>
</tr>
<tr>
<td>Nordby et al [39], 2022</td>
<td>Mental health promotion</td>
<td>SMS</td>
</tr>
<tr>
<td>Evaluate feasibility and acceptability of intervention</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Militello et al [40], 2022</td>
<td>Mental health promotion</td>
<td>App</td>
</tr>
<tr>
<td>Yang et al [41], 2022</td>
<td>Smoking cessation</td>
<td>App</td>
</tr>
<tr>
<td>Describing engagement</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hoel et al [42], 2022</td>
<td>Mental health promotion</td>
<td>App</td>
</tr>
<tr>
<td>Valle et al [43], 2020</td>
<td>Dietary lapse prevention or weight management behavior promotion</td>
<td>App</td>
</tr>
</tbody>
</table>

This study was also designed to evaluate the feasibility and acceptability of its mobile health intervention.

a SMS text messages were delivered as smartphone and smartwatch notifications.
Synthesis of Results

Operationalization of Engagement

Overview

Of the 22 included sources, 20 (91%) explicitly included at least 1 measure of engagement; 2 (9%) studies did not claim to measure engagement at all [25,32]; NeCamp et al [32] did not do so because of technical limitations. Though we did not chart the different terms used to refer to participant engagement, we noticed during our full-text screening that some studies did indeed use alternative terms in place of the term “engagement,” such as adherence [27] and investment [30].

Measures of Engagement

Table 2 summarizes the measures of engagement used in each study. Across all included studies, system usage data were by far the most frequently used measure of engagement. Sixteen (80%) out of the 20 studies that explicitly measured engagement included at least 1 measure of this category. Generally, researchers used 2 types of system usage data: (1) responsiveness to self-reports, logs, or EMAs [23,24,26,27,29,30,33,35-37,41,42] and (2) access or use of interventions [22,26,33,35,36,39-41,43].

Table 2. Measures of engagement used in microrandomized trials of mobile health (mHealth) interventions.

<table>
<thead>
<tr>
<th>Source</th>
<th>Evaluate effect of intervention components</th>
<th>Evaluate strategies to improve engagement</th>
<th>Evaluate feasibility and acceptability of intervention</th>
<th>Describing engagement</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SR&lt;sup&gt;a&lt;/sup&gt; or EMA&lt;sup&gt;b&lt;/sup&gt;</td>
<td>SU&lt;sup&gt;c&lt;/sup&gt;</td>
<td>Sensor data</td>
<td>Qualitative methods</td>
</tr>
<tr>
<td>Aguilera et al [23], 2021</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Battalio et al [24], 2021</td>
<td>✓ ✓</td>
<td>✓ ✓</td>
<td></td>
<td></td>
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<tr>
<td>Goldstein et al [26], 2021</td>
<td>✓</td>
<td></td>
<td></td>
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<tr>
<td>Klasnja et al [27], 2021</td>
<td>✓ ✓</td>
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<td>Klasnja et al [28], 2019</td>
<td>✓</td>
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<tr>
<td>Kramer et al [29], 2020</td>
<td>✓</td>
<td></td>
<td></td>
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<tr>
<td>Latham [30], 2021&lt;sup&gt;f&lt;/sup&gt;</td>
<td>✓ ✓</td>
<td>✓ ✓</td>
<td></td>
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<tr>
<td>Jeganathan et al [31], 2022</td>
<td>✓</td>
<td></td>
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<tr>
<td>Spruijt-Metz et al [33], 2022</td>
<td>✓ ✓</td>
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<tr>
<td>Wang et al [34], 2022</td>
<td>✓</td>
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<td>Dowling et al [35], 2022</td>
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<tr>
<td>Rodda et al [36], 2022</td>
<td>✓</td>
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<tr>
<td>Bell et al [22], 2020</td>
<td>✓</td>
<td></td>
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<tr>
<td>Bidargaddi et al [37], 2018</td>
<td>✓</td>
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<tr>
<td>Nahum-Shani et al [38], 2021</td>
<td>✓</td>
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<tr>
<td>Miliello et al [40], 2022</td>
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<td>Yang et al [41], 2022</td>
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<td>Valle et al [43], 2020</td>
<td>✓ ✓</td>
<td>✓ ✓</td>
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</tbody>
</table>

<sup>a</sup>SR: self-report data.
<sup>b</sup>EMA: ecological momentary assessment.
<sup>c</sup>SU: system usage data.
<sup>d</sup>SM: social media data.
<sup>e</sup>PP: psychophysiological data.
<sup>f</sup>This study was also designed to evaluate the feasibility and acceptability of its mHealth intervention.

Sensor data were the second most common measure of engagement. Overall, 35% (7/20) of the studies that explicitly measured engagement included at least 1 measure of this category [24,27,28,31,33,34,41]. Wang et al [34], for example, measured the proportion of days in a week that participants...
wore the study’s FitBit smartwatch to track their step counts and sleep duration.

Engagement was measured via self-reports or EMAs in 20% (4/20) of the studies that explicitly measured engagement [30,38-40]. Latham [30] evaluated a sleep intervention designed to improve the regularity of wake times in college students via prompts. One measure of engagement in this study was participants’ self-reported adherence to the sleep-related suggestions included in the prompt. Nahum-Shani et al [38] proposed to study how prompts to engage in self-regulatory strategies increased engagement in self-regulatory activities; researchers planned to measure engagement as self-reported engagement in self-regulatory activities during the hour after receiving a prompt. In their evaluation of a web-based intervention delivered via SMS text messaging, Nordby et al [39] measured engagement as the self-reported frequency of practicing the coping strategies taught in the web-based intervention. Militello et al [40] assessed the feasibility and acceptability of intervention prompts to encourage engagement in mindfulness activities guided by a mindfulness mobile app. Here, engagement was measured as self-reported performance of a mindfulness activity or exercise in the 24 hours after receiving an intervention prompt.

Only 1 study measured engagement with qualitative methods. In this study, researchers sought to describe engagement with an Acceptance and Commitment Therapy (ACT)–based mobile app in a clinical and a nonclinical sample [42]. The researchers inferred participant engagement by assessing whether participant responses reflected an understanding of the ACT intervention content. The following 3 indicators were used: the identification of the function of behavior, process alignment (whether the content of a given participant’s response is congruent with the core ACT process underlying the intervention prompt received), and the qualitative content of responses.

Only 8 (40%) out of the 20 studies that explicitly measured engagement used >1 method to measure engagement. Interestingly, no study used >2 methods. No studies measured engagement with social media data or psychophysiological measures.

Facets of Engagement

Table 3 summarizes the facets of engagement measured by each included study. The physical facet of engagement was the most frequently measured facet of engagement; all 20 studies that explicitly measured engagement included at least 1 measure of this facet [22-24,26-31,33-43]. Multimedia Appendix 2 [22-24,26-31,33-43] provides examples of how this facet of engagement was measured in each included study.

Only 1 study included a measure of the affective facet of engagement [30]. Recall that the affective facet of engagement “captures a wide range of positive affective reactions to a task or activity,” including the “the affective states that may underlie more enduring experiences of attachment, identification, and commitment” [11]. By asking participants how likely they were to complete the intervention (ie, their commitment to the intervention), it could be argued that Latham [30] measured this facet of engagement.

Similarly, only 1 study assessed the cognitive facet of engagement—recall that this involves the “selective attention and processing of information related to a task or activity” [11]. This processing of information related to a task was comprehensively measured by Hoel et al [42] using the qualitative measures described in Measures of Engagement section.
Table 3. Facets of engagement measured in microrandomized trials of mobile health (mHealth) interventions.

<table>
<thead>
<tr>
<th>Source</th>
<th>Physical</th>
<th>Affective</th>
<th>Cognitive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evaluate effect of intervention components</td>
<td>Aguilera et al [23], 2021 ✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Battalio et al [24], 2021 ✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Goldstein et al [26], 2021 ✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Klasnja et al [27], 2021 ✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Klasnja et al [28], 2019 ✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Kramer et al [29], 2020 ✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Latham [30], 2021a ✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Jeganathan et al [31], 2022 ✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Spruijt-Metz et al [33], 2022 ✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Wang et al [34], 2022 ✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Dowling et al [35], 2022 ✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Rodda et al [36], 2022 ✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Evaluate strategies to improve engagement</td>
<td>Bell et al [22], 2020 ✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Bidargaddi et al [37], 2018 ✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Nahum-Shani et al [38], 2021 ✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Nordby et al [39], 2022 ✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Evaluate feasibility and acceptability of intervention</td>
<td>Militello et al [40], 2022 ✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Yang et al [41], 2022 ✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Describing engagement</td>
<td>Hoel et al [42], 2022 ✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Valle et al [43], 2020 ✓</td>
<td>✓</td>
<td></td>
</tr>
</tbody>
</table>

aThis study was also designed to evaluate the feasibility and acceptability of its mHealth intervention.

Levels of Engagement

Table 4 summarizes the levels of engagement measured in each included study. Of the 20 studies that explicitly measured engagement, 14 (70%) studies measured Little e only, 2 (10%) studies measured Big E only, and 4 (20%) studies measured both Little e and Big E. Clearly, measures of engagement in MRTs of mHealth interventions are most often Little e measures.
Table 4. Levels of engagement measured in microrandomized trials of mobile health (mHealth) interventions.

<table>
<thead>
<tr>
<th>Source</th>
<th>Little e</th>
<th>Big E</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evaluate effect of intervention components</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aguilera et al [23], 2021</td>
<td>Yes</td>
<td>No</td>
<td>Response rates to daily mood rating SMS</td>
</tr>
<tr>
<td>Battalio et al [24], 2021</td>
<td>Yes</td>
<td>No</td>
<td>If end-of-day logs for smoking are completed</td>
</tr>
<tr>
<td>Goldstein et al [26], 2021</td>
<td>Yes</td>
<td>No</td>
<td>Percentage of interventions accessed</td>
</tr>
<tr>
<td>Klasnja et al [27], 2021</td>
<td>Yes</td>
<td>No</td>
<td>Adherence to wearing the FitBit</td>
</tr>
<tr>
<td>Kramer et al [29], 2020</td>
<td>Yes</td>
<td>No</td>
<td>Whether participants responded to first message of the chatbot in an intervention conversation</td>
</tr>
<tr>
<td>Latham [30], 2021</td>
<td>Yes</td>
<td>Yes</td>
<td>Percentage of sleep diaries completed</td>
</tr>
<tr>
<td>Jeganathan et al [31], 2022</td>
<td>Yes</td>
<td>No</td>
<td>Nonadherence with recommendations for watch wear time</td>
</tr>
<tr>
<td>Spruijt-Metz et al [33], 2022</td>
<td>Yes</td>
<td>No</td>
<td>Time since FitBit was last worn</td>
</tr>
<tr>
<td>Wang et al [34], 2022</td>
<td>Yes</td>
<td>No</td>
<td>Proportion of days that daily step/sleep minutes were provided within a week</td>
</tr>
<tr>
<td>Dowling et al [35], 2022</td>
<td>Yes</td>
<td>No</td>
<td>EMAc compliance</td>
</tr>
<tr>
<td>Rodda et al [36], 2022</td>
<td>Yes</td>
<td>No</td>
<td>EMA compliance</td>
</tr>
<tr>
<td>Evaluate strategies to improve engagement</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bidargaddi et al [37], 2018</td>
<td>No</td>
<td>Yes</td>
<td>Whether participants performed the self-monitoring intervention activity</td>
</tr>
<tr>
<td>Nahum-Shani et al [38], 2021</td>
<td>No</td>
<td>Yes</td>
<td>Whether participants engaged in self-regulatory activities 1 h after randomization</td>
</tr>
<tr>
<td>Nordby et al [39], 2022</td>
<td>Yes</td>
<td>Yes</td>
<td>Minutes spent on the intervention</td>
</tr>
<tr>
<td>Evaluate feasibility and acceptability of intervention</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Militello et al [40], 2022</td>
<td>Yes</td>
<td>Yes</td>
<td>Opening the application</td>
</tr>
<tr>
<td>Yang et al [41], 2022</td>
<td>Yes</td>
<td>Yes</td>
<td>Percentage of EMAs completed</td>
</tr>
<tr>
<td>Describing engagement</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hoel et al [42], 2022</td>
<td>Yes</td>
<td>No</td>
<td>Proportion of submitted and nonblank logs</td>
</tr>
<tr>
<td>Valle et al [43], 2020</td>
<td>Yes</td>
<td>No</td>
<td>Proportion of intervention messages viewed before end of day</td>
</tr>
</tbody>
</table>

aN/A: not applicable.
bThis study was also designed to evaluate the feasibility and acceptability of its mHealth intervention.
cEMA: ecological momentary assessment.

**Determinants of Engagement**

Table 5 presents the determinants, moderators, and covariates of engagement studied (if any) in MRTs that assessed or planned to assess engagement. Of the 20 included studies that measured engagement explicitly, 6 (30%) investigated the determinants of participant engagement. Of the 6 studies, 4 (67%) studies were designed to evaluate strategies to improve engagement and investigated the influence of notification-related variables on participant engagement as variables of interest [22,37-39]. The remaining 2 (33%) of the 6 studies were designed to evaluate the effect of intervention components on health.
outcomes or to describe engagement. The former study assessed a time-based variable as its variable of interest—the causal effect of being in an intervention week on participant engagement [34]. The latter study assessed task-related variables (lapses in self-monitoring and behavioral goal attainment) and an anthropometric variable (weight change) as determinants of participant engagement [43].

Of the 6 studies, only 3 (50%) studies designed to evaluate strategies to improve engagement investigated how the determinants of engagement were moderated. Two of these studies exclusively examined the moderating effect of time-related variables [22,37]. Concretely, Bell et al [22] investigated how the causal effect of sending a push notification (vs not sending it) on engagement was moderated by the number of days in the study. Bidargaddi et al [37], by contrast, investigated if the causal effect of sending (vs not sending) a push notification on engagement was moderated by the number of weeks in the study or by the day of the week (sent on a weekday or a weekend). The third study of this trio planned to study the moderating effect of a comprehensive set of physiological and psychosocial moderators representing vulnerability and receptivity, in addition to time-related moderators [38].

Table 5. Determinants, moderators, and covariates of engagement assessed in microrandomized trials of mobile health (mHealth) interventions.

<table>
<thead>
<tr>
<th>Source</th>
<th>Determinants</th>
<th>Moderators</th>
<th>Covariates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evaluate effect of intervention components</td>
<td>Wang et al [34], 2022</td>
<td>Time related</td>
<td>N/A²</td>
</tr>
<tr>
<td>Evaluate strategies to improve engagement</td>
<td>Bell et al [22], 2020</td>
<td>Notification related</td>
<td>Time related</td>
</tr>
<tr>
<td></td>
<td>Bidargaddi et al [37], 2018</td>
<td>Notification related</td>
<td>Time related</td>
</tr>
<tr>
<td></td>
<td>Nahum-Shani et al [38], 2021</td>
<td>Notification related</td>
<td>Psychological, societal, health behavior related, contextual, time related, physiological, and demographic</td>
</tr>
<tr>
<td></td>
<td>Nordby et al [39], 2022</td>
<td>Notification related</td>
<td>N/A</td>
</tr>
<tr>
<td>Describing engagement</td>
<td>Valle et al [43], 2020</td>
<td>Task related, anthropometric</td>
<td>N/A</td>
</tr>
</tbody>
</table>

²N/A: not applicable.

Discussion

Principal Findings

In this scoping review, we aimed to better understand the state of participant engagement measurement in MRTs of mHealth interventions. To do so, we quantified the proportion of existing and planned studies that have explicitly assessed engagement and investigated how engagement has been operationalized in these MRTs. Of the 22 eligible studies indexed by our search, 20 (91%) studies included at least 1 explicit measure of engagement. Overall, our findings suggest that MRTs of mHealth interventions have operationalized engagement in overly narrow terms. We also sought to identify the factors that have been studied as determinants of engagement in MRTs of mHealth interventions. We found that out of the 20 studies that measured engagement explicitly, only 6 (30%) studies investigated the determinants of engagement. Even fewer attempts had been made to investigate the moderators of engagement.

Operationalization of Engagement

Measures of Engagement

Objective measures of engagement—in particular, system usage data (16/20, 80%) and sensor data (7/20, 35%)—were the most common methods of measuring engagement in MRTs of mHealth interventions. The relative popularity of measuring engagement with objective measures, especially system usage data, in MRTs of mHealth interventions is not surprising. System usage has been a central focus in the extant mHealth intervention literature [16]. In fact, it is one of the most common measures of engagement in mHealth interventions [10,44,45]. Subjective measures of engagement, by contrast, were far less common: self-report or EMA (4/20, 20%) and qualitative methods (1/20, 5%). Unfortunately, the lack of attention to the subjective experiences of participants in engagement measurement is not unique to MRTs of mHealth interventions [14,17]. Surprisingly, only 8 (40%) out of the 20 studies measured engagement using >1 method (no study used >2 methods). Of these 8 studies, only half (4/8, 50%) used both subjective and objective measures of engagement.

Taken together, these findings highlight a pressing need for future MRTs of mHealth interventions to diversify the methods of engagement used; the aforementioned lack of diversity does not seem limited to mHealth interventions evaluated using MRTs [14]. Researchers should keep in mind that subjective and objective methods are complementary, not competing, methods to measure engagement—subjective methods provide unique information about participant engagement that objective methods do not capture and vice versa [13,14]. Let us consider...
the distinction between qualitative and sensor data measures of engagement. Using qualitative methods, we may glean interesting insights about how a participant feels about an intervention or how cognitively invested they are in the intervention. This is certainly not possible for sensor data extracted from a pedometer. However, with said sensor data, it is possible to obtain detailed information (unobtrusively) about health behavior participation and how it fluctuates over time. We recommend that future MRTs of mHealth interventions adopt a multimethod approach to engagement measurement [13] such that engagement data from several subjective and objective measures are collected and interpreted.

Facets of Engagement

In this review, we found that the physical facet of engagement was the dominant kind of engagement measured in MRTs of mHealth interventions. Indeed, all 20 studies included at least 1 explicit measure of this facet. Surprisingly, the affective and cognitive facets of engagement were only measured by 1 study each. Clearly, our findings suggest an imbalance in the kinds of engagement measured and that researchers’ conceptualizations of engagement, and consequently their operationalizations of engagement, are largely constrained to intervention-related task or activity performance. Given that self-report and qualitative measures of engagement are best suited to measure the affective and cognitive facets of engagement, we cannot rule out that this imbalance is a product of the lack of diversity in methods of measuring engagement described in Measures of Engagement subsection in the Discussion section.

From the theoretical position that engagement is a multidimensional latent construct composed of physical, affective, and cognitive facets, this imbalance is particularly worrying because it signals that the construct of engagement is not being adequately measured in MRTs of mHealth interventions. Scholars who adopt this position generally agree that no facet of engagement alone can constitute engagement. Instead, they concur that engagement involves the physical, emotional, and cognitive energies of a person working in concert [11]. Therefore, without measuring all 3 facets of engagement, it is not possible to accurately identify how engaged participants are with a task. We hope that this review will draw attention to this gap in engagement measurement and encourage future MRTs of mHealth interventions to incorporate more measures of the affective and cognitive facets of engagement.

On a related note, although an assessment of the quality of engagement measurement in MRTs of mHealth interventions is beyond the scope of this review, we did observe that many included studies relied on single items to measure engagement. Estimates of reliability were also rarely (if ever) reported. As single items have a bad reputation for being unreliable measures of psychological constructs [46], we encourage researchers to clearly report estimates of reliability (such as test-retest reliability) so that readers can evaluate for themselves how much variation in “engagement scores” can be attributed to measurement error.

Levels of Engagement

The distinction between Little e and Big E is an important consideration when studying engagement in digital health interventions. Recall that Little e and Big E can be construed as 2 distinct answers to the question “Engagement with what?” [11]. Our findings suggest that most explicit measures of engagement in MRTs of mHealth interventions are Little e measures (measures of engagement with the mHealth intervention) and that only a handful of studies have measured engagement with the health behavior of interest (or Big E).

Although this review focuses on explicit claims of engagement measurement, a careful analysis of the outcome measures used in all 22 studies makes it clear that many of these outcomes qualify as Big E measures, even though they were not explicitly conceptualized as such [15]. This was observed in 12 studies [24-29,31-36]. All 12 studies were designed to evaluate the effects of intervention components. Most of these studies measured the physical aspect of engagement using sensor data. If we account for such studies, we may conclude that all 22 studies of mHealth interventions included in this review included at least one measure of engagement and that out of the 22 MRTs of mHealth interventions included here, 4 (18%) studies measured Little e only, 4 (18%) studies measured Big E only, and 14 (64%) studies measured both Little e and Big E (Multimedia Appendix 3 [22-43]). It was difficult for us to decide whether the outcome measures of these 12 studies should be deemed measures of engagement in this review. Our concern stems from the fact that the inclusion of these outcomes as measures of engagement hinges on our use of the Little e and Big E distinction to understand how engagement has been operationalized. If this distinction was not invoked, there would be no clear evidence from these 12 studies to suggest that these outcome measures are measures of engagement or that the authors themselves considered them to be measures of engagement. Let us consider the engagement-related information extracted from Goldstein et al [26], which is one of the 12 studies. The outcome measure of this study, whether a dietary lapse was experienced since the last EMA, is a clear-cut measure of Big E. However, it was not included in the authors’ own list of engagement measures stated in the paper. If the authors themselves do not conceptualize these outcomes as measures of engagement, would it be appropriate to include these outcomes as measures of engagement in this review? Even if we were to include this outcome as a measure of engagement, can we assume that the underlying motivations of Goldstein et al [26]—in terms of modeling decisions and decisions about the study design—are similar to those of researchers who explicitly frame health behavior outcomes as measures of engagement? This is important because we cannot rule out the possibility that researchers’ choice of causal effects, moderators, and control variables are at least partly influenced by how they conceptualize outcome measures. On the basis of these considerations, we decided not to consider the outcome measures of these 12 studies as measures of engagement in this review.

Nevertheless, our findings clearly suggest the need for future MRTs of mHealth interventions to strike a balance between Little e and Big E measurement or at least be more intentional.
and explicit with Big E measurement (especially when using sensor data as an outcome measure). As the field begins to recognize that sustained engagement is not always required for participants to experience the intended health outcomes of an intervention [13], we encourage researchers to find this balance so that they can gain a sense of effective engagement in the interventions they develop—the sufficient amount of engagement needed to attain the intended outcome of the intervention [11,14].

Determinants of Engagement

We found that very few studies investigated the determinants of engagement (6/20, 30% of the studies that measured engagement). In studies that did assess the determinants of engagement, notification-related causal effects were most common. This is likely attributable to the fact that most of these studies were designed to evaluate strategies to improve engagement [22,37-39]. Even fewer studies (3/6, 50%) assessed the moderators of engagement. Although all 3 studies assessed time-related (time-variant) moderators such as the number of days in the study or the day of the week, only 1 study [38] planned to investigate time-invariant moderators (such as psychological or social variables) in addition to the time-related moderators. These findings suggest that there is a striking lack of attention to how engagement is determined and to the effect of time-invariant psychosocial moderators on engagement in existing MRTs of mHealth interventions. To advance our understanding of engagement in the multicomponent and adaptive mHealth interventions tested by MRTs, it is necessary for future MRTs to address this research gap.

To begin addressing this research gap, we recommend that researchers adopt existing theoretical frameworks to guide their selection of the determinants and moderators of participant engagement in MRTs of mHealth interventions. If widely adopted, this approach should ensure some semblance of parity in the kinds of determinants and moderators of engagement studied across MRTs and provide researchers with a common taxonomy (or at least a common language) to guide their inquiry. With this, researchers can compare and synthesize results from different MRTs to better understand how engagement is modulated across mHealth interventions tested with MRTs.

Researchers can consider studying the determinants and moderators of engagement through the lens of participant engagement frameworks. Recently, Nahum-Shani et al [11] proposed the affect-integration-motivation and attention-context-translation framework for participant engagement. In this paper, they outlined 3 areas, namely, attention, contextual influences, and the translation of motivation to behavior (attention-context-translation), that might influence the neural-based process (affect-integration-motivation) of how engagement with a task (eg, walking) is realized through engagement with a stimulus (eg, a prompt to take a walk). It would be interesting for future MRTs to examine how constructs from each of these 3 areas contribute to participant engagement. Alternatively, researchers can consider selecting theoretically relevant determinants and moderators from the Big Five Personality trait framework [47], which is composed of trait openness, conscientiousness, extraversion, agreeableness, and neuroticism. This approach might be a good first step toward clarifying the role of individual differences in participant engagement, considering the lack of attention given to the psychological characteristics of participants in the extant MRT literature and the relevance of personality to health behaviors and outcomes [48]. Researchers should pay particular attention to the role of conscientiousness as it seems to be the most relevant to mHealth engagement [49] and it has been consistently linked to positive health behaviors [50,51]. These 2 frameworks are by no means exhaustive. We encourage researchers interested in understanding the determinants and moderators of engagement to seek out other appropriate frameworks to advance this line of research.

Limitations

There are 3 notable limitations of this scoping review. First, at the time of conducting our database searches, there was no available Medical Subject Heading in PubMed for MRTs (or equivalent controlled vocabularies for other databases). Therefore, our database searches might not have picked up papers and protocols that did not use the phrase "micro-randomisation trial" or "micro-randomized trial" as a keyword or in their title and abstract. Nevertheless, we believe that the main findings of this scoping review still hold true, as our database and manual searches would have indexed most mHealth intervention MRTs planned and conducted to date. Second, we did not use existing frameworks such as the Frequency, Intensity, Time, and Type principle [14] to further categorize engagement measured using system usage data. This has been done in previous scoping reviews [17] and is necessary to obtain a nuanced understanding of engagement measurement in mHealth interventions. Unfortunately, we were not able to do so, as some studies and protocols did not clearly operationalize their measurement of engagement in exact terms. Finally, it must be noted that because of the inclusion and exclusion criteria, we were not able to include several well-designed MRTs in this review because they were not strictly evaluations of mHealth interventions—they were designed either to evaluate digital but not mHealth interventions [52,53] or to evaluate engagement strategies only [54-56]. To fully understand the extent of engagement measurement in digital health interventions evaluated by MRTs, we encourage future reviews to broaden their inclusion and exclusion criteria to include these 2 types of evidence sources.

Conclusions

In this scoping review, we demonstrate that although most MRTs of mHealth interventions have measured engagement explicitly, they have operationalized engagement in overly narrow terms; there is an overemphasis on using objective measurements of engagement, measuring the physical facet of engagement, and measuring engagement with the mHealth intervention (as opposed to engagement with the health behavior of interest). There is also a lack of attention to how engagement is determined and moderated in these existing trials. We hope that by mapping the state of engagement measurement, this review will encourage researchers to pay more attention to these issues when planning engagement measurement in future MRTs. Although these issues are by no means unique to mHealth.
interventions evaluated with MRTs, the relative infancy of the MRT design suggests that there is still time and opportunity for the field to course correct and establish best practices for the measurement of engagement in MRTs of mHealth interventions.

Acknowledgments
The authors would like to thank Loh Mee Lan from the National University of Singapore Libraries for her guidance in formulating the database search strategies used in this review. This scoping review was supported by the Khoo Bridge Funding Award, the Academic Research Fund Tier 2 grant (Ministry of Education T2EP2012-0013) from the Ministry of Education, Singapore, and the start-up funding from Duke-NUS Medical School awarded to author BC.

Conflicts of Interest
None declared.

Multimedia Appendix 1
All charted data for the included evidence sources.
[XLSX File (Microsoft Excel File), 29 KB - mhealth_v11i1e44685_app1.xlsx]

Multimedia Appendix 2
Engagement measures of the included evidence sources organized according to the method of engagement measurement used, the facets of engagement measured, and the levels of engagement measured.
[XLSX File (Microsoft Excel File), 35 KB - mhealth_v11i1e44685_app2.xlsx]

Multimedia Appendix 3
Levels of engagement measured in microrandomized trials of mobile health (mHealth) interventions if 12 outcome measures are considered measures of Big E.
[PDF File (Adobe PDF File), 128 KB - mhealth_v11i1e44685_app3.pdf]

References


Abbreviations

ACT: Acceptance and Commitment Therapy
EMA: ecological momentary assessment
mHealth: mobile health
MRT: microrandomized trial
OSF: Open Science Framework
PRISMA-ScR: Preferred Reporting Items for Systematic Reviews and Meta-Analysis extension for Scoping Reviews
RCT: randomized controlled trial
Review

Conversational Agents and Avatars for Cardiometabolic Risk Factors and Lifestyle-Related Behaviors: Scoping Review

Lynnette Nathalie Lyzwinski1,2, MPhil, PhD; Mohamed Elgendi3, PhD; Carlo Menon1,3, PhD

1Menrva Research Group, Schools of Mechatronic Systems Engineering and Engineering Science, Simon Fraser University, Metro Vancouver, BC, Canada
2Faculty of Health Sciences, Simon Fraser University, Burnaby, BC, Canada
3Biomedical and Mobile Health Technology Lab, Department of Health Sciences and Technology, ETH Zurich, Zurich, Switzerland

Corresponding Author:
Lynnette Nathalie Lyzwinski, MPhil, PhD
Menrva Research Group
Schools of Mechatronic Systems Engineering and Engineering Science
Simon Fraser University
250-13450 102 Avenue
Metro Vancouver, BC, V3T 0A3
Canada
Phone: 1 778 302 1151
Email: lnl2@sfu.ca

Abstract

Background: In recent years, there has been a rise in the use of conversational agents for lifestyle medicine, in particular for weight-related behaviors and cardiometabolic risk factors. Little is known about the effectiveness and acceptability of and engagement with conversational and virtual agents as well as the applicability of these agents for metabolic syndrome risk factors such as an unhealthy dietary intake, physical inactivity, diabetes, and hypertension.

Objective: This review aimed to get a greater understanding of the virtual agents that have been developed for cardiometabolic risk factors and to review their effectiveness.

Methods: A systematic review of PubMed and MEDLINE was conducted to review conversational agents for cardiometabolic risk factors, including chatbots and embodied avatars.

Results: A total of 50 studies were identified. Overall, chatbots and avatars appear to have the potential to improve weight-related behaviors such as dietary intake and physical activity. There were limited studies on hypertension and diabetes. Patients seemed interested in using chatbots and avatars for modifying cardiometabolic risk factors, and adherence was acceptable across the studies, except for studies of virtual agents for diabetes. However, there is a need for randomized controlled trials to confirm this finding. As there were only a few clinical trials, more research is needed to confirm whether conversational coaches may assist with cardiovascular disease and diabetes, and physical activity.

Conclusions: Conversational coaches may regulate cardiometabolic risk factors; however, quality trials are needed to expand the evidence base. A future chatbot could be tailored to metabolic syndrome specifically, targeting all the areas covered in the literature, which would be novel.

(JMIR Mhealth Uhealth 2023;11:e39649) doi:10.2196/39649

KEYWORDS
chatbots; avatars; conversational coach; diet; physical activity; cardiovascular disease; hypertension; cardiometabolic; behavior change; hypertension diabetes; metabolic syndrome; mobile phone

Introduction

Background

Metabolic syndrome (MetS) is a highly prevalent condition that affects up to approximately 30% of adults aged >65 years worldwide [1]. It consists of multiple symptoms, namely abdominal obesity, glucose intolerance, hypertension, and high cholesterol as well as low high-density lipoprotein [2]. It is associated with a substantially increased risk of premature morbidity and mortality from diabetes and cardiovascular disease (CVD) [2]. Low levels of physical activity (PA) are
strongly associated with MetS, including obesity and overweight [3], high blood pressure [4], and insulin intolerance [5]. Furthermore, low levels of activity are significantly associated with increased risk of complications of MetS, including diabetes and CVD [5,6]. In addition, research has found that losing weight by approximately 5% to 10% results in significantly reduced MetS-associated markers [1] in patients with existing disease, highlighting that MetS may be modifiable through lifestyle-related weight interventions. Dietary modifications, including reduced sodium, sugar, and fat intake, are also highly beneficial for reducing the risk of the syndrome and its complications [7].

In recent years, mobile health (mHealth) has increasingly been used to support behavior changes related to weight loss, including improving dietary intake and physical activity [8]. Research on the use of mHealth interventions has found support for a moderate effect size for assisting with weight loss [8]. This includes the use of SMS text messaging for behavior change and mHealth apps that target weight loss using a range of behavior change techniques (BCTs) [9], including self-monitoring, feedback, goal setting, education, tips, personal tailoring, reminders, encouragement, and social and professional support [8]. mHealth is a form of health care that enables timely accessibility, portability, and personalized medicine tailored to the needs of the user [10,11]. It includes smartphones, PDAs, MP3 players, iPads (Apple Inc), smart clothing, and smart watches [10,11].

Emerging research in the mHealth field has focused on developing conversational agents that can simulate human professional interactions for managing different health problems [12], including weight issues [13]. Furthermore, avatars have also been developed to display a conversational coach in addition to written conversational text, simulating real-life interactions with a professional, such as a live fitness coach [14,15]. Having a conversational coach complement or replace metabolic-related health advice from professionals may increase accessibility and enable more timely health monitoring and diagnosis of health conditions [15] such as MetS if physicians also gain access to patient data. Given that technology in the field is advancing, it is time to determine whether these conversational agents are effective for assisting with MetS-associated risk factors, including overweight, obesity, physical inactivity, and unhealthy dietary intake. There is also a need to better understand what types of weight-related and MetS-related studies have been undertaken using conversational agents and to identify challenges with the technology and future areas of research.

Aims
This review aimed to better understand the evidence surrounding the use of conversational coaches for metabolic-related risk factors and biomarkers. Furthermore, this review aimed to determine whether conversational coaches are effective for improving weight-related behaviors and metabolic indicators and whether conversational agents are acceptable for consumers as agents of behavior change.

Research Questions

- Research question (RQ) 1: How effective are conversational agents (chatbots and avatars) for weight-related behaviors, including diet and exercise?
- RQ 2: How effective are conversational agents for improving metabolic risk factors, including blood pressure, cholesterol, abdominal obesity, and glucose (diabetes management)?
- RQ 3: What are consumers’ perspectives on the use of chatbots?

Methods
A systematic review of PubMed and MEDLINE was conducted in December 2021 for all relevant studies on conversational coaches for metabolic risk factors published over the last 10 years. Google Scholar was also searched for any additional papers along with manual hand searching.

Inclusion and Exclusion Criteria
This review included studies on chatbots or avatar conservational agents that acted as coaches for improving metabolic health behaviors, including dietary intake (sodium and sugar intake), PA, and weight (including abdominal obesity). Studies that evaluated one or more physiological indicators of metabolic health or risk factors for MetS, such as diabetes, glucose intolerance, hypertension, cholesterol, and serum triglycerides, were also included. Studies must have been published in the English language to be included. Chatbots that were used for survey reasons but not primarily for targeting weight-related or metabolic risk factors were excluded. Studies whose primary focus was not on conversational coaches were excluded (including those that had an avatar element but did not primarily focus on evaluating it). Studies on wearables that did not include avatars or chatbots were excluded. Studies in pregnant women were excluded.

Search
The keywords included word variations for “chatbot,” “virtual assistant,” “virtual coach,” or “avatar”; weight-related behaviors, including “diet,” “exercise,” or “weight”; and metabolic risk factors, including “hypertension,” “cholesterol,” or “diabetes.” The search strategy is shown in Textbox 1.
Textbox 1. PubMed search strategy example.

1. Cardiometabolic risk factors
   - **Weight**
   - **Diet and physical activity**
   - **Hypertension**
   - **Cholesterol**
     - “cholesterol”[MeSH Terms] OR cholesterol[tiab]
   - **Diabetes**

AND

2. Technology
1 AND 2

Screening and Data Extraction

Titles were screened for relevance to the RQs, followed by abstract and full-text retrieval of eligible studies that met the inclusion criteria. A second reviewer (LL) screened the abstracts and full texts against the inclusion and exclusion criteria to ensure agreement. Quantitative and qualitative data were extracted and summarized in a tabular format, including study characteristics, measures, outcomes, and intervention details.

Results

General Description

LL and ME screened the final selected papers individually. A total of 52 full texts were selected [13,14,16-65]; however, after double peer screening, 1 protocol and 1 dated technology were removed. The final number included 50 papers [13,14,16-59,61-63,66]. Details of the search process and reasons for exclusion are illustrated in Figure 1 [67].

Most of the studies were feasibility and usability studies. A few studies were qualitative and explored consumer perspectives on conversational agents for weight-related behaviors [14,19]. The countries where the studies were conducted included Australia, the United States, Italy, Spain, and Taiwan [13,14,16-29]. Most of the studies explored virtual agents for diet and exercise, with only 2 (4%) exploring chatbots for hypertension management [17,19]. The majority were conducted among adults, but 3 (6%) were conducted among teenagers and preteens [14,26,29]. The study characteristics and results are summarized in Table 1.
Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart of the search and screening process. MetS: metabolic syndrome.
<table>
<thead>
<tr>
<th>Study and year</th>
<th>Location, N, and design</th>
<th>Sex (%)</th>
<th>Age (years)</th>
<th>Health targets and measures</th>
<th>Technology and procedures</th>
<th>Outcomes</th>
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</thead>
<tbody>
<tr>
<td>Echeazarra et al [17], 2021</td>
<td>Location: Spain, N=112, Design: 2-year RCT&lt;sup&gt;a&lt;/sup&gt;</td>
<td>Female: 42</td>
<td>Mean 52.1</td>
<td>BP&lt;sup&gt;b&lt;/sup&gt;</td>
<td>Tensiobot (telegram app)</td>
<td>No significant differences in adherence between groups</td>
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<td>Reminders to check BP</td>
<td>Bot group had higher levels of knowledge on good practice skills for BP (t=2.11; df=82.3; 95% CI 0.39-12.6; P&lt;.05)</td>
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<td>Education on how to properly check BP using videos</td>
<td>Measurements (P&lt;.05)</td>
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<td>Warnings and graphic feedback on BP</td>
<td>Bot found to be acceptable/likable</td>
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<td>GPs&lt;sup&gt;c&lt;/sup&gt; can connect to the app to access patient data</td>
<td>Adherence after intervention: 85%</td>
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<td>Advice offered 24/7</td>
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<tr>
<td>Griffin et al [19], 2021</td>
<td>Location: United States, N=15, Design: mixed methods questionnaires with semistructured interviews qualitative</td>
<td>Female: 53</td>
<td>Mean 59 (SD 11)</td>
<td>BP</td>
<td>Theoretical discussion around chatbots for hypertension medication management</td>
<td>Most patients were interested in and open to trying a chatbot for hypertension medication management</td>
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<td>Privacy concerns and usability with mobile phones</td>
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<tr>
<td>Larbi et al [20], 2021</td>
<td>Location: Switzerland, N=30, Design: feasibility study</td>
<td>Female: 50</td>
<td>Range 18-69</td>
<td>PA&lt;sup&gt;d&lt;/sup&gt;</td>
<td>MYA social media chatbot</td>
<td>Perceptions of usefulness and informativeness: 53%</td>
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<td>User friendly: 83%</td>
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<td>Failed to understand user input: 63.3%</td>
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<td>Potential confusion with using the technology 43.3%</td>
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<tr>
<td>Lin et al [27], 2021</td>
<td>Location: Taiwan, N=96, Design: factorial experimental study with 4 arms</td>
<td>Female: 53</td>
<td>Mean 21.5; range 18-42</td>
<td>PA (core muscle exercise)</td>
<td>VR&lt;sup&gt;e&lt;/sup&gt; avatar</td>
<td>Increase in PA (vector movement) of 986.7 (SD 1.03) points in normal realistic avatar relative to muscular avatar</td>
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<td>Higher self-efficacy for core muscle exercise in normal avatars vs muscular avatars in female participants (+0.66, SD 0.1 points) and higher levels than in male participants (+0.9, SD 0.2 points)</td>
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<td>P&lt;.05</td>
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<tr>
<td>Dol et al [37], 2021</td>
<td>Location: The Netherlands, N=71, Design: qualitative study</td>
<td>Female: 100</td>
<td>Mean 44.4 (SD 12.86); range 19-70</td>
<td>Emotional eating</td>
<td>Conversational coach for emotional eating</td>
<td>The design of the conversational coach should integrated dialectal behavioral coaching strategies, as preferred by participants with emotional eating behavior</td>
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<tr>
<td>Study and year</td>
<td>Location, N, and design</td>
<td>Sex (%)</td>
<td>Age (years)</td>
<td>Technology and procedures</td>
<td>Outcomes</td>
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<tr>
<td>Lin et al [27], 2021</td>
<td>Location: Taiwan; N=104; Design: experimental design study</td>
<td>Female: 50</td>
<td>Mean 70.39 (SD 6.51); range 60-88</td>
<td>Assigned to either age-matched or young avatars for PA Theory: Proteus effect of avatar embodiment</td>
<td>Older male participants assigned to young avatars had higher perceived exertion than counterparts assigned to older ones (+1.56, SD 0.31 points; male participants only)</td>
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<td>Watched videos in a digital gym where they exercised</td>
<td>Female participants assigned to young avatars had higher self-efficacy for future exercise than counterparts (+0.45 points) and male participants</td>
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<td>Wore a head-mounted display</td>
<td>P &lt; .05</td>
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<tr>
<td>Maher et al [13], 2021</td>
<td>Location: Australia; N=31; Design: proof-of-concept study</td>
<td>Female: 67</td>
<td>Range 45-75</td>
<td>PA, Mediterranean diet, and weight</td>
<td>Mean increase in diet score: 5.7 (95% CI 4.2-7.3)</td>
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<td>Mean PA increase: 109.8 min (95% CI 1.9-217.9; P &lt; .01)</td>
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<td>Mean weight loss: 1.3 kg (95% CI -2.5 to -0.7; P &lt; .05)</td>
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<td>No significant changes in blood pressure</td>
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<tr>
<td>Hickman et al [40], 2021</td>
<td>Location: United States; N=109; Design: 2-arm RCT</td>
<td>Female: 59</td>
<td>Mean 52 (SD 11)</td>
<td>Hypertension, quality of the physician-patient interaction</td>
<td>Avatar intervention or video on hypertension management</td>
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<td>Scores for the quality of the patient-provider interaction were better over time (F3=5.23; P &lt; .01) in the within-subjects analysis along with a time by experimental condition interaction (F3=2.91; P &lt; .05)</td>
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<td>Between-subject effects per treatment were insignificant</td>
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<td>No significant changes in blood pressure</td>
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<tr>
<td>Napolitano et al [49], 2021</td>
<td>Location: United States; N=136; Design: feasibility study (12 weeks)</td>
<td>Female: 100</td>
<td>Mean 27.8 (SD 5.4)</td>
<td>Weight, diet, and PA; exercise self-efficacy</td>
<td>Conversational coach gave lessons on health behaviors</td>
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<td>No significant results were found for differences in weight, PA, or consumption of fast food between the intervention arm and control groups</td>
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<td>High attrition 44%</td>
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<td></td>
<td>Goal achievement for nutrition &lt;10%</td>
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<tr>
<td>Santini et al [55], 2021</td>
<td>Location: Austria, Italy, and Netherlands; N=60 (2 waves); Design: qualitative study with focus groups and phone interviews</td>
<td>Female: 53.3% wave 1; 51.6% wave 2</td>
<td>Mean 61.9</td>
<td>Health behaviors, diet, and PA</td>
<td>Embodied coach for diet and PA</td>
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<td>Desire for the avatar to motivate older adults to exercise</td>
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<td></td>
<td>Supportive tone and language that is not authoritarian or patronizing</td>
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<tr>
<td>Krishnakumar et al [44], 2021</td>
<td>Location: India; N=102; Design: pre-post intervention (1 arm) 16 weeks</td>
<td>Female: 31.4</td>
<td>Mean 50.8</td>
<td>Diabetes (blood sugar), diet, PA, and weight (logged)</td>
<td>Welthy CARE mobile app</td>
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</tr>
</tbody>
</table>

Mean increase in diet score: 5.7 (95% CI 4.2-7.3)
Mean PA increase: 109.8 min (95% CI 1.9-217.9; P < .01)
Mean weight loss: 1.3 kg (95% CI -2.5 to -0.7; P < .05)
Scores for the quality of the patient-provider interaction were better over time (F3=5.23; P < .01) in the within-subjects analysis along with a time by experimental condition interaction (F3=2.91; P < .05)
No significant changes in blood pressure
No significant results were found for differences in weight, PA, or consumption of fast food between the intervention arm and control groups
High attrition 44%
Goal achievement for nutrition <10%
Desire for the avatar to motivate older adults to exercise
Supportive tone and language that is not authoritarian or patronizing
<table>
<thead>
<tr>
<th>Study and year</th>
<th>Location, N, and design</th>
<th>Sex (%)</th>
<th>Age (years)</th>
<th>Health targets and measures</th>
<th>Technology and procedures</th>
<th>Outcomes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dhinagaran et al [36], 2021</td>
<td>Location: Singapore N=60 Design: one arm web-based feasibility study</td>
<td>Female: 62 Mean: 33.7</td>
<td>Diet, PA, sleep, and stress</td>
<td>Chatbot for diabetes prevention, diet, exercise delivered over Facebook Messenger (Meta Platforms Inc)</td>
<td>The use of the Wellthy CARE digital therapeutic for patients with T2D showed a significant reduction in the mean levels of HbA1c (−1.16% (95% CI −1.40 to −0.92); P&lt;.01); FBG (−11 mg/dL), and PPBG (−22 mg/dL); P&lt;.05</td>
<td>Weight decreased by 1.32 kg (95% CI −0.63 to −2.01 kg) after 16 weeks</td>
</tr>
<tr>
<td>To et al [61], 2021</td>
<td>Location: Australia N=116 Design: quasi-experimental study (6 weeks)</td>
<td>Female: 81.9 Mean: 49.1 (SD 9.3)</td>
<td>PA</td>
<td>Fitbit plus a chatbot in the Messenger app</td>
<td>Engagement: 50%</td>
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</tr>
<tr>
<td>Mitchell et al [48], 2021</td>
<td>Location: United States N=158 Design: mixed methods survey with qualitative interviews study</td>
<td>Female: 100 Mean: 56 (SD 11) intervention; 57 (SD 11) control</td>
<td>Diabetes</td>
<td>Avatar for diabetes self-management</td>
<td>Useability score: 89.4%</td>
<td></td>
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<tr>
<td>Strombotne et al [58], 2021</td>
<td>Location: United States N=590 Design: quasi-experimental study</td>
<td>Female: 11 Mean: treatment=58.1; control=57.7</td>
<td>Diabetes and risk factors</td>
<td>Conversational coach and ketogenic diet</td>
<td>BP decrease (systolic): 1.4 mm Hg (95% CI −2.72 to 0.14)</td>
<td>Diastolic BP levels decreased: −1.43 (95% CI −2.72 to −0.14) mm Hg</td>
</tr>
<tr>
<td>Alves Da Cruz [31], 2020</td>
<td></td>
<td>Female: 48.1 Mean: 63.4 (SD 12.7)</td>
<td>HR, BP, and RR</td>
<td></td>
<td>BMI: −1.07 (95% CI −1.95 to −0.19) kg/m²</td>
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<tr>
<td>Location, N, and design</td>
<td>Sex (%)</td>
<td>Age (years)</td>
<td>Health targets and measures</td>
<td>Technology and procedures</td>
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<tr>
<td>Brazil, N=27, Design: cluster randomized crossover trial</td>
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<td>Avatar with exergames for PA in patients undergoing cardiovascular rehabilitation</td>
<td>Increase in HR (z=82.8; $P&lt;.01$) and RR (z=12.9; $P&lt;.01$) during and (5 min) after exergame</td>
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<tr>
<td>Location: Brazil, N=27, Design: cluster randomized crossover trial</td>
<td>Female: 36.5, Mean 65.3 (SD 13.8)</td>
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<td></td>
<td>Changes in systolic BP but not diastolic with differences within moments z=11.26 ($P&lt;.01$)</td>
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<tr>
<td>Adriana et al [43], 2020</td>
<td>High desirability for telehealth consultations with a cardiologist combined with a conversational agent</td>
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<td></td>
<td>With no statistical significance between groups</td>
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<tr>
<td>Location: Poland, N=249, Design: cross-sectional study</td>
<td>Female: 36.5</td>
<td>Mean 20.0 (SD 2.2); range 18-37</td>
<td>Cardiac frequency, step counts, accelerometer, and HR monitor</td>
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<tr>
<td>Naylor et al [50], 2020</td>
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<td>Children wore Fitbit with a personalized dog avatar for socializing and support (digital fitness kiosk); theory informed (social cognitive theory)</td>
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<tr>
<td>United States, N=42 (child and parent dyads [n=40 completed baseline and follow-up measures])</td>
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<td>Completion rate: 81.63%; Mean number of PA goals reached: 3.28</td>
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<tr>
<td></td>
<td>Female: 55.2</td>
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<td></td>
<td></td>
<td>Mean number of PA goals: 3.28</td>
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<td>Treatment: mean 8.06 (SD 1.10); control: mean 7.5 (SD 1.38)</td>
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<td>Mean time playing with pet: 20.35 min</td>
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<td>Children using Fitbit for self-report on motivation for PA</td>
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<td>Mean number of active min: 66 min (no statistical significance was found)</td>
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<tr>
<td>Study and year</td>
<td>Location, N, and design</td>
<td>Sex (%)</td>
<td>Age (years)</td>
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<tr>
<td>Davis et al [16], 2020</td>
<td>Location: Australia N=28  Design: pilot single-arm study</td>
<td>Female: 68  Mean: 56.2 (SD 8); range 45-75</td>
<td>Diet: Mediterranean diet adherence tool. Weekly log for diet and step count; activity tracked using a wrist worn tracker (Garmin) that syncs with Paola. Minutes of moderate to vigorous PA assessed with Active Australia Survey</td>
<td>Conversational assistant Paola for diet and PA consisted of educational modules, weekly check-ins, and 24/7 availability for PA and diet questions</td>
<td>12-week pilot</td>
<td>Higher cardiac output (frequency) from 6 to 12 min in users of avatars that had a similar appearance (face)  Higher output in users with avatars that additionally wore sports clothing at 6-7 and 10-minute periods  Support for the Proteus effect hypothesis  No changes in step count</td>
</tr>
<tr>
<td>Navarro et al [23], 2020</td>
<td>Location: Spain N=42  Design: 3 arms—2 avatars vs control</td>
<td>Female: 100  Mean: 13 (SD 11.2); range 9-28  Use of a digital dog, • High trust to share personal information with the agent  • Tailored coaching for habits  • Participants were satisfied with the agent  • High trust to share personal information to the coach</td>
<td>• Avatar: ideal (perfect body) or normal (matching the participant) and web-based intervention without the avatar  • The conversational coach resembles a human  • Integrated BCTs: goal setting, self-monitoring, feedback, and social support/counseling  • Health coach for PA  • As part of a PA program using a Google Home device (Google LLC)</td>
<td>• Increased PA in all groups (F1,39=15.8; P&lt;.01; web-based intervention effects)  • No effects of time by avatar assignment, ie, interaction with avatars  • Usability score: 73.75 (SD 13.31) (indicates high usability of the coach)</td>
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<tr>
<td>Balsa et al [32], 2020</td>
<td>Location: Portugal N=20  Design: usability study with qualitative interviews</td>
<td>Female: 60%  Mean: 67 (SD 5.84)  Diet and PA questionsnaires via chatbot and motivation (HAPA³)  Diet and PA and basic psychological needs  Use of a digital dog, with and without a points-based reward system</td>
<td>• Usability was high  • 80% of the participants did not experience challenges when interacting with the conversational coach</td>
<td>Usability rate: 96%  Progress toward goals frequency: 81%</td>
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<td>Chin et al [35], 2020</td>
<td>Location: United States N=15  Design: feasibility study</td>
<td>Female: 100  Mean: 28.5 (SD 5.84)  Diet and PA and basic psychological needs  Use of a digital dog, with and without a points-based reward system  Usefulness rate: 96%  Progress toward goals frequency: 81%</td>
<td>• Health coach for PA  • As part of a PA program using a Google Home device (Google LLC)  • Participants were satisfied with the agent  • Tailored coaching for habits  • High trust to share personal information to the coach</td>
<td>• Increased PA in all groups (F1,39=15.8; P&lt;.01; web-based intervention effects)  • No effects of time by avatar assignment, ie, interaction with avatars  • Usability score: 73.75 (SD 13.31) (indicates high usability of the coach)</td>
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<td>Fadhil et al [18], 2019</td>
<td>Location: Italy N=19  Design: validation study (4 weeks)</td>
<td>Female: 42  Mean: 11.2 (SD 0.85); range 9-13  Diet and PA questionnaires via chatbot and motivation (HAPA³)  Diet and PA and basic psychological needs  Use of a digital dog, with and without a points-based reward system  Usefulness rate: 96%  Progress toward goals frequency: 81%</td>
<td>• CoachAI text based conversational agent  • Tailored coaching for habits  • High trust to share personal information to the coach</td>
<td>• Increased PA in all groups (F1,39=15.8; P&lt;.01; web-based intervention effects)  • No effects of time by avatar assignment, ie, interaction with avatars  • Usability score: 73.75 (SD 13.31) (indicates high usability of the coach)</td>
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<td>Ahn et al [30], 2019</td>
<td>Location: United States N=67  Design: field study (3 days)</td>
<td>Female: 61.19  Mean: 15.2; range 9.7-18.5  Weight management; pre-diabetes  Weight management; pre-diabetes</td>
<td>• Health coach for PA  • As part of a PA program using a Google Home device (Google LLC)  • Participants were satisfied with the agent  • Tailored coaching for habits  • High trust to share personal information to the coach</td>
<td>• Increased PA in all groups (F1,39=15.8; P&lt;.01; web-based intervention effects)  • No effects of time by avatar assignment, ie, interaction with avatars  • Usability score: 73.75 (SD 13.31) (indicates high usability of the coach)</td>
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<td>Stephens et al [26], 2019</td>
<td>Location: United States N=23  Design: feasibility study</td>
<td>Female: 57  Mean: 15.2; range 9.7-18.5  Weight management; pre-diabetes  Weight management; pre-diabetes</td>
<td>• Health coach for PA  • As part of a PA program using a Google Home device (Google LLC)  • Participants were satisfied with the agent  • Tailored coaching for habits  • High trust to share personal information to the coach</td>
<td>• Increased PA in all groups (F1,39=15.8; P&lt;.01; web-based intervention effects)  • No effects of time by avatar assignment, ie, interaction with avatars  • Usability score: 73.75 (SD 13.31) (indicates high usability of the coach)</td>
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<td>Study and year</td>
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| Srivastana et al [57], 2019    | Location: United States, N=10, Design: usability study                                   | Female: 70 | Range 44-67 | Prediabetes                 | • Tess text-based chatbot counsellor for healthy behavior change usability assessed with progress toward goals and engagement                                                                                                                                             | • Success of modules 60% as they meet weight loss of 5%  
• Compliance with dietary recommendations: 59%-87%  
• Compliance with PA: 52%-93%                                                                                                                                  |
| Thompson et al [59], 2019      | Location: United States, N=27, Design: pilot feasibility study                            | Female: 73 (teens) | Range 10-15 | Diabetes                    | • Conversational agent with human features  
• Conversations around diabetes education                                                                                                                                                                                                                                        | • Attrition: low (<10%)  
• High satisfaction: >80%  
• Technical issues <10%  
• Teens and families had a positive experience                                                                                                                |
| Thompson et al [29], 2018      | Location: United States, N=48, Design: laboratory-based study                            | Female: 50   | Range 12-14 | PA                          | • PA exgame with an avatar coach                                                                                                                                                                                                                                                | • Completion: 87.5%; teens enjoyed the game (mean enjoyment score 68%)  
• Vigorous PA during 74.9% of the game                                                                                                                        |
| Duncan-Carncesiali et al [38], 2018 | Location: United States, N=198, Design: cross-sectional, survey-based design using quantitative and qualitative paradigms | Female: 97.5 | Range 26-76 | Diabetes                    | • Avatar for diabetes management                                                                                                                                                                                                                                                 | • Ethnicity including Arab or Middle Eastern, Asian, and White or European descents as well as age were significantly associated with an excellent rating of the video with $P<0.05$
• Usability index of 44.18 (SD 21.18; low)                                                                                                                        |
| Klaassen et al [42], 2018      | Location: N/A, N=21, Design: usability study                                            | Female: 52   | Mean 13.9   | Diabetes                    | • Conversational coach game with feedback  
• Integrates BCTs including information on consequences                                                                                                                                                                                                                           | • Preference for the robot (mean friendship score 4.0, SD 0.6) over the avatar (mean friendship score 2.9, SD 0.7) as a companion  
• Usability moderate: 58.7 (SD 24.5)  
• Similarity of avatar to robot led to greater friendship ($P<.01$)                                                                                       |
| Sinoo et al [56], 2018         | Location: Netherlands, N=21, Design: experimental study                                | Female: 37   | Mean 9.2 (SD 1.1) | Diabetes self-management | • Avatar for gameplay and diabetes self-management vs robot                                                                                               | • Symptom recognition increased: 24%  
• Satisfaction: 87.3%  
• Knowledge increase: 15.7%                                                                                                                                       |                                                                                                                                     |
| Tongpeth et al [62], 2018      | Location: Australia, N=22 (development of the application), N=10 (feasibility testing), Design: pilot feasibility | Female: 10 | Mean 52.2 (SD 10.4) | Cardiovascular: acute coronary syndrome management | • An interactive, avatar-based education application for improving patients’ knowledge of, and response to, acute coronary syndrome symptoms                                                                                                               | • Symptom recognition increased: 24%  
• Satisfaction: 87.3%  
• Knowledge increase: 15.7%                                                                                                                                       |
<table>
<thead>
<tr>
<th>Study and year</th>
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<tbody>
<tr>
<td>Friedrichs et al [63], 2014</td>
<td>Location: Netherlands, N=958, Design: 3-arm RCT</td>
<td>Female: 60.4</td>
<td>Mean 42.9 (SD 14.5)</td>
<td>PA; Dutch Short questionnaire</td>
<td>Avatar with a web intervention or a digital web-based text condition versus control</td>
<td>Significant increases in PA in the intervention arms versus control with B=0.39 in the avatar arm and B=0.44 in the text arms ($P&lt;.05$)</td>
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<td>No differences between the text arm or the avatar arm for PA</td>
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<tr>
<td>Stein et al [25], 2017</td>
<td>Location: United States, N=70, Design: longitudinal observational study</td>
<td>Female: 74.5</td>
<td>Mean 47 (SD 1.8); range 18-76</td>
<td>Weight and dietary intake</td>
<td>Lark Weight Loss Health Coach (participants were a part of a diabetes prevention weight loss program)</td>
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<td>Advice on dietary intake and PA</td>
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<td>BCTs used include motivation, encouragement, reminders, and education</td>
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<tr>
<td>Thompson [66], 2016</td>
<td>Location: United States</td>
<td>Female: 50</td>
<td>Range 12-14</td>
<td>Preferences for a PA intervention</td>
<td>Exergame with a self-representation avatar</td>
<td>31% increase in healthy eating</td>
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<td></td>
<td>N=48 (round 1)</td>
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<td>Mean weight change: $-2.4$ kg (SE 0.82; 95% CI $-4.03$ to $-0.77$)</td>
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<td>N=43 (round 2)</td>
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<tr>
<td></td>
<td>Design: mixed methods survey with qualitative interviews</td>
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<td></td>
<td>Behm-Morawitz et al [33], 2016</td>
<td>Location: United States</td>
<td>Female: 100</td>
<td>Range 18-61</td>
<td>Weight and PA self-efficacy</td>
<td>Avatar (embodied) and video game to promote PA</td>
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<td></td>
<td>N=90, female=100% (the 2 male participants were excluded)</td>
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<td>Findings support the use of the avatar for weight management $t_{18}=2.15$ ($P&lt;.05$) with the intervention losing 1.75 lbs versus 0.91 lbs in the control</td>
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<td>Design: qualitative research and RCT</td>
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<td></td>
<td>No effects on dietary self-efficacy</td>
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<td>Strong correlation with avatar sense of self-presence and confidence in meeting health goals ($r=0.95$; $P&lt;.01$)</td>
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<td>Themes: avatar benefits include motivation and assisting with self-efficacy for PA</td>
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<td>Barrier: games are not for everyone</td>
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<tr>
<td>Kuo et al [45], 2016</td>
<td>Location: Taiwan, N=76</td>
<td>Female: 63.15</td>
<td>Mean 21.2</td>
<td>Eating behavior observed in laboratory</td>
<td>Avatar that embodied the participants or was a weight-reduced (thinner) version of them</td>
<td>Avatars that embodied a thinner version of the participants shaped eating behaviors more compared with identical self-avatars; including selecting less ice cream (Cohen $d=0.35$; $F_1,73=7.8$; $P&lt;.01$) and opted for sugar free drinks (Cohen $d=0.29$, $F_1,73=6.0$; $P&lt;.01$)</td>
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<td></td>
<td>Design: 2-arm intervention in laboratory</td>
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<tr>
<td>Ruiz et al [54], 2016</td>
<td>Location: United States N=41 Design: laboratory study</td>
<td>Female: 0 Mean 64 (SD 7)</td>
<td>Cardiovascular behavioral risk factors (diet and exercise)</td>
<td>• Avatar vs a voice (nonanimated) for behavior change linked with CVD</td>
<td>Avatar increased intentions (+1.56 points) to improve lifestyle behaviors relative to controls (Cohen d=0.77 P&lt;.01; t36=2.48)</td>
<td>Differences in confidence to change risk of heart disease was nonsignificant</td>
</tr>
<tr>
<td>LeRouge et al [14], 2015</td>
<td>Location: United States N=41 Design: user-centered design, 3 phases with focus group and interviews</td>
<td>N/A Teenagers: 12-17 Perceptions of the avatar for diet and exercise</td>
<td>• Interactive avatar coach</td>
<td>• Desire for a fun human-like interaction</td>
<td>• Desire for a lifestyle coach and personal embodiment avatar and an authoritarian one</td>
<td>• Desire for customization of the avatar</td>
</tr>
<tr>
<td>Thomas et al [28], 2015</td>
<td>Location: United States N=37 Design: feasibility and usability study with pre-post test</td>
<td>Female: 100 Mean 55.0 (SD 8.2)</td>
<td>Weight-related eating behaviors</td>
<td>• Conversational coach for weight (focuses on dietary intake and managing eating behaviors)</td>
<td>• The coach assisted with perceptions of increased self-control over eating (confidence to control eating: +1 point (SD 0.2; P&lt;.01) and skills for controlling eating +0.7 points (SD 0.1; P&lt;.01)</td>
<td>There were no significant differences between the intervention group and control group in terms of knowledge, with P=.95</td>
</tr>
<tr>
<td>Ruiz et al [53], 2014</td>
<td>Location: United States N=150 Design: RCT</td>
<td>Male: 100 Mean 62 (SD 7.9)</td>
<td>Diabetes (knowledge)</td>
<td>• Computer program with an avatar to increase diabetes knowledge and medication (adherence)</td>
<td>• Satisfaction levels were higher in the digital intervention group (F4=3.11; P&lt;.01)</td>
<td>Healthy weight avatars linked with greater scores in motivation for Nintendo exercise (F1,134=5.49; P&lt;.05 [boys]) attitude, and performance (F1,134=2.27; P&lt;.05 [girls])</td>
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<tr>
<td>Li et al [46], 2014</td>
<td>Location: Singapore N=140 Design: factorial design experiment</td>
<td>Female: 41 Range 9-12 PA attitudes, motivation, and game performance</td>
<td>• Assigned to varying avatars (normal and overweight)</td>
<td>• The avatar helpful: 87.5%</td>
<td>• Mean weight loss after 4 weeks: 1.6 (SD 1.7) kg</td>
<td>All women found that it helped with their diet and exercise</td>
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<tr>
<td>Napolitano et al [22], 2013</td>
<td>Location: United States N=128 (phase 1) N=8 (phase 2) Design: mixed methods (pilot usability testing) study with interviews</td>
<td>Female: 100 Mean 34.1 (SD 13.0); range 18-60 (phase 1)</td>
<td>Weight, PA [14], and weight self-efficacy; satisfaction; preferences survey and interviews</td>
<td>• Avatar for diet and exercise</td>
<td>• The avatar helpful: 87.5%</td>
<td>All women found that it helped with their diet and exercise</td>
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<td>Bickmore et al [34], 2013</td>
<td>Location: United States N=122 Design: 4-arm RCT (2 months)</td>
<td>Female: 61 Mean 33.0 (SD 12.6); range 21-69</td>
<td>Diet (NIH/NCI fruit and vegetable scan) and PA (IPAQ)</td>
<td>• Animated counselor for diet and PA (separate and combined)</td>
<td>• All women found that it helped with their diet and exercise</td>
<td>Most were interested in the avatar</td>
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| Johnson-Glenberg et al [41], 2013 | Location: United States N=19 Design: pilot feasibility study (pre-post study) N/A Grades 4-12 (ages 9-18) Diet (nutrition and food choice test and knowledge) | N/A     |             | Diet and exercise game (exergame) with an alien interactive coach | Differences in dietary knowledge of nutrition pre and post intervention (t=4.13; *P*<.01) and knowledge of the MyPlate content in the study (t=3.29; *P*<.01) | • Participants completing a 3D VR intervention mediated by avatars resembling the participants showed significant improvement in PA (*P*<.05)  
• No significant effects of the intervention on obese or overweight participants                                                                 |
Weight
A few studies evaluated the effects of conversational assistants for weight loss [13,22-24,44]. The study by Maher et al [13] in Australia found that the conversational assistant (chatbot) Paola assisted with a weight loss of 1.3 kg at 12 weeks follow-up (95% CI –0.1 to –2.5). In addition, there was a mean waist circumference reduction of 2.5 cm at follow-up compared with baseline (95% CI –3.5 to –0.7). The chatbot used a range of BCTs, including goal setting, self-monitoring, education, social support, and feedback to users on PA and the Mediterranean diet [13]. A study in the United States found that the Lark Weight Loss Coach, an artificial intelligence–powered bot, assisted participants with a weight loss of 2.38% (95% CI –3.75 to 1.0) with a mean use of 15 weeks [25]. The conversational agent was informed by cognitive behavioral therapy and used a range of BCTs, including education, encouragement, and reminders surrounding dietary and PA targets [25]. The determinants of weight loss included the duration of using the artificial intelligence program and engaging with it, logging meals, and the number of counseling sessions completed [25]. A large study in the United States examining the use of an avatar coach that targeted self-efficacy and modelled vicarious experiences for diet and PA (4 weeks) found that women lost an average of 1.6 (SD 1.7) kg at follow-up [22]. A study in India found that an avatar coaching app with calls from health professionals assisted with a weight loss of 1.39 kg (95% CI –0.63 to –2.01; P < .01) at 16 weeks [44]. A randomized controlled trial (RCT) with a qualitative component found that avatars increase motivation and PA self-efficacy linked with weight loss [33]. However, some studies did not report any significant weight loss [34,49].

Diet
A few studies evaluated the effects of conversational coaches (chatbots and avatars) on dietary intake and found that overall, the coaches assisted with ameliorating dietary habits and goals [13,16,25,28,34,45,49]. A study in the United States found that healthy dietary intake improved in 30% of participants who were using a conversational weight loss coach [25]. Another study found that eating behaviors improved in users of a conversational eating coach, which included increases in the mean scores for the perceptions of skills to eat healthily and self-control over their eating habits (0.7 increase in points) as well as confidence to control food consumption in social situations (1.0 increase in points; P < .01) [28]. The Paola chatbot study found a mean increase in the Mediterranean diet score [68] of 5.8 points at 12 weeks follow-up [13]. Similarly, a study of Karen, an animated counselor, found significant increases (F(1,103)=4.5; P < .01) in fruit and vegetable intake in the diet intervention arm relative to the control group [34]. A further study found that eating behaviors were shaped by the appearance of the avatar, with healthier eating behavioral patterns in participants who had thinner avatars including reduced portions of ice cream and opting for healthier sugar-free drink alternatives [45].

Physical Activity
A few conversational assistant PA coaches, including chatbots and avatars, were evaluated, and overall, they assisted with increasing PA [13,16,21,23,24,27,55,63]. Most of them involved exergames with the avatar. However, one of the studies did not find any improvements in PA among the 2 avatars, attributing improvements only to the web-based part of the intervention [23], and another study did not find a difference between the web-based intervention and the chatbot (only when considering a standard control) [63]. A preliminary usability study in Australia found that step count goals increased 59% of the time in users of the chatbot that targeted PA and that participants had a preference for personalization and greater knowledge-based content [16]. Another pilot study of Paola, the chatbot in Australia, found that it assisted with increasing mean step count by 109 minutes per week at 12 weeks follow-up (95% CI 1.9-217.7) [13]. A study involving an exergame that used a PA chatbot in teens found that 75% of the time, participants engaged in 15.88 (SD 5.8) minutes of vigorous PA throughout the game [29]. Participants also wanted the avatar to have a supportive and nonpatronizing or nondisparaging tone in interactions regarding PA and found that it could motivate older adults when adequately personalized [55]. Similarly, a study in children also found that they desired the option to personalize the avatar, including controlling and customizing its physical appearance during game play when exercising [66].

Proteus Effect
The Proteus effect is a phenomenon wherein individuals embody and emulate the behaviors of their virtual characters such as avatars [69,70]. A few studies demonstrated support for the Proteus effect when it came to PA behaviors, although the type of avatar varied. A study in Taiwan found that younger looking avatars were associated with higher levels of PA than older looking avatars but only in women. Male participants had higher levels of PA than female participants who used an older looking avatar, highlighting differences between sexes [27]. A further study found a higher cardiac output resulting from increased intensity of PA in adult users of an avatar that resembled them and wore gym clothes when compared with avatars that appeared unfamiliar like strangers in regular clothing, which reduced heart rate [24]. Similarly, a study in Taiwan found increases in physical activity assessed in movements (986.7 points higher) in users of a “normal avatar”, more closely resembling them than the most muscular avatar [21]. They also found that self-efficacy was higher (0.66 points) for core muscle exercises in female participants assigned to normal avatars relative to their muscular counterparts and male participants assigned to the same standard avatar (0.9 points higher), with P < .05 [21]. Similarly, dietary behavior was also shaped by thinner embodied avatars in another study [43].

Diabetes
Most diabetes studies were feasibility studies. The results of diabetes conversational coaches were mixed. A few studies did not have positive findings concerning the applications with avatars for diabetes [42,53]. However, one study reported a usability score of 73, which is relatively high. Notably, the study integrated a range of BCTs, including goal setting, feedback, self-monitoring, social support, and counseling [32]. Low usability scores were reported in a few studies, including one that reported an overall score of 44.58 (SD 21.18) [42].
Similarly, an RCT of a diabetes coaching avatar did not find that knowledge increased relative to controls, but intervention participants in the computer-based programmed dynamic avatar had higher satisfaction levels ($F_i=3.11; P<.01$) [53]. Another study in the United States in participants with prediabetes found that 60% of patients had successfully completed the modules and met weight targets during 6 months of use (60% success rate) [57]. Engagement was also moderately high (50%) in a study in Singapore involving a chatbot, although usability was high along with retention (93%) [36]. In a study in teenagers, attrition was also low, and 80% of the participants were satisfied with the conversational diabetes coach [59]. A study that evaluated a coaching application for diabetes found an improvement of −11 mg/dL in fasting blood glucose levels [44]. However, the intervention also involved phone calls from health professionals [44]. Similarly, an avatar application with a ketogenic diet program assisted with a reduction in hemoglobin A1c levels of 0.69% (SE 0.168%) [58]. Qualitative research found that avatars created an environment of social presence that facilitated social support and coherence for patients with diabetes [48]. In another study of avatars combined with robots, children preferred robots over avatars, but their friendship increased if the two had a greater similarity, which impacted usability [56].

CVD and Associated Risk Factors

A few studies evaluated the use of conversational coaches for CVD. One of them was a pilot study of the Tensiobot chatbot [17], a coaching application that teaches users how to properly check their blood pressure using recommended practice guidelines and provides users with graphic feedback and reminders. The study found that the chatbot group did not differ from the control group in terms of adhering to blood pressure measurement recommendations. However, there were significantly higher levels of knowledge (+6.53 points) with regard to checking blood pressure in the chatbot group than in the control group ($P<0.05$) [17]. Blood pressure (diastolic) was significantly reduced, that is, by 1.43 mm Hg (SE 0.65; 95% CI −2.72 to −0.14; $P<0.01$), in users of an avatar application that also involved a ketogenic diet [58]. In addition, a mixed methods study with a qualitative component found that users in general were interested in trying a hypertension chatbot for medication management as well as for health communication and self-care [19]. In addition to these studies, a general diet and PA chatbot further found that participants in the intervention group had significantly higher levels of knowledge (+5.23 points) with regard to blood pressure in the chatbot group than in the control group ($P<0.01$) [17]. Blood pressure (diastolic) was significantly reduced, that is, by 1.43 mm Hg (SE 0.65; 95% CI −2.72 to −0.14; $P<0.01$), in users of an avatar application that also involved a ketogenic diet [58]. In addition, a mixed methods study with a qualitative component found that users in general were interested in trying a hypertension chatbot for medication management as well as for health communication and self-care [19]. In addition to these studies, a general diet and PA chatbot study evaluated changes in blood pressure, but these changes were nonsignificant [13]. A study in Poland found high desirability for a CVD voice technology coach, in addition to accessing phone-based telemedical services by health professionals [43]. A further study in Brazil evaluated avatars for cardiovascular rehabilitation and found that an avatar with an exergame influenced heart rate, systolic blood pressure, and respiratory rate during the intervention and up to 5 minutes after its completion [31]. Furthermore, a study found that the avatar intervention increased the intent to improve lifestyle behavioral risk factors in patients relative to controls ($P=0.01$), although confidence did not change [54]. Finally, a study evaluated a cardiovascular educational avatar application and found that it increased symptom recognition by 24% and knowledge of CVD by 15%, with a high satisfaction rate of 87% among patients [62].

User Perceptions

Several studies found that users were interested in using conversational coaches for lifestyle behaviors [14,19,22]. Overall, participants enjoyed using the chatbots and avatars or found them helpful for diet, exercise, and hypertension management [17,22,25,26,29]. User-friendliness was reported by 83% of the participants in a study that evaluated a PA social media chatbot [20]. Similarly, 87.5% of women in a weight loss avatar intervention found it helpful [22]. With the exception of studies on diabetes conversational coaches, adherence or completion of tasks was high across studies on lifestyle (diet and PA) conversational coaches, ranging from 85% to 90% [13,16,17,29]. The qualitative study themes were related to the desirability for a conversational coach for hypertension and weight-related behaviors, especially for one that simulates human interaction closely, provides advice and goals for meals when cooking, and provides educational support [14] including for hypertension management [14,19].

Technological Challenges

A few tech challenges were brought up across the studies. Although users found that the conversational coach answered basic questions correctly, failure to understand and respond to more complex or spontaneous questions was reported in the studies. The percentage of failure for spontaneous or complex questions was 79% in one study [16], and participants in another study gave a high ranking for the chatbot’s failure to recognize their input [20]. Paola chatbot correctly answered spontaneous questions on diet in 4 out of 20 attempts, with a success of 20%, while the percentage of correctly answered simple and predetermined questions and responses was 96% and 97% [16].

Discussion

Principal Findings

This review aimed to better understand the effectiveness of virtual coaches for managing metabolic health and weight-related risk factors. It appears that virtual coaches hold potential for assisting patients with improving their dietary intake and PA behaviors, leading to subsequent weight loss. However, more studies that are larger and sufficiently powered RCTs are needed to establish a stronger evidence base. RCTs are the gold standard of evidence but are often costly and time-consuming [71,72]. Most of the studies were limited, as they were pilot studies. Ideally, it would be of interest to research long-term weight changes and cardiometabolic risk factor modifications over longer periods.

It appears that PA interventions may benefit from using avatars that embody the participant. The Proteus effect is based on the hypothesis that users adjust their behavior by modeling the virtual character with which they interact [73]. Thus, it seems that incorporating an avatar may enhance mHealth chatbot interventions, as it adds the element of user interaction and promotes the modeling of behavior through embodiment [73]. However, 1 (2%) study did not find that the avatars enhanced the effects of the web-based intervention [23].

https://mhealth.jmir.org/2023/1/e39649
We also found that consumers seemed to be interested in and enthusiastic about trying virtual coaches for managing their weight-related behaviors and blood pressure. Adherence to the intervention was also high throughout the studies, which indicates that this technology is acceptable and usable for patients. However, there is a need to undertake qualitative research on developing a MetS coach to further understand consumer perspectives. The main barrier to consider when developing future virtual agents is that the virtual agents did not always answer correctly to spontaneous responses. As consumers want personalized and tailored mHealth for weight-related behaviors [74], future applications should ensure that the virtual agents are sufficiently advanced to be able to interact with users in a natural and personalized manner.

It appears that diabetes virtual coaches should be improved to maximize engagement and adherence, as not all studies found that they were helpful. Although outside the scope of this review, we note that some studies used BCTs, which could suggest that future applications may benefit from integrating BCTs [13,20,22,25,32,42,51]. In addition, we identified some studies on blood pressure and CVD management, which demonstrated preliminary improvement in patients with hypertension as well as knowledge of CVD. However, we did not identify any virtual coaches for managing MetS. Therefore, there is a need to develop virtual coaches specifically tailored to this syndrome and its associated risk factors. Such virtual coaches could be integrated into a combined synchronized application that involves diabetes and CVD education and monitoring.

MetS is linked with high blood pressure, which is one of the main hallmarks of the disease. The theoretical mechanisms underpinning the development of hypertension in patients with MetS have included a combination of endothelial dysfunction, systemic inflammation, adiposity, and oxidative stress [75]. Dysfunction in the renin-angiotensin system has also been theorized to be a determinant [75]. Obesity itself has also been identified as a risk factor for high blood pressure in MetS [76]. Blood pressure is modifiable to some extent through lifestyle changes previously described, including dietary sodium restriction, PA, stress reduction [77], and medication [78]. Future virtual coaches may target hypertension as part of a MetS intervention, and this review found that patients are willing to try chatbots for managing their blood pressure.

MetS is also associated with high glucose levels of at least 100 mg/dL when patients are fasting [78], which indicates that they are in the prediabetes stage, as diabetes begins at fasting glucose levels of 126 mg/dL [79]. In a recent longitudinal study, patients who reduced their fasting blood glucose levels decreased their overall risk of diabetes by 54% when compared with their counterparts who did not improve their blood sugar levels (95% CIs exclude 1) [80]. A recent study found that individuals who consumed high amounts of sugar were 32% more likely to have MetS than their counterparts [81]. Thus, a future MetS virtual coach could target blood glucose monitoring and offer personalized advice on optimum sugar intake.

In addition to targeting dietary intake, PA is integral to managing this syndrome. A meta-analysis found that the risk of cardiovascular events was reduced by 30% in physically active individuals compared with those who were inactive [6]. A longitudinal study in middle-aged women found that increasing step counts significantly reduced, by 30%, the risk of MetS in this population and that they had clinically improved levels of the protective cholesterol high-density lipoprotein, whereas their serum triglycerides had significantly decreased [82]. A review found that walking on a daily basis reduced the risk of type 2 diabetes by nearly half [5]. Furthermore, recent research suggests that sedentary behavior, including sitting time, is an independent and significant risk factor for MetS syndrome [83]. Thus, PA chatbots and avatars, which were found to increase PA time, steps, and self-efficacy in this review, could be integrated into a comprehensive future MetS interventions.

Given that chatbots and avatars hold potential for increasing PA and reducing sedentary behavior, as well as improving dietary intake, studies are needed to evaluate their effectiveness for managing the symptoms and risk factors associated with MetS specifically.

In addition, stress is often an underlying determinant of maladaptive weight-related behaviors, including binge eating, emotional eating, and an unhealthy dietary intake as well as weight gain [84-88]. Future avatar and chatbot interventions for cardiometabolic factors could also consider integrating psychological supportive interventions such as mindfulness-based stress reduction, which assists with weight and stress [89-93], as an element.

Conclusions

In summary, we found that virtual coaches hold promise for regulating diet, PA, weight, and possibly hypertension. However, studies on virtual coaches are few in number; therefore, more research, including RCTs, is needed to confirm the effectiveness of virtual coaches. Overall, most participants in the reviewed studies were interested in using virtual coaches, including chatbots and avatars, for regulating their weight-related behaviors, and study adherence was good. Future interventions could be ameliorated to reduce technical challenges associated with these conversational agents and ensure that they respond correctly to complex and spontaneous questions. Furthermore, future research could involve developing a comprehensive conversational agent for MetS, such as a health coach that simultaneously targets diet (sodium, sugar, and fat intake), exercise, weight (including abdominal obesity), blood pressure, and diabetes, and evaluating it. This would include a health coach that simultaneously targets diet (sodium, sugar, and fat intake), exercise, weight (including abdominal obesity), blood pressure, and diabetes.

Conflicts of Interest

None declared.
References


Abbreviations

BCT: behavior change technique  
CVD: cardiovascular disease  
MetS: metabolic syndrome  
mHealth: mobile health  
PA: physical activity  
RCT: randomized controlled trial  
RQ: research question

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Original Paper

Understanding Mobile Health and Youth Mental Health: Scoping Review

Xiaoxu Ding¹,², MSc; Kelli Wuerth³, PhD; Brodie Sakakibara¹,²,⁴, PhD; Julia Schmidt¹,², PhD; Natalie Parde⁵,⁶, PhD; Liisa Holsti¹,², PhD; Skye Barbic¹,²,³,⁷, PhD

¹Faculty of Medicine, Department of Occupational Science and Occupational Therapy, University of British Columbia, Vancouver, BC, Canada
²Faculty of Graduate Studies, Rehabilitation Science, University of British Columbia, Vancouver, BC, Canada
³Foundry, Providence Health Care, Vancouver, BC, Canada
⁴Faculty of Medicine, Centre for Chronic Disease Prevention and Management, University of British Columbia, Kelowna, BC, Canada
⁵Department of Computer Science, University of Illinois Chicago, Chicago, IL, United States
⁶Natural Language Processing Laboratory, University of Illinois Chicago, Chicago, IL, United States
⁷Centre for Health Evaluation & Outcome Sciences, Vancouver, BC, Canada

Corresponding Author:
Xiaoxu Ding, MSc
Faculty of Medicine
Department of Occupational Science and Occupational Therapy
University of British Columbia
T325 - 2211 Wesbrook Mall | Musqueam Territory
Vancouver, BC, V6T 2A1
Canada
Phone: 1 236 992 8222
Fax: 1 604 822 7624
Email: xxd51@student.ubc.ca

Abstract

Background: A total of 75% of people with mental health disorders have an onset of illness between the ages of 12 and 24 years. Many in this age group report substantial obstacles to receiving quality youth-centered mental health care services. With the rapid development of technology and the recent COVID-19 pandemic, mobile health (mHealth) has presented new opportunities for youth mental health research, practice, and policy.

Objective: The research objectives were to (1) synthesize the current evidence supporting mHealth interventions for youths who experience mental health challenges and (2) identify current gaps in the mHealth field related to youth’s access to mental health services and health outcomes.

Methods: Guided by the methods of Arksey and O’Malley, we conducted a scoping review of peer-reviewed studies that used mHealth tools to improve youth mental health (January 2016-February 2022). We searched MEDLINE, PubMed, PsycINFO, and Embase databases using the following key terms: (1) mHealth; (2) youth and young adults; and (3) mental health. The current gaps were analyzed using content analysis.

Results: The search produced 4270 records, of which 151 met inclusion criteria. Included articles highlight the comprehensive aspects of youth mHealth intervention resource allocation for targeted conditions, mHealth delivery methods, measurement tools, evaluation of mHealth intervention, and youth engagement. The median age for participants in all studies is 17 (IQR 14-21) years. Only 3 (2%) studies involved participants who reported their sex or gender outside of the binary option. Many studies (68/151, 45%) were published after the onset of the COVID-19 outbreak. Study types and designs varied, with 60 (40%) identified as randomized controlled trials. Notably, 143 out of 151 (95%) studies came from developed countries, suggesting an evidence shortfall on the feasibility of implementing mHealth services in lower-resourced settings. Additionally, the results highlight concerns related to inadequate resources devoted to self-harm and substance uses, weak study design, expert engagement, and the variety of outcome measures selected to capture impact or changes over time. There is also a lack of standardized regulations and guidelines for researching mHealth technologies for youths and the use of non–youth-centered approaches to implementing results.
Conclusions: This study may be used to inform future work as well as the development of youth-centered mHealth tools that can be implemented and sustained over time for diverse types of youths. Implementation science research that prioritizes youths’ engagement is needed to advance the current understanding of mHealth implementation. Moreover, core outcome sets may support a youth-centered measurement strategy to capture outcomes in a systematic way that prioritizes equity, diversity, inclusion, and robust measurement science. Finally, this study suggests that future practice and policy research are needed to ensure the risk of mHealth is minimized and that this innovative health care service is meeting the emerging needs of youths over time.

(Keywords: adolescent; COVID-19; engagement; health outcome; illness; implementation; mental disorder; mental health; mHealth intervention; mHealth tools; mHealth; policy; scoping review; young adult; youth)

Introduction

Mental Illness

Mental health disorders are the leading cause of disability worldwide and are considered a global public health challenge [1,2]. Globally, 1 in 4 people are affected by mental health disorders each year; up to 50% of people experience mental health challenges in their lifetime [3]. The global burden of disease (GBD) is compounded by the “mental health treatment gap,” referring to those people in need of mental health treatment but who have not received it. People with mental health challenges experience different levels of barriers to accessing specialized care when needed [4]. Such barriers are multifaceted and may include poor mental health literacy, social stigma, trust and confidentiality issues with health professionals, and systemic difficulties such as financial hardship [5].

A total of 75% of people with mental health disorders have an onset of illness between the ages of 12 and 24 years [6]. This is a peak period of development for youths (defined here as ages 12-24 years); it is often the life stage to pursue education or begin a career, to build social relationships, and to explore new interests [7]. Yet, youths experience the worst levels of access to mental health care from poorly designed, grossly underresourced, and typically unfriendly health care services [8]. Current research indicates the need for a full range of interventions for youths [9], including health promotion [10,11], early intervention [12], and long-term supports such as integrated self-management [13], community outreach [14], and hospital care [15]. With existing barriers compounded by the COVID-19 pandemic, in-person mental health care is more challenging than ever to navigate and access for youths [16]. In response, mobile health (mHealth), a term used to describe the collective set of digital mental health interventions, has been proposed as a solution to meet the needs of youths across the world.

mHealth

In 2022, mobile phone users reached 6.5 billion worldwide, accounting for approximately 80% of the global population. In developed countries such as Canada and the United States, 97% of people own a mobile phone and 85% use a smart phone [17,18]. Such mass usage is motivating the rapid growth of mobile device–based apps covering multiple domains of health, including physical activity and fitness, diet, emotional and mental health, and health services. mHealth technologies have been used to track vital body signs, such as blood pressure, heart rate, exercise, sleep activity, nutritional values in meals, mental health and wellness, anxiety, and mood [20]. A total of 54,603 health care and medical apps were available on the Google Play Store in August 2022, up by almost 4% compared to the previous quarter [21].

While the pace of new mHealth technologies is growing rapidly, the regulations and standards for their use have not yet followed. In a recent study of nearly 300 apps for mental health, less than one-third received input from a mental health expert [22]. There is also little consensus regarding standards for mHealth tools, not to mention the effectiveness of mHealth interventions on diverse populations, including youths experiencing mental health challenges.

In summary, the field of mHealth often presents a dichotomy of opportunity and risk. On the one hand, the lack of standards and regulation for mHealth apps presents global concerns for the safety of youths, notably personal security and the uptake of misinformation [23-25]. On the other hand, mHealth may have an increasingly important role in health promotion, education, and interventions to bridge the gap for those who cannot access in-person services [26]. A greater understanding is needed to learn about how youths use mHealth technologies in their daily lives, with specific emphasis on understanding how they navigate safety risks and use these technologies to improve health and wellness outcomes.

The purpose of this scoping review is to synthesize the current evidence supporting mHealth interventions for youths accessing support for mental health challenges. This will facilitate understanding of what is missing in the field of mHealth and support recommendations for research, practice, and policy. The specific objectives are to (1) synthesize the current evidence supporting mHealth interventions for youths who experience mental health challenges and (2) identify current gaps in the mHealth field, with an overarching goal of improving youths’ mental health service access, outcomes, and experiences.

Methods

Overview

We conducted a scoping review to examine the extent, range, and nature of mHealth and to identify gaps in the existing literature on this emerging topic. This scoping study followed
the 5 stages of Arksey and O’Malley’s scoping study framework [27] to (1) identify the research question; (2) identify relevant studies; (3) select studies; (4) chart the data; and (5) collate, summarize, and report the results.

**Step 1: Identify the Research Question**

What is known in the existing literature about the feasibility and effectiveness of mHealth intervention for youths, aged 12-24 years, facing mental health challenges?

**Step 2: Identify Relevant Studies**

Under the guidance of a medical librarian, a comprehensive search of the following electronic databases was conducted: MEDLINE (Ovid), Embase (Ovid), PsycINFO (EBSCO), and PubMed (see Multimedia Appendix 1 for example search). We consulted with mHealth stakeholders and youths to decide on the range of dates to search. Our expert team highlighted rapid changes in the field, notably the influence of TikTok after its launch in 2016. To ensure relevance and reference value, we decided to only review articles published during the past 6 years (January 1, 2016, to February 7, 2022) to manage the scope, breadth, and rapidly changing information available. Key terms derived from the research question were selected and expanded to create a comprehensive list of search terms, including “telemedicine,” “telerehabilitation,” “mobile applications,” “mHealth (mobile health),” “eHealth (electronic/digital health),” and “telehealth,” as well as a combination of the following mental health condition-related terms: “mental disorders,” “anxiety,” “depression,” “eating disorder,” “schizophrenia,” “bipolar,” “obsessive compulsive disorder,” and “posttraumatic stress disorder,” along with a list of key terms to define the age group of this review: “adolescent,” “teen,” “youth,” and “young adult.” Combinations of these terms, along with Medical Subject Heading (MeSH) terms, were tested iteratively in each of the databases selected to inform the new combination of different terms leading to relevant literature. All searches included at least one identifier for mHealth (eg, telehealth and eHealth), 1 identifier for mental health condition (eg, depression and anxiety), and 1 identifier for age range (eg, youth and young adult). The lead author reviewed the title and abstract of each study to determine eligibility based on predetermined inclusion and exclusion criteria (described below) after duplicates were removed. After the completion of the initial review, the articles were thoroughly reviewed by the lead author based on the research topic.

**Step 3: Select Studies**

The following inclusion criteria were considered: (1) published in English; (2) published between January 1, 2016, and February 7, 2022; (3) included human subjects, whose ages fall between 12 and 24 years; (4) included at least one mHealth intervention tool targeting 1 or more mental health conditions for youths; and (5) referenced literature from peer-reviewed journals and book chapters. Exclusion criteria were as follows: (1) editorial comments, commentaries, book reviews, and opinion articles; (2) incomplete studies (eg, description of intervention, protocols, ideas from symposia, and conference summaries); (3) articles without full text available. Relevant systematic reviews were included in the study to serve as background literature but were excluded from the data extraction and analysis process to focus on intervention studies.

**Step 4: Chart the Data**

Through careful review of the literature, the researchers (XD and SB) identified the key components and issues discussed in all relevant studies. This information was recorded in a data extraction sheet, along with information on each study (author, publication year, population demographics, location, study design, level of evidence, characteristics of the intervention, targeted health condition, and outcomes).

**Step 5: Collate, Summarize, and Report Results**

The information was synthesized and used to map out the scope and breadth of included literature on the topic of mHealth intervention for youths’ mental health challenges.

**Results**

**Overview**

As noted in Figure 1, the search identified 4270 citations for initial screening. As noted in Figure 1, a total of 1411 duplicates were removed, resulting in 2859 citations for title and abstract reviews. A further 2413 articles were excluded because their title or abstract did not address mHealth interventions for youths’ mental health, leaving 446 citations. After full text review, a total of 151 articles met the inclusion criteria for this study. Table 1 summarizes the countries of origin of the included studies.
Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) diagram describing the search process and the number of articles meeting inclusion criteria for this study (N=151).
Table 1. Countries of origin of papers included in the scoping review.

<table>
<thead>
<tr>
<th>Country</th>
<th>Articles (N=151), n %</th>
</tr>
</thead>
<tbody>
<tr>
<td>United States</td>
<td>61 (40)</td>
</tr>
<tr>
<td>Australia</td>
<td>28 (19)</td>
</tr>
<tr>
<td>Canada</td>
<td>10 (7)</td>
</tr>
<tr>
<td>Sweden</td>
<td>10 (7)</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>8 (6)</td>
</tr>
<tr>
<td>New Zealand</td>
<td>7 (5)</td>
</tr>
<tr>
<td>China</td>
<td>4 (3)</td>
</tr>
<tr>
<td>Nigeria</td>
<td>3 (2)</td>
</tr>
<tr>
<td>Finland</td>
<td>3 (2)</td>
</tr>
<tr>
<td>The Netherlands</td>
<td>3 (2)</td>
</tr>
<tr>
<td>Japan</td>
<td>2 (1)</td>
</tr>
<tr>
<td>Germany</td>
<td>2 (1)</td>
</tr>
<tr>
<td>Korea</td>
<td>1 (1)</td>
</tr>
<tr>
<td>India</td>
<td>1 (1)</td>
</tr>
<tr>
<td>Spain</td>
<td>1 (1)</td>
</tr>
<tr>
<td>Iceland</td>
<td>1 (1)</td>
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<tr>
<td>Denmark</td>
<td>1 (1)</td>
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<tr>
<td>Belgium</td>
<td>1 (1)</td>
</tr>
<tr>
<td>Italy</td>
<td>1 (1)</td>
</tr>
<tr>
<td>Norway</td>
<td>1 (1)</td>
</tr>
<tr>
<td>Israel</td>
<td>1 (1)</td>
</tr>
<tr>
<td>France</td>
<td>1 (1)</td>
</tr>
</tbody>
</table>

Level of Evidence

As shown in Table 2, four levels of evidence were adopted to show the power of evidence among included youths’ mHealth interventions for mental health research [28,29].

Table 2. Design of studies included in the scoping review.

<table>
<thead>
<tr>
<th>Level of evidence</th>
<th>Study design</th>
<th>Articles, n</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>Randomized controlled trials</td>
<td>60</td>
</tr>
<tr>
<td>II</td>
<td>Nonrandomized experimental studies (quasi-experimental, pre-post, and cohort)</td>
<td>34</td>
</tr>
<tr>
<td>III</td>
<td>Cross-sectional, longitudinal surveys, and mixed method study with nonexperimental quantitative part</td>
<td>27</td>
</tr>
<tr>
<td>IV</td>
<td>Descriptive, case studies, and qualitative studies</td>
<td>30</td>
</tr>
</tbody>
</table>

As shown in Table 2, study types and designs varied. The highest level of evidence included experimental studies identified as randomized controlled trials (60/151, 40%). The second highest level of evidence included studies that were nonrandomized trials, such as quasi-experimental design (usually with 2 groups) or 1-group pre-post design (34/151, 23%). The third level of evidence included studies that only conducted feedback surveys to their participants once after the intervention, longitudinal observational studies, and mixed methods design with these mentioned quantitative parts (27/151, 18%). Last, some of the included studies had lower levels of evidence, including descriptive studies, case studies, and qualitative studies describing the outcome of mHealth interventions (30/151, 20%).

Age

All included studies have a general targeted age group of “young people,” “adolescent,” or “youth.” The median age for participants in all studies was 17 (IQR 14-21) years, with 2 outliers (with participants aged 61 years [30] and 62 years [31]) coming from the studies targeting “university students.”
Sex and Gender
A total of 20 (13%) papers did not provide any statistics on sex or gender. Only 3 (2%) studies involved participants who reported their sex or gender beyond binary options. One study focused on eating disorders and had 1 intersex participant [32]. The other 2 studies prioritized mental health in 2-spirited, lesbian, gay, bisexual, transgender, queer/questioning, intersex, and gender (2SLGBTQIA+) groups: 1 included 108 sexual minority young adults [33] and the other included 565 participants with a combination of transgender, genderqueer, gender expansive, intersex, agender, 2-spirited, and third gender identities [34]. The remaining 148 (98%) studies had a total of 6478 (34.2%) men and 12,480 (65.8%) women as participants.

Organizational Affiliation
The included studies took place in various settings. They were coded into the following 4 different categories, inspired by Marshall et al [22]: (1) research developed under clinic or hospital-related setting (97/151, 64%); (2) research developed in a university (28/151, 19%); (3) research developed in other nonuniversity schools and institutions (9/151, 6%); and (4) insufficient information to tell (17/151, 11%).

Modes of Delivery of mHealth Interventions
As noted in Table 3, a variety of modes are used to deliver services. These included web pages (54/151, 36%), smartphone apps (51/151, 34%), phone calls and SMS text messages (10/151, 9%), and innovative virtual reality (VR) tools (3/151, 2%).

Table 3. Delivery modes among studies included in the review.

<table>
<thead>
<tr>
<th>Delivery modes</th>
<th>Studies, n (%)</th>
<th>Randomized controlled trials, n/N (%)</th>
<th>Positive results, n/N (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Web pages</td>
<td>54 (36)</td>
<td>33/54 (61)</td>
<td>48/54 (89)</td>
</tr>
<tr>
<td>Smartphone apps</td>
<td>51 (34)</td>
<td>13/51 (26)</td>
<td>40/51 (78)</td>
</tr>
<tr>
<td>Video conferencing</td>
<td>20 (13)</td>
<td>3/20 (15)</td>
<td>15/20 (75)</td>
</tr>
<tr>
<td>SMS text messages</td>
<td>10 (7)</td>
<td>5/10 (50)</td>
<td>7/10 (70)</td>
</tr>
<tr>
<td>Chatbox</td>
<td>4 (3)</td>
<td>2/4 (50)</td>
<td>4/4 (100)</td>
</tr>
<tr>
<td>Phone calls</td>
<td>3 (2)</td>
<td>1/3 (33)</td>
<td>2/3 (67)</td>
</tr>
<tr>
<td>Virtual reality</td>
<td>3 (2)</td>
<td>0/3 (0)</td>
<td>3/3 (100)</td>
</tr>
<tr>
<td>Mixed modes</td>
<td>6 (4)</td>
<td>3/6 (50)</td>
<td>4/6 (67)</td>
</tr>
<tr>
<td>Total</td>
<td>151 (100)</td>
<td>60/151 (N/A)</td>
<td>123/151 (N/A)</td>
</tr>
</tbody>
</table>

*Positive results: researchers stated overall positive effect of intervention or received positive feedback from users to show promising practical usage of the intervention. Negative results: researchers see no changes in mental health symptoms before and after the intervention or receive negative feedback from users.

**N/A:** Not applicable.

Targeted Conditions
The number and percentage of health conditions targeted using mHealth interventions are summarized in Table 4.
Table 4. Health conditions and measurement tools among included studies.

<table>
<thead>
<tr>
<th>Health condition</th>
<th>Studies, n (%)</th>
<th>Measurement tools (scales) used, n</th>
</tr>
</thead>
<tbody>
<tr>
<td>General health</td>
<td>26 (15)</td>
<td>66</td>
</tr>
<tr>
<td>Anxiety</td>
<td>35 (20)</td>
<td>52</td>
</tr>
<tr>
<td>Depression</td>
<td>32 (19)</td>
<td>68</td>
</tr>
<tr>
<td>Suicide, self-harm, or violence</td>
<td>11 (6)</td>
<td>15</td>
</tr>
<tr>
<td>Substance use</td>
<td>10 (6)</td>
<td>22</td>
</tr>
<tr>
<td>Eating disorder</td>
<td>10 (6)</td>
<td>10</td>
</tr>
<tr>
<td>Stress or mood related</td>
<td>9 (5)</td>
<td>20</td>
</tr>
<tr>
<td>Sleep disorder</td>
<td>6 (4)</td>
<td>9</td>
</tr>
<tr>
<td>ASDa</td>
<td>5 (3)</td>
<td>4</td>
</tr>
<tr>
<td>STD or STIb</td>
<td>5 (3)</td>
<td>10</td>
</tr>
<tr>
<td>Psychosis</td>
<td>4 (2)</td>
<td>5</td>
</tr>
<tr>
<td>ADHDc</td>
<td>4 (2)</td>
<td>8</td>
</tr>
<tr>
<td>PTSDd</td>
<td>4 (2)</td>
<td>3</td>
</tr>
<tr>
<td>OCDe</td>
<td>3 (2)</td>
<td>1</td>
</tr>
<tr>
<td>FASDf</td>
<td>2 (1)</td>
<td>N/Ag</td>
</tr>
<tr>
<td>Others</td>
<td>6 (4)</td>
<td>N/A</td>
</tr>
<tr>
<td>Total</td>
<td>172b (N/A)</td>
<td>N/A</td>
</tr>
</tbody>
</table>

a ASD: autism spectrum disorder.
b STD or STI: sexually transmitted disease or sexually transmitted infection.
c ADHD: attention-deficit/hyperactivity disorder.
d PTSD: posttraumatic stress disorder.
e OCD: obsessive-compulsive disorder.
f FASD: fetal alcohol spectrum disorder.
g N/A: not applicable.

* The total number of conditions exceeds the total number of studies because there are articles targeting more than 1 condition.

Measurement Approaches Used in the Studies

A wide range of tools were employed to measure outcomes in mHealth intervention research (Table 4). A detailed table listing the outcome measures and the references to the studies using them can be found in Multimedia Appendix 2.

COVID-19

Of the 151 studies included within the given time period, 68 (45%) were published after the COVID-19 outbreak, with most (44/151, 65%) published in 2020. The numbers of studies published each year are as follows: 11 studies in 2016; 21 studies in 2017; 19 studies in 2018; 32 studies in 2019; 44 studies in 2020; 23 studies in 2021; and 1 study in February 2022.

The following 8 studies directly addressed health conditions or service delivery modalities influenced by the pandemic: (1) treatment of eating disorders in adolescents [35]; (2) group-based psychiatric care using telehealth [36]; (3) a web-based art therapy group for learning disabled young adults using WhatsApp [37]; (4) telehealth versus in-person intensive outpatient program (IOP) for eating disorders during versus before COVID-19 [32]; (5) a well-being app to support young people living in New Zealand [38]; (6) peer-to-peer live-streaming intervention to promote physical activity and reduce anxiety during homeschooling [39]; (7) a mindfulness-based mHealth intervention among psychologically distressed university students in quarantine [40]; and (8) smartphone application for adolescents with anorexia nervosa [41].

Discussion

Overview

This scoping review provides a comprehensive synthesis of mobile mental health intervention research for youths. The study identified that the number of interventions is proliferating over time, with limited emphasis on study quality, youths’ engagement, youth-centered outcome assessment, implementation standards, or consideration for equity, diversity, and inclusion in research. Youths’ engagement was rarely mentioned as a part of any research study method, and most studies focused primarily on youths who identified within the gender binary. Few studies discussed the implementation and scale of interventions in diverse settings (Table 3) and even
fewer studies showed an impact of mHealth interventions over time for diverse types of youths. With significant growth and investment in the area, this review may inform direction for future research and advance practices within mHealth intervention approaches for youths who experience mental health challenges or illnesses.

Among the studies that met the inclusion criteria, depression (32/151, 19%), anxiety (35/151, 20%), and general mental health concerns (26/151, 15%) accounted for over half of the studies, and the remaining 17 addressed other mental health concern categories. According to a GBD systematic analysis of mental health conditions relevant to this study, the top concerns for all youths are self-harm, depressive disorders, interpersonal violence, anxiety disorders, HIV/AIDS, conduct disorder, and drug use disorder [42]. The point estimate of alcohol and drug use disorders combined is very close to the prevalence of depression, serving as 2 of the most concerning mental health disorders worldwide [43]. The high prevalence of depressive and anxiety disorders corresponds with the allocation of research priorities in studies included in this review, suggesting the current focus for youths’ mental health care services. Nevertheless, while self-harm and interpersonal violence ranked high on the GBD mental health conditions list, there were comparatively limited research studies for these categories. Substance use disorders are also underrepresented in existing mHealth studies for youths. More attention and resources should be given to the development of mHealth intervention tools targeting self-harm, interpersonal violence, and substances use among diverse youths.

From a global health perspective, 95% (143/151) of studies came from developed countries. This result is not surprising, as mHealth resources are almost exclusively concentrated in high-income countries, although the prevalence of depression and anxiety in high-income countries is not significantly higher than in the rest of the world [44]. Therefore, more future mHealth research needs to be conducted in low- and middle-income countries, especially when one of the advantages of remote healthcare access is cost-effectiveness. Previous studies have demonstrated adapting interventions developed in high-income countries for use in low- and middle-income countries, such as India, Sierra Leone, Romania, Malaysia, and South Africa [45,46]; these lessons could be adapted for mHealth interventions for youths’ mental health.

Delivery Modes

With respect to delivering mHealth interventions, most studies employed web pages (54/151, 36%) and smartphone apps (51/151, 34%), and these modes also had the largest number of randomized controlled trials conducted. The results show web-based mHealth tools have the strongest evidence for improving mental health conditions in youths, but the effectiveness of other intervention modes cannot be ruled out. Web-based intervention tools require youths to have internet access, and the use of computers may not be convenient in home and school settings, so the development of mHealth interventions has gradually evolved to include smartphones, smart devices, wearables, and newer technologies, including VR and augmented reality [47]. However, with the rising number of options available for mHealth intervention delivery, youths’ intention to use has become a more complicated question. Currently, many studies contributing to the adoption research of mHealth for youths are based on the technology acceptance model, an information systems theory that models user’s acceptance of technology mainly based on perceived usefulness and perceived ease of use [48-50]. Yet, it is essential to realize that participants in research studies are provided with a predetermined type of intervention by the researchers, often with limited youths’ engagement. That is, unlike in a real-world environment where diverse users who need support must seek it themselves, participants in the research settings did not actively choose which kind of mHealth intervention to use. Therefore, future studies need to consider the youth-intended delivery modes during mHealth intervention development from a user perspective, especially when considering innovative technologies, such as VR, artificial intelligence chat, and gaming. Future research should also consider implementation research, not only to understand the efficacy and effectiveness of the interventions but also their capacity to be sustained over time in diverse settings.

Measurement

The measurement tools used in the studies (Multimedia Appendix 2) can be broadly defined as either (1) measuring the outcome of a patient’s condition or (2) measuring the subject usability of a product or service. As displayed in Table 4, depression, anxiety, and general mental health categories each adopted more than 50 measurement tools. The review also identified numerous measurement scales used for each health condition. For example, 7 sleep-relevant measurements were used in 6 sleep-related studies [51-56], but the researchers did not provide a rationale as to why they chose the scale used among all available sleep-related measurements, nor was evidence provided about the fitness of the tools for youths in the varying contexts. Similar complications were presented in other included studies with varying health conditions. Future research should focus on developing a guideline for researchers to follow when selecting the most appropriate measurement scales in both research and clinical settings and on validating measurement scales designed for use with youths with consideration for equity, diversity, inclusion, and psychometric rigor.

Evaluation of mHealth Products

The percentage of positive results is considerably high among all included studies (123/151, 81%). Study aims included “feasibility,” “effect,” “acceptability,” “efficacy,” “fidelity,” “effectiveness,” and “cost-effectiveness,” with research designs including experiments, surveys, and interviews. Questions remain as to whether positive results translate to real-world applications or which types of outcomes possess high level of evidence in the knowledge translation process for health care services. In a Canadian study where participants were asked to rate mHealth apps objectively, results were highly variable, and 28% of reviewers were not even sure about the overall quality of the health product [57]. The same characteristics in different studies also vary within a wide range. For instance, the intervention durations ranged from as short as 7 days [58] or 2
sessions [59] to as long as 24 weeks [60] or 24 months [61]. The number of participants among all studies ranges from 2 [62] to 2532 [63]. Intervention types also varied significantly. Such variations raise concerns about the lack of a standardized evaluation strategy. To address the complex uncertainty in evaluating mHealth tools, a multifaceted evaluation framework needs to be adopted to assess the different perspectives, elements, and features of an intervention that leads to a final mHealth product. Using non–youth-centered frameworks to evaluate mHealth products can consequently produce ambiguous or incorrect information on their effectiveness, leading to misuse, misdiagnosis, wasted time, and, worst of all, negative health impacts and experiences [64].

Remote Care Transition

Several included studies discuss how to support youths during the COVID-19 pandemic [65,66]. With many people transitioning to work-from-home or hybrid arrangements during and after the pandemic, there arose an imminent need for a mental health technology revolution, and web-based health service delivery has emerged as a preferred tool [67].

Childs and colleagues [36] illustrated the feasibility of a rapid transition to telemedicine services during the pandemic. Yale New Haven Psychiatric Hospital decided to discontinue in-person IOP services within 3 business days of the World Health Organization’s pandemic declaration [36]. The first mobile service was available within a week, and subsequent treatment plans and adolescent ambulatory services were developed to reach IOP level. The study demonstrated that it took a comprehensive program 2 months to transition from 100% in-person service prepandemic (March) to 100% telehealth service after the start of the pandemic (May 2020), showing the feasibility of the deployment of mHealth tools in clinical settings and the smooth transition from physical to virtual health care access. One notable limitation of this study is that the clinicians focused on the transition process rather than the effectiveness of the intervention tool.

Another youths’ mHealth intervention study showed the transition to virtual services was not always desired by clients. The authors presented a case where a participant refused to cooperate, and the telemedicine service increased the tension between the participant and family members [35]. When developing mHealth interventions targeting youths’ mental health, it is important to consider how to achieve optimal patient engagement when physical contact with a service provider is not an option. Last, it is still unknown whether these transitioned services will continue to be provided virtually on an ongoing basis. Future research is needed to investigate the long-term influence of such transitions and determine the feasibility of normalizing mHealth services.

Youths’ and Stakeholder Engagement

Engagement with mHealth interventions is thought to be important for intervention effectiveness by increasing acceptability, satisfaction, intervention adherence, and levels of attention and enjoyment [68]. This can be extended to engaging youths in mHealth research to provide comprehensive, ongoing, tailored, and interactive support to improve health [69].

Current youth mHealth research often engages youths by asking for feedback in a survey or interview to test usability, feasibility, and acceptability [31,70,71], or by including young users as participants in experiments to evaluate the effectiveness and efficiency of an intervention. However, few studies mentioned how they engaged youths in the development phase and followed design thinking with the priority population. Youths and other stakeholders (eg, family and caregivers, service providers, and graphic designers) can contribute more than just feedback on the provided services; they can be offered opportunities to participate in the product and service design stages to make sure the end product is tailored to their needs and preferences. A previous conceptual model indicated that, during the optimization phase of an intervention [72], participants need to understand how the provided materials can inspire them and facilitate their thoughts to improve self-efficacy, which increases capability for self-monitoring and self-regulation and can lead to improved health outcomes and behavioral changes [72,73]. Researchers proposed a supportive accountability model that emphasized the importance of human support in mHealth interventions to increase adherence to trustworthy, benevolent, and professional information [74]. To summarize, it is crucial to apply such theoretical models to interventions targeting youths’ mental health as well. mHealth researchers and developers ought to involve youths in every stage of design, development, and implementation. Our team is currently studying youths’ engagement in the mHealth development phase to understand youths’ information preferences and make sure mHealth interventions are designed to convey the benefits of human support, similar to in-person services.

Policy

More than two-thirds of the studies took place in a clinical setting, yet none of the studies reviewed provided systematic frameworks or models to help translate, scale, and sustain available mHealth tools to clinical practice. If health care stakeholders and policy makers aim to scale up and normalize mHealth services in the near future, it is essential to understand the feasibility and impact of implementing new mHealth tools in current models of care (eg, health care and schools). Guidelines and standards may be critical to ensuring that mHealth interventions are trustworthy and can be value added to health services that are delivered to youths and their families.

Strengths and Limitations

This review has a broad scope of attempting to draw a picture of existing mHealth intervention tools specifically designed for younger populations and how their effectiveness is being assessed. This scoping review addressed a broad term list and a large number of parameters. Inclusion and exclusion criteria were strictly set from the beginning and determined by experts in the field and a medical librarian, and diversity is presented for all included studies. There are unlimited possibilities for future work, particularly with the uncertainty of the COVID-19 pandemic and the ongoing response of the health care system to remote health access. Regarding weaknesses, the lack of critical appraisal is a widely recognized limitation for scoping...
reviews [75]. The scope of this review may be broad, but the depth and the quality of all included papers were not systematically critiqued. We also acknowledge that our search strategy may have missed key terms (eg, internet-based interventions) and intervention descriptions (eg, asynchronous vs synchronous) that may have limited our ability to completely summarize all relevant articles. In addition, the COVID-19 pandemic has not come to an end, and there is still ongoing research about long-term COVID-19 symptoms. Thus, the results relevant to remote care transition and COVID-19 should be interpreted with some caution.

Conclusions
As the need for mental health services continues to accelerate [76], mHealth technologies provide a solution to support diverse youths who may not be able to access in-person services. The impact of mHealth interventions on youths’ mental health has been increasingly recognized by researchers, service providers, and policy makers. Results of our scoping review demonstrate a range of studies that capture the exponential growth of mHealth interventions for youths, with significant potential to be value-added for youths who are seeking support for mental health challenges. However, the review also highlighted notable gaps in research that include youths’ voice throughout the research process, notably diverse youths in both developing and developed countries. Future research is needed that adopts an equity, diversity, and inclusion lens, prioritizes understanding how current mHealth technologies can be adopted into existing models of care, and develops guidelines, standards, and evaluation frameworks to support future mHealth development and implementation. As the field continues to expand rapidly, more global resources are needed to monitor technological advancements to provide quality mHealth services to every youth where and when they need them.

Conflicts of Interest
None declared.

Multimedia Appendix 1
Sample Literature Search Sheet.

[DOCX File, 13 KB - mhealth_v11i1e44951_app1.docx]

Multimedia Appendix 2
List of measurement scales and studies using them.

[DOCX File, 41 KB - mhealth_v11i1e44951_app2.docx]

References


47. Giansanti D. Towards the evolution of the mHealth in mental health with youth: the cyber-space used in psychological rehabilitation is becoming wearable into a pocket. Mhealth 2020;6:18 [FREE Full text] [doi: 10.2196/mhealth.2019.11.02] [Medline: 32270010]


53. Ding et al. JMIR MHEALTH AND UHEALTH 2023 | vol. 11 | e44951


Abbreviations

2SLGBTQIA+: 2-spirited, lesbian, gay, bisexual, transgender, queer/questioning, intersex, and agender
GBD: global burden of disease
IOP: intensive outpatient program
MeSH: Medical Subject Heading
mHealth: mobile health
VR: virtual reality
Review

Influencing Factors to mHealth Uptake With Indigenous Populations: Qualitative Systematic Review

Andrew Goodman¹²*, AdvDip; Ray Mahoney³*, PhD; Geoffrey Spurling⁴*, MBBS, PhD; Sheleigh Lawler¹*, PhD

¹School of Public Health, The University of Queensland, Turrbal, Jagera Country, Herston, Australia
²Australian eHealth Research Centre (AEHRC), Commonwealth Scientific and Industrial Research Organisation (CSIRO), Turrbal, Jagera Country, Herston, Australia
³College of Medicine and Public Health, Flinders University, Kaurna Country, Adelaide, Australia
⁴General Practice Clinical Unit, The University of Queensland, Turrbal, Jagera Country, Herston, Australia

*all authors contributed equally

Corresponding Author:
Andrew Goodman, AdvDip
School of Public Health
The University of Queensland
266 Herston Road
Turrbal, Jagera Country, Herston, 4006
Australia
Phone: 61 733655393
Fax: 61 733655442
Email: Andrew.Goodman@csiro.au

Abstract

Background: The advancements and abundance of mobile phones and portable health devices have created an opportunity to use mobile health (mHealth) for population health systems. There is increasing evidence for the feasibility and acceptance of mHealth with Indigenous populations. Providing a synthesis of qualitative findings of mHealth with Indigenous populations will gain insights into the strengths and challenges to mHealth use in Indigenous populations.

Objective: This review aimed to identify and synthesize qualitative data pertaining to the experiences and perceptions of mHealth from the perspectives of end users (patients and service providers) living in the colonial settler democracies of Canada, Australia, New Zealand, the United States, the Pacific Islands, and the Sápmi region of northern Europe.

Methods: In May 2021, systematic searches of peer-reviewed, scientific papers were conducted across the 5 databases of PubMed, CINAHL, Embase, PsycINFO, and Web of Science. Qualitative or mixed method studies were included where a mHealth intervention was the primary focus for responding to health challenges with Indigenous populations. Two authors independently screened papers for eligibility and assessed the risk of bias using a modified version of the Critical Appraisal Skills Programme. A meta-aggregative approach was used to analyze the findings of included studies.

Results: Seventeen papers met the eligibility criteria, 8 studies with patients, 7 studies with service providers, and 2 studies that included both patients and service providers. Studies were conducted in Australia (n=10), Canada (n=2), New Zealand (n=2), Papua New Guinea (n=1), the United States (n=1), and Samoa (n=1). Our interpretation of these qualitative findings shows commonalities between Indigenous patients’ and service providers’ perceptions of mHealth. We summarize our findings in six themes: (1) mHealth literacy, (2) mHealth as a facilitator for connection and support, (3) mHealth content needed to be culturally relevant, (4) mHealth security and confidentiality, (5) mHealth supporting rather than replacing service providers, and (6) workplace and organizational capacity.

Conclusions: This research suggests that mHealth can meet the needs of both patients and service providers when the mHealth intervention is culturally relevant, accounts for digital and health literacy, incorporates interactive components, is supported by workplaces, fits into health provider workflows, and meets security and confidentiality standards. Future mHealth research with Indigenous populations should partner with key representatives (eg, patients, service providers, and executive leaders) in the mHealth design appropriate to the purpose, people, setting, and delivery.

(JMIR Mhealth Uhealth 2023;11:e45162) doi:10.2196/45162

https://mhealth.jmir.org/2023/1/e45162
KEYWORDS
mHealth; Indigenous; Canada; Australia; New Zealand; United States; Papua New Guinea; Samoa; qualitative; systematic review; feasibility; acceptability; users; design; workflow

Introduction
The technological advancements and abundance of mobile phones and portable health devices have created a plethora of mobile health (mHealth) tools. mHealth is defined as “the use of mobile devices—such as mobile phones, patient monitoring devices, personal digital assistants and wireless devices—for medical and public health practice” [1]. These include mobile phone apps, text messages, portable monitoring devices and electronic patient information.

Systematic reviews globally have suggested mHealth is a broadly feasible and effective resource for a range of health conditions including: behavior change [2,3], noncommunicable disease management [4-9], perinatal care [10,11] medication adherence [12], and mental health well-being [13,14]. Likewise, health care workers suggest mHealth improves patient health outcomes and increases peer communication and care coordination [15,16].

There is a growing number of qualitative studies exploring the views and perceptions of mHealth from 2005 onward, resulting in a number of qualitative systematic reviews [16-21]. Findings from these reviews provide a collective insight into user perceptions and experience of mHealth to influence future research and implementation. These systematic reviews predominantly focus on non-Indigenous populations and fail to explore the user experiences of Indigenous people and their service providers. We need to ensure a space is kept privileging Indigenous worldviews as it pertains to mHealth. mHealth interventions are being explored with Indigenous populations with increasing interest [22-24]. Reviews examining the applicability of mHealth for Indigenous populations exist, and these indicate it is an acceptable health resource [23,24]. Yet, these reviews include qualitative data as only a peripheral focus and are inconsistent with the intervention type [23], and outcomes [24].

Providing a synthesis of qualitative findings of mHealth with Indigenous populations will gain insights to the strengths and challenges to mHealth use in Indigenous populations. This review aimed to identify and synthesize qualitative data pertaining to the experiences and perceptions of mHealth with Indigenous populations and the service providers that work with Indigenous populations.

Methods
Overview
A systematic search was conducted of peer-reviewed literature for this qualitative synthesis. A protocol of this qualitative synthesis was registered with the International Prospective Register of Systematic Reviews (PROSPERO; registration number CRD42021251861). We extracted qualitative data pertaining to the experiences and perceptions of both patients (Indigenous peoples) and service providers (either Indigenous or non-Indigenous health policy makers, health care professionals, and researchers) who work with Indigenous peoples from Canada, Australia, New Zealand, the United States, the Pacific Islands, and the Sápmi region of northern Europe. We define Indigenous Peoples as “distinct social and cultural groups that share collective ancestral ties to the lands and natural resources where they live, occupy or from which they have been displaced” [25].

Search Strategy and Selection Criteria
A comprehensive list of search terms and strings were developed with the assistance of a librarian with expertise in systematic reviews. Systematic searches of peer-reviewed, scientific papers in English were conducted across 5 databases in May 2021: PubMed, CINAHL, Embase, PsycINFO, and Web of Science. Qualitative or mixed method studies were included where a mHealth intervention was the primary focus for responding to health challenges with Indigenous populations. As such, experimental and quasi-experimental studies were considered, as long as they met the following inclusion criteria:

- Participants: Indigenous people of all ages from Canada, Australia, New Zealand, United States, the Pacific Islands, the Sápmi region of northern Europe; OR are service providers (either Indigenous or non-Indigenous) who work with Indigenous persons from Canada, Australia, New Zealand, the United States, the Pacific Islands, the Sápmi region of northern Europe; OR where participants are multicultural, outcomes for Indigenous persons are reported specifically.
- Interventions: primary focus was a mHealth intervention delivered using a wireless device (eg, mobile or tablet app, website designed for mobile, messaging [SMS, voice, multimedia messaging system, etc]). The mHealth intervention aims to address a health challenge (eg, diagnosis of disease, substance use, health behaviors, quality of life, health knowledge, self-efficacy, caregiver support, etc).
- Outcomes: studies reported on one or more outcomes including user; experiences, perceptions, barriers, and enablers via qualitative research methods (eg, interviews and focus groups).

A sample of the search strings using text words and subject heading keywords for PubMed can be found in Multimedia Appendix 1. The use of proximity operators, truncation, and phrase searching was used to widen the search to capture all iterations of both the mHealth and Indigenous themes. The 2 search strings were then combined to narrow the results—enabling discovery of all possible scientific papers, which capture mHealth interventions with Indigenous populations from Canada, Australia, New Zealand, the United States, the Pacific Islands, and the Sápmi region of northern Europe. The qualitative papers were then identified via screening by 2 researchers (AG and SL).
Data Extraction and Quality Appraisal

Initial database searches and duplicate removal were conducted by 1 author (AG). Screening, review, and extraction were assisted by the web-based systematic review program Covidence (Veritas Health Innovation) [26]. Two authors (AG and SL) independently screened titles and abstracts against the inclusion criteria, and papers clearly not meeting the inclusion criteria were excluded.

Subsequently, 2 authors (AG and SL) screened the full-text papers independently and then discussed for comparison. Any differing views were resolved through discussion. Manual searches of reference lists were conducted on full-text papers included in the review. A final list of full-text papers and their citations which met inclusion criteria were downloaded and saved using Covidence software.

The quality of the included studies was appraised using a modified version of the Critical Appraisal Skills Programme (CASP) qualitative checklist [27]. An additional question from the Joanna Briggs Institute (JBI) was added that related to locating the researchers cultural or theoretical standpoint [28], improving the cultural rigor of this critical appraisal tool.

Data Analysis and Synthesis

The data included in the analysis were all text included in the “Results” or “Findings” sections of the papers (excluding purely quantitative findings) and was extracted from the papers into NVivo 12 Plus software (QSR International) [29]. Characteristics of each study to be extracted for descriptive purposes included: Indigenous identification, study location (country), year, sample size, participant demographic characteristics (age, gender), data collection, and analysis methods.

A meta-aggregative approach was used to analyze the findings [30]. This analysis approach privileges the findings, presented as “themes” or “constructs” in qualitative research, as identified by the researchers (not the reviewer). This method helps ensure the expanse and breadth of cultural learnings identified by researchers conducting the original studies are not lost by the reviewers.

Results

Overview

From database searches, 2608 unique papers were identified; 2 additional papers were located by manual searches. In total, 2610 titles and abstracts were reviewed against the inclusion criteria, of which 2548 were excluded, leaving 62 papers for full-text review. Following the full-text review, 45 papers were excluded, leaving 17 studies included in this qualitative systematic review (Figure 1).
Description of Included Studies

All 17 studies included in this review were published between 2013 and 2021. Eight were studies specifically with Indigenous patients [31-38]. Seven studies were with service providers (either Indigenous or non-Indigenous) who work with Indigenous peoples [39-45]. Two studies involved both patients and service providers in data collection [46,47], so findings were considered for both.

Characteristics of the 17 studies are shown in Table 1. Ten papers involved Aboriginal and Torres Strait Islander peoples of Australia [31,36-38,40,42,44-47], 2 with the First Nations, Inuit, or Métis peoples of Canada [34,39], 2 with the Māori peoples of Aotearoa, New Zealand [33,35], 1 paper with the Indigenous peoples of Papua New Guinea [43], 1 paper with the Native Hawaiian and Pacific Islander peoples of Hawaii, the United States [41], and 1 paper with the Indigenous peoples of Samoa [48]. We were unable to identify any papers with Indigenous people of the Sápmi region of northern Europe that met the review criteria.
<table>
<thead>
<tr>
<th>Studies</th>
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<th>Type of mHealth delivery</th>
<th>Participants (roles)</th>
<th>Method</th>
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<td>App[c]</td>
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<td>Interviews[d,f]</td>
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<td>Focus group and &quot;bus stop activity&quot;[d,i]</td>
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<td>Interviews[df]</td>
<td>10</td>
</tr>
<tr>
<td>Yazdanshenas et al [41]</td>
<td>Native Hawaiian and Pacific Islander (United States)</td>
<td>Hypertension</td>
<td>Text message</td>
<td>20 (executive leader, church leader, community advocate, and health care providers)</td>
<td>Interviews[h]</td>
<td>7</td>
</tr>
<tr>
<td>Dingwall et al [40]</td>
<td>Aboriginal and Torres Strait Islander (Australia)</td>
<td>Mental health well-being</td>
<td>App[e]</td>
<td>15 (health professionals, managers, program coordinators, and an Aboriginal elder)</td>
<td>Interviews[d]</td>
<td>10</td>
</tr>
<tr>
<td>Kurumop et al [43]</td>
<td>Papua New Guinea</td>
<td>Malaria</td>
<td>SMS Text message</td>
<td>17 (health workers)</td>
<td>Focus group[h]</td>
<td>9</td>
</tr>
</tbody>
</table>

**Both Indigenous patients and service providers**
Thematic Synthesis

Overview

Our interpretation of these qualitative findings shows commonalities between Indigenous patients and service providers perceptions of mHealth. We have collectively termed both as “end users” hereafter unless explicitly stated otherwise. Common themes across end users were: the importance of mHealth or digital literacy, mHealth as a facilitator for connection and support, mHealth content that needed to be culturally relevant, and data security and confidentiality. Two themes emerged that were unique to service providers including the importance of mHealth supporting rather than replacing service providers, and the role of workplace champions and organizational capacity for influencing uptake and sustainability of mHealth.

mHealth Literacy

Access to the required hardware (mobile or smartphones and touch screen tablets) and systems (network coverage and IT) was identified as an important influence to mHealth uptake by end users. Service providers noted barriers to accessing the mHealth hardware and systems with reasons including regionality and workplace restrictions [40,42,43,45,46]. Service providers held a perception that mobile phones were not prevalent or accessible to patients due to cost [46] and remote location [42]. However, Indigenous patients saw themselves as competent and confident users of technology and mobile phones for everyday life [31,33-38,46,47]. Yet, technology difficulties and lack of device access were still raised in several studies [31,34-36,46,47]. Some studies noted concerns end users had relating to the digital literacy required for mHealth [40,42,44].

Low levels of IT literacy pose a challenge to electronic mental health adoption. Unfamiliarity with different ways of using technologies impedes the utilization of the approach by both service providers and community members. Poor IT literacy within communities was attributed to limited access to technology... [42]

Limited confidence in using new technology such as mHealth initiatives was identified as a barrier to uptake for service providers [40,44]. The investment of time and effort into appropriate mHealth training and ongoing support was suggested as a mitigation strategy for technical difficulties for end users [36,40].

Age and generational implications were raised as influential factors to the uptake of mHealth. Whether implicitly or explicitly, end users perceived mHealth would be more applicable and accepted by younger people [31,33,40-42,44,46]. Service providers perceived that older people have limited or no access to mobile phones and thus would have lower digital literacy [40,41,46]. Interestingly, these age-related barriers were not reflected by Indigenous patients in this Australian study.

Most older interviewees did not appear to have any major issues with knowledge on how to access phone features. [36]

End users noted the importance of mHealth resources easy to understand and use for a confident user experience. A notable motivation for service providers to use a mHealth resource was for it to be uncomplicated and easy to use [39,40,45-47]. Likewise, Indigenous patients advised that if mHealth platforms were complex, slow, or used too much data, uptake and sustained use was less likely [31,33,35,38,46]. The importance of clear and concise language and the avoidance of jargon in mHealth messaging was noted to encourage comprehension for end users [31,37,38,41,43,47,48]. Service providers stated the importance of mHealth content being appropriate to the learning...
styles, health knowledge, and communication styles of their patients [39-41,43,44,46,47]. Indigenous patients were enthusiastic about the potential benefits mHealth provided in accessing relevant information for their health journey [33-35,37,38,46-48].

Participants spoke of parents being technologically savvy, and parents referred to accessing apps, YouTube clips, social media and the internet from their mobile phones for infant feeding information and support prior to the Growing healthy program. [47]

The incorporation of visual and audio capabilities was suggested by end users to create a better understanding of the content [31,35-41,44,46-48]. mHealth may provide an appropriate tool to bridge health knowledge gaps [42] and enable education and empowerment for health care.

Several interviewees described how the iECG device provided unique opportunities to engage patients in education around AF and their heart, and to empower patients to find out more about their heart health. [45]

mHealth as a Facilitator for Connection and Support

End users found mHealth an appropriate resource to facilitate engagement, connection, and support within health care systems. Indigenous patients appreciate that mHealth facilitated connection to support people, along with health care providers [31,33-38,47,48]. Likewise, service providers viewed mHealth as important for connection to patients with the added facility to connect with professional colleagues [40-42,46].

mHealth was found to provide a sense of reassurance and encouragement across a range of health journeys for Indigenous patients, including perinatal health [35,47], patients living with mental health challenges [34,37], and people on a smoking cessation journey [36,48]. Indigenous patients suggested mHealth could enable a web-based community to connect with others on similar health journeys [31,33-38,46]. Moreover, Indigenous patients appreciated the capability of mHealth to share health knowledge with family and support people in their lives [33,35,47,48].

Participants valued sharing advice and experience-based information with their families, partners or wider virtual communities, such as Facebook groups. [35]

Service providers found that mHealth encouraged trust with patients while creating a collaborative environment with other health staff [40-42,46]. mHealth was found to provide professional peer support [40,46] while streamlining clinical communication and encouraging service provider collaborations [42].

Communication across services working with the same client may help to ensure nonoverlapping of interventions and resources. [42]

Australian service providers noted mHealth broke down the barriers of patient engagement, “equalising the power imbalance often present in their relationships with clients” [40]. Service providers attributed this to the app acting as an impartial entity, encouraging person-centered care [40]. First Nations, Inuit, and Métis youth in Canada explained that having a mobile phone would enable them to connect with health professionals as well as on behalf of peers in emergency situations [34]. Youth in Australia found that mHealth provided connection to service providers while adding anonymity and privacy to the navigation of their mental health journey.

Some may have felt known in a small community or simply hesitant to engage a service because they felt uncomfortable. The app allowed them a choice in health care that was previously unavailable. [37]

mHealth Content Needed to Be Culturally Relevant

End users stated the importance of mHealth including culturally relevant imagery and language to enable engagement, trust, and relatable connection. The inclusion of culturally relevant language and imagery was important for Indigenous patients to encourage engagement and build trust in mHealth content [31,33,37,38,46-47]. Likewise, service providers suggested the need for culturally applicable imagery and language in mHealth content in several studies [39-41,43,44,46,47]. End users suggested the translation of mHealth content to traditional language would enable comprehension of content as well as increase uptake [31,33,40,43,46].

Culturally relevant graphics, voices, animation, and optional short video clips may assist in engagement with the content, improve understanding, and overcome literacy issues. [31]

Recommended features of a technology resource included a look and feel that was user-friendly, aesthetically pleasing (e.g., more visuals, Indigenous artwork and potentially Indigenous language for more remote communities), easy to read, quick to navigate, and interactive (e.g., notifications, touch screen, user online status shown). [46]

Yet, the acknowledgment of diversity in cultural relevance was an important implication noted by Indigenous patients [31,33,38], namely, the tailoring of dialect [31,38] and that content be appropriate to the local cultural peoples [33], to ensure mHealth is not dismissive of cultural diversity.

Findings suggest mHealth can assist in developing cultural competence through gaining a better understanding of cultural diversity, histories, and traditional languages. In Australia, Indigenous patients advised the importance of including cultural determinants such as colonization, intergenerational trauma, and identity within mHealth content [31,38]. In Aotearoa, New Zealand, Māori patients chose to use traditional terminology in the thematic findings of mHealth exploration, acknowledging the importance of the cultural determinants of health [33,35]. mHealth was found to be an important resource to support culturally competent health care delivery for locum service providers in Canada.
Respondents expressed gratitude that the app now exists as an important tool for use in training and orienting new hires to Nunavut's cultural and language context. [39]

**mHealth Security and Confidentiality**

Security and privacy consistently emerged with Indigenous patients across several studies with differing views and implications [31,34,35,37,46]. Povey et al. [31] found Indigenous patients were largely dismissive of privacy issues with regard to mHealth, noting that personal information held on phones such as photos, or emails being seen would worry them more. There were, however, concerns raised about the privacy and confidentiality of information being shared during group discussions embedded in mHealth [46]. In addition, Māori women felt a sense of intrusion when using their mobile phone to seek health advice [35]. This intrusion was due to third-party systems, not necessarily a mHealth resource.

...emphasised privacy concerns whereby they encountered personalised advertising on Google and Facebook that was based on previous searches done on the device. [35]

Importantly, mHealth offered the opportunity of anonymous support for patients wishing not to engage with health services face to face [31,34,37]. Access to their own phone provided a sense of privacy and a safety net for Indigenous patients in Canada [34]. Likewise, Indigenous patients in Australia appreciated the facility of remote support seeking with the avoidance of unwanted in-person contact.

The ability to interact with the app privately, without anyone else needing to be present, meant that youth who may have been reluctant or afraid to speak to family members or health care professionals in a face-to-face setting could still access support. [37]

**mHealth Supporting Rather Than Replacing Service Providers**

Service providers stated the importance of mHealth needing to support established workloads and practices rather than being an onerous addition to established workloads. Service providers raised uncertainties about the sustainability of mHealth, and how their roles and responsibilities may change with the implementation of mHealth [40-42,44,46]. The perceived “lack of fit” with established work practices was a professional barrier identified [40,42,44]. Service providers suggested that mHealth should be considered as a complementary resource in addition to “in person” and physical resources [40,41,46]. Service providers in Australia found mHealth may be more useful for staff lacking experience and confidence in health practice.

Gatekeepers less experienced in suicide prevention may find a resource more useful than more experienced or confident gatekeepers. [46]

Service providers saw the benefit of mHealth as an educational tool to develop skills and knowledge. Service providers in Australia liked the health promotion opportunity a smartphone-enabled electrocardiogram (ECG) provided [45]. Service providers in Papua New Guinea valued the guidance capabilities mHealth provided them for clinical malaria treatment procedures [43]. Service providers in Australia identified mHealth as an appropriate resource to gain professional skills and knowledge in interviewing and counseling [40,44]. A smartphone-enabled ECG (ie, iECG) was found to have an indirect educational effect on service providers in Australia.

Some staff also spoke of how using the device for screening led them to want to learn more about AF and cardiovascular disease themselves in their professional role. [45]

**Workplace and Organizational Capacity**

Workplace leadership, capacity, and strategic direction emerged as influencing factors to the uptake and sustainability of mHealth for service providers working with Indigenous populations [39,40,42,44,45].

Workplaces that have leaders and champions to drive and support mHealth were a central factor in enabling mHealth uptake. The presence of enthusiastic managers and eager IT champions had a positive effect on the workforce’s interest in mHealth resources with service providers in Australia [42,44]. Workplace leaders that did not perceive the need for or effectiveness of mHealth were often a barrier to the uptake by service providers [42,44]. The advocacy of mHealth from leadership was an influencing factor to acceptance:

Having leaders within the organization showing interest and providing direct support was perceived to facilitate uptake. It created incentives and provided opportunities for service providers to reflect and evaluate the utility of the electronic mental health approach. [42]

Workplace staff capacity and retention contributed to the opportunities service providers had to commit to mHealth implementation [40,42,44]. High turnover of staff contributed to a lack of sustained mHealth knowledge and skill within the workplace [40,42,44]. The significance of investment into continued staff training and development was seen as important for mHealth success [40,42,44]. Limited workload capacity due to underresourcing impeded mHealth delivery [40,42,44] and restricted service providers’ capacity to engage in mHealth.

...in many services, demanding workloads left the workers with little or no opportunity to incorporate new skills into their existing work practices... [44]

A workplace culture that supports and drives the use of health innovations was shown to positively impact service providers’ perception of mHealth. The absence of health innovation priorities in workplace strategies caused a sense of ambivalence and ineptness toward the need for mHealth among service providers [39,42,44]. Workplaces that invested in systems, valued innovation, and had supportive leadership, positively influenced service providers’ perception and engagement with mHealth tools [40,42,44]. Alignment of the health innovation with organizational principles was found to influence uptake.
Uptake of electronic mental health approaches was dependent upon the perceived fit of the innovation to the organization’s priorities. [42]

Discussion

Principal Results

This review found that both Indigenous patients and service providers are enthusiastic about the role that mHealth can play in health service delivery.

Common themes across end users were: importance of mHealth or digital literacy, mHealth as a facilitator for connection and support, mHealth content needed to be culturally relevant, and data security and confidentiality are a priority. Two themes emerged that were unique to service providers: the importance of mHealth supporting rather than replacing service providers and the role of workplace champions and organizational capacity for influencing the uptake and sustainability of mHealth.

In this review, most included studies stated the importance of relevant cultural imagery and language, which enabled greater comprehension of mHealth messaging and increased engagement by end users [31-33,37-41,43,44,46,47]. Cultural content needs to account for the heterogeneity of Indigenous peoples, appropriate to location, language, people, and knowledge systems. This creates a challenge for mHealth developers and researchers alike in having 1 product with the capability to be distributed to a culturally diverse audience. Regarding language, Varnfield et al [49] increased their scope of patient engagement with their mHealth app being “available in several different selected languages.” This demonstrates that mHealth has the potential to be adaptive with its content.

Similar to the included study findings of this review, mHealth has been shown to enable patients to engage with their health care providers more effectively as well as connect with peers on similar health care journeys [21]. Moreover, our findings support other reviews reporting health care providers who found mHealth improved communication between their patients and colleagues [15,16].

Our findings showed the importance of workplaces and their leadership in influencing the uptake of mHealth [39,40,42,44,45]. Likewise, Palacholla et al [50] found leadership and organizations that were supportive and facilitated digital health adoption in clinical settings. An important factor when implementing health service innovation is localized agenda setting being led by need, want, and appropriateness [51]. Within a mHealth context, Gagnon et al [52] found health professionals considered their workplace environment as one of the top contributing factors to adoption. Engaging health care organizations as a partner to support mHealth may offer the greatest opportunity for sustained uptake.

Other systematic reviews conducted to understand the influencing factors to mHealth uptake show a strong correlation with the findings presented here. Namely, the principal influencers for adoption are the mHealth design, personal perceptions of mHealth, and the workplace environment [16,21,52], which suggest that co-design may offer an effective methodology for sustained mHealth uptake with Indigenous populations and service providers that work with Indigenous populations.

Early engagement with the Indigenous community within eHealth research and implementation has shown to offer the greatest opportunity for acceptability, and local advocacy [22,23,53,54]. Moreover, this model of prioritizing community partnership and co-design is recommended by governing ethical guidelines on research with Indigenous peoples internationally to achieve beneficial research outcomes [55-58]. Despite this, Eyles et al [59] found a lack of co-design methods for minority and Indigenous groups internationally in the development of mHealth interventions. With the novelty of mHealth along with the cultural considerations involved in the study population, it would be practical to enter a colearning and cocreation relationship to achieve mutually beneficial outcomes.

In conclusion, there has been considerable growth in qualitative research exploring contextual factors in relation to mHealth uptake in non-Indigenous populations, yet less so for Indigenous populations. To our knowledge, this is the first review of qualitative studies that provides an understanding of the influential factors for both patients and service providers for Indigenous populations in relation to mHealth.

Strengths, Limitations, and Future Directions

Having 2 reviewers from diverse cultural backgrounds and gender orientations independently screening improved the quality of this meta-synthesis. The authors are a multidisciplinary team with a breadth of expertise in this review focus (psychology, digital health, qualitative research, and Indigenous health). Using a meta-aggregative approach to analyze the findings ensured cultural learnings identified by researchers’ conducting the original studies were not lost by the reviewers. The quality appraisal tool used a modified version of the CASP qualitative checklist, with the additional question locating the researchers’ cultural or theoretical standpoint, improving the cultural rigor of this critical appraisal tool. Most studies were of medium to high quality, and the quality appraisal tool can be found in Multimedia Appendix 2.

Our review has some limitations; first, the searches were restricted to peer-reviewed literature published in 5 databases (PubMed, CINAHL, Embase, PsyCINFO, and Web of Science). Second, publication bias may have occurred due to the subjective quantifying of studies reporting on one or more outcomes via qualitative research methods. Finally, the results of this study are based on the meta-synthesis of qualitative data, which is inherently subjective. There are studies included from all countries (except the Sápmi region), but there are still only a few studies in each country, and so more work is needed. Papers need to report not only on patients’ perspective but other end users to gain a full understanding of the perceptions of mHealth in supporting health care with Indigenous populations.

Conclusions

This review used meta-aggregation to summarize the findings of 17 qualitative studies on the experiences and perceptions of mHealth with Indigenous populations and the service providers that work with Indigenous populations. mHealth end users are enthusiastic about the role that mHealth can play in Indigenous
health service delivery. There is a need for mHealth design to center end users within a co-designed approach with Indigenous people. There is recent work driving this agenda in an Australian context [60]. Allowing end users to suggest localized agenda setting through co-design may provide an opportunity for ownership, championship, and mitigation of barriers in mHealth implementation. Future research should partner with key representatives (eg, patients, health care professionals, and executive leaders) in the mHealth design appropriate to the purpose, people, setting, and delivery.

Acknowledgments
To ensure a culturally inclusive lens, our authorship reflects a diversity of the background, career stage, gender, and race. Specific to the focus of the manuscript AG and RM are Indigenous, and GS and SL are non-Indigenous. AG is an Aboriginal PhD candidate from Iningai country in Central West Queensland, Australia. AG has spent more than 13 years as an Indigenous health worker in Queensland alongside rural and remote Aboriginal and Torres Strait Islander people in the discipline of cardiac and health care services. RM is Aboriginal, a descendant of the Bidjara people of Central Western Queensland, Australia. RM is an Aboriginal health leader and researcher and has worked extensively to implement best practice cardiovascular care, particularly for Aboriginal and Torres Strait Islander peoples. GS is a General Practitioner at the Inala Indigenous Health Service in Brisbane, Queensland, and a General Practice academic at The University of Queensland. SL is a public health academic, with research interests in broad reach interventions to improve health outcomes in priority populations. We thank The University of Queensland for the support of this review via an Indigenous higher degree by research Development Grant. The funder of the study had no role in study design, data collection, data analysis, data interpretation, or writing of the report. All authors had full access to the full data in the study and accept responsibility to submit for publication.

Data Availability
The search strategy is available in Multimedia Appendix 1. Any additional data are available upon request from the corresponding author.

Authors’ Contributions
AG and SL conceptualized the study design, retrieved, analyzed, and interpreted the research data on which the scholarly work is based. AG and SL prepared the manuscript with significant input and critical review from RM and GS. All authors have read and approved the manuscript.

Conflicts of Interest
None declared.

Multimedia Appendix 1
Qualitative systematic review search string example.
[PNG File, 250 KB - mhealth_v11i1e45162_app1.png ]

Multimedia Appendix 2
CASP tool with additional JBI question.
[PDF File (Adobe PDF File), 98 KB - mhealth_v11i1e45162_app2.pdf ]

References


Abbreviations

CASP: Critical Appraisal Skills Programme
ECG: electrocardiogram
mHealth: mobile health
PROSPERO: International Prospective Register of Systematic Reviews
Abstract

Background: Over the past few decades, there has been a rapid increase in the number of wearable sleep trackers and mobile apps in the consumer market. Consumer sleep tracking technologies allow users to track sleep quality in naturalistic environments. In addition to tracking sleep per se, some sleep tracking technologies also support users in collecting information on their daily habits and sleep environments and reflecting on how those factors may contribute to sleep quality. However, the relationship between sleep and contextual factors may be too complex to be identified through visual inspection and reflection. Advanced analytical methods are needed to discover new insights into the rapidly growing volume of personal sleep tracking data.

Objective: This review aimed to summarize and analyze the existing literature that applies formal analytical methods to discover insights in the context of personal informatics. Guided by the problem-constraints-system framework for literature review in computer science, we framed 4 main questions regarding general research trends, sleep quality metrics, contextual factors considered, knowledge discovery methods, significant findings, challenges, and opportunities of the interested topic.

Methods: Web of Science, Scopus, ACM Digital Library, IEEE Xplore, ScienceDirect, Springer, Fitbit Research Library, and Fitabase were searched to identify publications that met the inclusion criteria. After full-text screening, 14 publications were included.

Results: The research on knowledge discovery in sleep tracking is limited. More than half of the studies (8/14, 57%) were conducted in the United States, followed by Japan (3/14, 21%). Only a few of the publications (5/14, 36%) were journal articles, whereas the remaining were conference proceeding papers. The most used sleep metrics were subjective sleep quality (4/14, 29%), sleep efficiency (4/14, 29%), sleep onset latency (4/14, 29%), and time at lights off (3/14, 21%). Ratio parameters such as deep sleep ratio and rapid eye movement ratio were not used in any of the reviewed studies. A dominant number of the studies applied simple correlation analysis (3/14, 21%), regression analysis (3/14, 21%), and statistical tests or inferences (3/14, 21%) to discover the links between sleep and other aspects of life. Only a few studies used machine learning and data mining for sleep quality prediction (1/14, 7%) or anomaly detection (2/14, 14%). Exercise, digital device use, caffeine and alcohol consumption, places visited before sleep, and sleep environments were important contextual factors substantially correlated to various dimensions of sleep quality.

Conclusions: This scoping review shows that knowledge discovery methods have great potential for extracting hidden insights from a flux of self-tracking data and are considered more effective than simple visual inspection. Future research should address the challenges related to collecting high-quality data, extracting hidden knowledge from data while accommodating within-individual and between-individual variations, and translating the discovered knowledge into actionable insights.

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KEYWORDS

sleep tracking; knowledge discovery; data mining; personal informatics; self-experimentation; sleep health; scoping review; mobile phone
**Introduction**

In tandem with the advent of consumer wearable technologies, there has been a growing interest in using consumer sleep tracking technologies for personal health management. Being aware of the importance of having a good night’s sleep, many individual users are routinely monitoring their sleep [1-3], and sleep tracking has been a popular topic, especially in the quantified-self community. Consumer sleep tracking technologies are largely divided into 2 types: smartphone dependent and smartphone independent. Smartphone-dependent sleep tracking technologies leverage the integrated sensors of a smartphone (eg, accelerometer, gyroscope, and microphone) to measure body movements and ambient sound, based on which a user’s sleep states can be estimated. Smartphone-independent sleep tracking technologies use independent hardware with multiple sensing modalities, such as accelerometers and photoplethysmography. These devices often come in the form of a wristband (eg, Fitbit [Fitbit Inc] and Apple Watch [Apple]), headband (eg, SleepShepherd [Sleep Shepherd] and Neuroon [Vandrico Inc]), or finger ring (eg, Oura [Oura Health Oy]), and they rely on proprietary sleep staging algorithms to calculate sleep metrics based on measurable physiological signals [4]. The accuracy of these consumer technologies has been significantly improved over the years. Recent models have proven to be reasonably accurate, especially in measuring the time of sleep onset and offset, total sleep duration, and sleep efficiency (SE) [5-7]. A recent study comparing 7 consumer sleep tracking devices with polysomnography (the gold standard of sleep measurement) demonstrated that their validity could outperform medical-grade actigraphy [6]. In the past decade, sleep tracking has become one of the most studied topics in the research field of personal informatics. At the intersection of ubiquitous computing, human-computer interaction, and sleep science, researchers from multiple disciplines have made joint efforts to investigate the validity of existing consumer sleep tracking devices [5-10], develop accurate sleep staging algorithms tailored to consumer sleep tracking devices [11-15], develop smartphone apps for visualizing personal sleep data [16-19], develop artificial intelligence–based sleep coaching systems that help people improve sleep hygiene [20], and understand the challenges for sleep tracking technologies to eventually improve sleep health [3,21-23]. At a higher level, sleep tracking studies have mostly been guided by general self-tracking frameworks, such as the lived informatics model [24] and the Preventive Health care on Individual Level framework [25]. Both frameworks emphasize the iterative exploration and analysis of the self-tracking data to gain insight and drive behavioral changes.

One of the known challenges in sleep tracking is how to empower layperson users to make sense of their sleep data and to identify lifestyle or environmental factors that they can modify for better sleep [22]. In the field of health informatics, health data analytics could be divided into multiple levels according to their analytical capabilities [26]. Depending on its outcomes, health analytics can be descriptive, diagnostic, predictive, or prescriptive in nature [27]. At the lowest level lies *descriptive analytics*, which answers the question, *what happened?* This level of analytics describes data *as is* without applying complex calculations and exploration. Common techniques at this level, such as standard reports and alerts, focus on categorizing, characterizing, aggregating, and classifying data to understand the past and current states. Existing sleep tracking analytics is mostly centered on this level, which aims to help users gain a *nice-to-know* validation of their subjective perception of sleep. At the second level is *diagnostic analytics*, which focuses on possible antecedents and answers the question, *why did it happen?* This level of analytics requires extensive exploration and directed analysis and inference based on existing data to identify the potential problems and their probable causes. At the third level lies the *predictive analytics*, which focuses on the possible consequences and answers the question, *what is likely to happen next?* Sleep tracking technologies at this level should be able to predict users’ sleep quality in the near or far future by examining their historical self-tracking data, detecting patterns, and then leveraging the patterns to forecast. The highest level of analytics is *prescriptive analytics*, which answers the question, *what should be done about it?* It uses domain knowledge in medicine and health science in addition to data to generate recommendations for health interventions (eg, recommendations for better sleep).

Table 1 provides a mapping of the 4 levels of the analytics framework by Burke [26] for sleep tracking. The descriptive analytics would focus on answering questions such as “How many hours did I sleep last night?” “How many awakenings did I have last night?” and “What is the average deep sleep ratio during the past one month?” So far, sleep tracking has predominantly centered on such descriptive analytics, typically by visualizing data with charts and tables on a dashboard. This type of application could be meaningful in understanding users’ current sleep patterns. However, with a flux of multiple models of sensor data, simple data visualization may miss important patterns that are not easily observable through visual inspection. As the complexity of sleep tracking data increases, it becomes necessary to examine the data in a more structured manner using advanced analytics. For example, diagnostic analytics could help answer questions such as “Was my sleep normal?” or “Why did I have so many awakenings last night?” Predictive and prescriptive analytics could answer questions such as “How will my sleep quality be in five years if I keep going to bed at 2:00 am?” or “Will I sleep better tonight if I work out 10 minutes longer in the morning?” To achieve advanced analytics, it is necessary to combine different streams of contextual information into a sleep analysis. Although many consumers’ sleep tracking systems support the simultaneous collection of multiple streams of contextual information, these data are often visualized separately and rarely integrated with sleep analysis. Currently, there is a paucity of advanced analytics in sleep tracking research.

Knowledge discovery is the process of finding meaningful patterns from data, and data mining is a central step within a knowledge discovery process. Popular data mining techniques, such as association rules mining and anomaly detection, are widely used in many application domains to detect hidden patterns in large data sets [26]. In this paper, we present a scoping review on the application of knowledge discovery
methods in sleep tracking. Such a review is useful for technical researchers interested in applying a wide range of machine learning and data mining techniques to the personal health domain as well as for sleep scientists who want to leverage the latest wearable technology combined with a data-driven approach for personalized and nonpharmaceutical interventions. Previous reviews on consumer sleep tracking technologies have dominantly focused on the utility and validity of these devices, especially in terms of their strengths and limitations relative to more widely accepted devices [4,28,29]. To the best of our knowledge, this scoping review is the first to focus on the advanced data analytics related to sleep tracking. An advanced data-driven approach has the potential to discover meaningful patterns or hidden correlations that could be used to guide behavioral change for better sleep. On the basis of the scoping review, we highlight the research opportunities for data-driven sleep computing.

Table 1. Level of analytics and its mapping to sleep tracking.

<table>
<thead>
<tr>
<th>Analytics level</th>
<th>Questions answered</th>
<th>Mapping to sleep tracking</th>
</tr>
</thead>
<tbody>
<tr>
<td>Descriptive</td>
<td>What has happened?</td>
<td>“How many hours did I sleep last night?”</td>
</tr>
<tr>
<td>Diagnostic</td>
<td>Why did it happen?</td>
<td>“Why did I have so many awakenings last night?”</td>
</tr>
<tr>
<td>Predictive</td>
<td>What is likely to happen next?</td>
<td>“How will my sleep quality be in five years if I keep going to bed at 2:00 am?”</td>
</tr>
<tr>
<td>Prescriptive</td>
<td>What should be done about it?</td>
<td>“Will I sleep better tonight if I work out 10 minutes longer in the morning?”</td>
</tr>
</tbody>
</table>

**Methods**

**Research Questions**

This scoping review was guided by the problem-constraints-system framework, which is widely used for conducting a literature review in computer science. The problem-constraints-system framework focuses on 3 different aspects of a research topic in computing research: a specific problem of interest (P); systems, applications, or algorithms (S) for tackling the problem; and constraints (C). After iterative brainstorming, we proposed the following 4 research questions (RQs) to anchor the entire review process:

- **RQ1:** What is the general research trend of knowledge discovery in sleep tracking?
- **RQ2:** What sleep quality metrics and contextual factors were considered, and how were they measured?
- **RQ3:** What knowledge discovery methods or algorithms were applied? What knowledge was discovered?
- **RQ4:** What challenges exist? What are the opportunities for future research?

**Search Strategy and Query String**

In this review, we focused on the application of data mining to identify the relationships between sleep and contextual factors with consumer wearable devices. Therefore, search results must contain all 4 pertinent aspects: sleep metrics, contextual factors, wearable devices, and knowledge discovery. Automated searches were conducted in a number of databases, including the Web of Science, Scopus, ACM Digital Library, IEEE Xplore, ScienceDirect, Springer, Fitbit Research Library, and Fitabase. As our review was centered on the computing aspect rather than the clinical aspect of sleep tracking, we used databases that focus more on engineering and computer science publications, including the ACM Digital Library, IEEE Xplore, ScienceDirect, and Springer. PubMed was not used because we were not interested in cohort studies or medical assessments. We also included gray literature such as the Fitbit Research Library and Fitabase because of their relevance to our topics of interest. The query strings were slightly different for each database but always contained 4 main keyword combinations: “sleep,” “lifestyle” AND “contextual,” “data mining” OR “knowledge discovery,” and “wearable device.” Synonyms words and words of related concepts (eg, “self-tracking,” “sensors,” “machine learning,” “correlation,” and “statistics”) were also listed to avoid missing out on related publications. The search strategy varied for each search engine, as each of them had different rules and options. The query string was truncated in some databases (eg, Web of Science, ScienceDirect, and IEEE Xplore) either because long query strings resulted in many irrelevant entries or because of word limit. We included several types of publications, including journal articles, conference proceeding papers, workshop presentations, patents, and gray literature, to gain a broad scope of the research topic. Editorial articles, theses, and dissertations were also excluded.

**Study Selection**

The study selection process is shown in the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart in Figure 1. We applied the following exclusion criteria to filter out irrelevant papers retrieved from the databases: (1) studies not related to human sleep (eg, animal studies and sleep mode of sensor system), (2) clinical studies aiming at treating sleep disorders, (3) hypothesis-driven laboratory-based studies using invasive sleep tests (eg, polysomnography), (4) validation studies focusing on comparing wearable devices with medical devices, (5) studies focusing on estimating sleep architecture based on concurrent physiological signals, and (6) papers not written in English. We retrieved the returned entries from each database and imported them into the web-based review management software Rayyan (Rayyan). All databases provided tools to export the returned entries in a single file, except for the Fitbit Research Library and Fitabase. We exported only 400 of the 2072 papers from the ScienceDirect because the rest of the papers were not relevant to our review topic. For the ScienceDirect database, the returned items were first listed using the “relevant order” tool provided by the database. We used an a priori condition to include the first 400
items. For the remaining items, we separated them into groups of 200 items and randomly checked 50 items in each group. We found that from the 400th item onward, the studies were off the topic according to our exclusion criteria. Thus, we eliminated these items because they did not help address our central RQs. For example, the keyword “contextual” led to the retrieval of papers in civil engineering on checking bedroom quality with air condition, ambient light, and noise exposure. Those were excluded based on the exclusion criterion 1. The keyword “wearable device” led to the retrieval of papers in electrical and mechanical engineering on hardware design for sensors, batteries, and ergonomic design. Those were excluded based on the exclusion criterion 4. For the Fitbit Research Library, 2 papers were missing because they were either retracted or no longer available. Entries in Fitbase were screened for duplicity before manually adding to Rayyan because Fitbase does not support automatic export. As many of the Fitbase entries were duplicates of publications from other databases, only 37 papers were added to Rayyan.

Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart of article screening process.

In total, 1999 papers were imported to Rayyan. Screening for duplication and written language was performed automatically in Rayyan. After the rapid screening step, the first author performed title and abstract screening and suggested the inclusion of 341 papers. The second author repeated the title and abstract screening of the 341 papers while paying special attention to the exclusion criteria 3 and 5. Any conflicts were resolved through discussion with the first author. After the screening and eligibility checks, 29 papers remained. Both authors read the full text of the 29 papers in detail and finally selected 14 papers for the scoping review.

Results

General Research Trend (RQ1)
Ubiquitous and personal sleep tracking has become an active research area since approximately 2011, when a few pioneer studies were published in the human-computer interaction community [17,18,30]. Since then, a large number of studies...
on sleep tracking have been published, but most of them are
dominantly centered on the validation of existing sleep tracking
devices or systems [5-10], on the development of new sleep
staging algorithms [11-15], or on the investigation into users’
experience with the technologies [3,21-23]. In contrast, studies
that focus on knowledge discovery in sleep tracking data are
scarce and ad hoc. The screening process identified only 14
relevant studies, of which more than half (8/14, 57%) were
conducted in the United States, followed by Japan (3/14, 21%).
The other publications were from China, Korea, Finland, and
Australia. Only 5 (36%) of the 14 publications were journal
articles, and the rest were conference proceeding papers.
Chronologically, studies by Jayarajah et al [31] and Gelman
and Hill [32] were one of the earliest studies in this field. The
authors developed a binary tree model to predict good and poor
sleep based on app use activity and social time during the day.
Since 2015, the topic of knowledge discovery in sleep tracking
has begun to attract more attention along with the advances in
consumer sleep tracking technologies. As a result, the number
of publications has increased slightly in the subsequent years,
but the total amount is still limited.

A common objective of these studies was to help users gain
insights into how their sleep quality was associated with other
aspects of their daily lives. Some of the specific motivations
are as follows:

- Identify aspects of daily life that demonstrate significant
  associations with personal sleep quality from self-tracking
data [16,20,33]
- Highlight the potential for sleep metrics from wearable
devices to provide novel insights into data generated from
a large cohort [34-36]
- Detect aberrant sleep patterns or typical events during sleep
  by considering individuals’ sleep baselines [37,38]
- Guide users in designing self-experiments to identify
  personal modifiable lifestyle factors for better sleep health
  [20]
- Develop a recommender system that provides both general
  and personalized recommendations for better sleep health
  [20]

The studies reviewed in this paper demonstrated a tendency to
analyze sleep tracking data along with a flux of contextual
factors. These factors were used as independent variables for
predicting sleep quality and, to a lesser degree, for identifying
antecedent events that affect sleep quality. In the scheme of
traditional sleep science studies, only a limited number of
independent variables were considered, and the confounding
effect of noninterested factors needed to be controlled through
a rigid experiment design. In comparison, data collection
experiments in ubiquitous sleep tracking studies are often
conducted in a naturalistic environment, making it challenging
to control for confounding factors. Therefore, advanced data
analysis techniques are required to control the effects of
confounding factors during the analysis. Another line of research
effort is the personalized detection of aberrant sleep. Although
sleep quality assessment may sound straightforward using
clinical standards [39], it remains challenging if personal
differences in sleep needs should be taken into consideration.
Studies in this direction are limited, and we identified only 2
relevant studies [37,40].

Quantification and Measurement of Sleep and
Contextual Factors (RQ2)

Human sleep can be quantified along multiple dimensions, such
as sleep duration, sleep continuity, sleep timing, and subjective
perception of the sleep event [41]. We found that not all studies
used the same set of metrics to characterize sleep quality. Even
the same sleep metric may be capsulated in different
terminologies across studies. To facilitate cross-study
comparisons, we mapped the sleep metrics in each study to
standard clinical terms, whenever possible. Original sleep
metrics that have no corresponding clinical terms were simply
left as they were. As presented in Table 2, the most used sleep
metrics among the reviewed studies were subjective sleep
quality (4 studies), sleep efficiency (SE, 4 studies), sleep onset
latency (SOL; 4 studies), and time at lights off (3 studies). Ratio
parameters such as deep sleep ratio and rapid eye movement
ratio were not used in any of the studies. Moreover, the cutoff
between good and poor sleep varied from study to study. A few
studies have adopted clinical cutoffs, particularly for the
Pittsburgh Sleep Quality Index (5) [31], SE (85%) [42], wake
after sleep onset (30 minutes) [16], and total sleep time (7-9
hours) [16]. The rest chose to use heuristic cutoffs that did not
comply with the clinical guidelines.
Table 2. Sleep quality metrics, measurement methods, and cutoff of good or poor sleep.

<table>
<thead>
<tr>
<th>Clinical term, original term, and measurement method</th>
<th>Cutoff</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Subjective sleep quality</strong></td>
<td></td>
</tr>
<tr>
<td>Pittsburgh Sleep Quality Index [31,38]</td>
<td>Good: ≤5 and poor: &gt;5 [31]; good: ≤7 and poor: &gt;7 [38]</td>
</tr>
<tr>
<td>Sleep rating (SleepAsAndroid app) [20]</td>
<td>N/A&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>Leeds Sleep Evaluation Questionnaire [19]</td>
<td>N/A</td>
</tr>
<tr>
<td>Sleep rating (SleepApp) [19]</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>SE&lt;sup&gt;b&lt;/sup&gt;</strong></td>
<td></td>
</tr>
<tr>
<td>SE (Fitbit) [33]</td>
<td>Good: ≥95% and poor: &lt;95%</td>
</tr>
<tr>
<td>Efficiency (MS Band) [43]</td>
<td>N/A</td>
</tr>
<tr>
<td>SE (Polar) [40]</td>
<td>Good: &gt;mean (SD) and poor: &lt;mean (SD)</td>
</tr>
<tr>
<td>SE (Garmin) [42]</td>
<td>Good: ≥85% and poor: &lt;85%</td>
</tr>
<tr>
<td><strong>SOL&lt;sup&gt;c&lt;/sup&gt; (minutes)</strong></td>
<td></td>
</tr>
<tr>
<td>Minutes to fall asleep (Fitbit) [16]</td>
<td>N/A</td>
</tr>
<tr>
<td>SOL (SleepAsAndroid app) [20]</td>
<td>N/A</td>
</tr>
<tr>
<td>Sleep latency (Garmin) [42]</td>
<td>Good: ≤15, average: 15-30, and poor: &gt;30</td>
</tr>
<tr>
<td>Time to fall asleep (MS Band) [43]</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Time at lights off</strong></td>
<td></td>
</tr>
<tr>
<td>Bedtime (Fitbit) [35]</td>
<td>Normal bedtime: median of a participant’s bedtimes; deviation categories were 1-30 minutes, 30-60 minutes, 1-2 hours, 2-3 hours, and ≥3 hours</td>
</tr>
<tr>
<td>Bedtime (Fitbit) [37]</td>
<td>N/A</td>
</tr>
<tr>
<td>Bedtime as estimated by the time of the last network signal [36]</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Wake after sleep onset (minutes)</strong></td>
<td></td>
</tr>
<tr>
<td>Awake minutes (Garmin) [42]</td>
<td>Good: ≤20 and poor: &gt;20</td>
</tr>
<tr>
<td>Minutes awake (Fitbit) [16]</td>
<td>Good: ≤30 and poor: &gt;30</td>
</tr>
<tr>
<td><strong>Number of awakenings &gt;5 minutes</strong></td>
<td></td>
</tr>
<tr>
<td>Awakenings &gt;5 minutes (Garmin) [42]</td>
<td>Good: ≤1 and poor: &gt;1</td>
</tr>
<tr>
<td>Number of wakeups (MS Band) [43]</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Time in bed (minutes)</strong></td>
<td></td>
</tr>
<tr>
<td>Time in bed (MS Band) [34]</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Total sleep time (minutes)</strong></td>
<td></td>
</tr>
<tr>
<td>Minutes asleep (Fitbit) [16]</td>
<td>Good: 420-540 and poor: &lt;420 or &gt;540</td>
</tr>
<tr>
<td><strong>Original metrics (no corresponding medical term)</strong></td>
<td></td>
</tr>
<tr>
<td>Sleep ratio—the ratio of the sleep minutes with normal heart rate versus total sleep time (Fitbit) [44]</td>
<td>Good: &gt;90%, normal: 60%-90%, and bad: &lt;60%</td>
</tr>
<tr>
<td>Number of awakenings per hour [20]</td>
<td>N/A</td>
</tr>
<tr>
<td>Awakening count including restlessness (Fitbit) [16]</td>
<td>N/A</td>
</tr>
<tr>
<td>Permutation entropy of Fitbit measured sleep state time series [37]</td>
<td>N/A</td>
</tr>
</tbody>
</table>

<sup>a</sup>N/A: not applicable.
<sup>b</sup>SE: sleep efficiency.
<sup>c</sup>SOL: sleep onset latency.

Sleep quality metrics were measured using 3 methods: questionnaire based, app based, and wearable based. The Pittsburgh Sleep Quality Index was the most widely used questionnaire to measure the subjective perception of sleep duration, continuity, efficiency, and satisfaction [31,38]. The SleepAsAndroid app was used to collect sleep data based on
user movement patterns in the study by Daskalova et al [20], and the SleepApp was used to collect users’ subjective sleep quality ratings in the study by Ravichandran et al [19]. Although sleep tracking apps such as SleepAsAndroid were widely downloaded and used by millions of users, their ability to distinguish between quiet awakenings, deep sleep, or empty beds was still limited [20]. In a related vein, studies by Jayarajah et al [31] and Faust et al [36] have defined sleep time as the longest period during which there was no activity on users’ smartphones. However, the authors acknowledged that this method was not reliable because not everyone had the habit of using smartphones until they fell asleep. Most studies (9/14, 64%) used commercial wearable devices such as Fitbit [16,33,35,37,44], Microsoft Band (MS Band) [34,43], Garmin [42], and Polar [40]. Although all 3 methods are noninvasive, easy to use, and allow longitudinal collection of sleep data, each method has some limitations. The questionnaire-based method is subject to memory recall bias. Sleep data collected by sleep tracking apps and wearable sleep trackers provide an objective description of sleep quality and sleep structure. However, they may also be prone to measurement errors because of hardware and software limitations [7,28]. They also require users to place the smartphone nearby or to wear the device continuously, which may cause discomfort during long-term use. Moreover, despite being small and convenient, consumer wearable trackers cannot provide hypnogram information that is as detailed as medical devices.

Along with sleep quality metrics, researchers have considered a wide range of contextual factors in their studies. As presented in Table 3, the contextual factors of interest include the sleep environment [16,20,42], daily activities [16,19,20,31,36,37,40,42,43], physiological states [16,35,36,43,44], and mental states [16,19]. It was a common practice to collect demographic information (eg, age, gender, and BMI) and medical history using questionnaires at the beginning of a sleep tracking study [16,35,36,43,44]. Other contextual factors were recorded during the data collection experiments. Researchers have been curious about how web activities of university students could be coupled with their sleep quality [31,34,36]. These studies developed their own tools to track users’ web-based behavior and linked them to sleep quality metrics. Using consumer wearable trackers such as Fitbit, MS Band, and Garmin, researchers were able to expand their list of factors to include, for example, bedtime, steps, distance, hours of exercise, and calories burned [16,19,20,31,36,37,40,42,43]. Biosignals such as heart rate during sleep and daytime activities were included in the studies by Faust et al [35], Farajtabar et al [43], and Choi et al [44]. Several studies have also manually collected input features such as coffee, alcohol, mood, and stress [16,19,20]. These factors may have a significant effect on the circadian cycle of hormone secretion and thus may provide useful information for sleep quality prediction. However, collecting these data are nontrivial, as users tend to forget to log the data on a daily basis. How to collect these data more efficiently and how to reduce the risk of missing data remain challenging.
<table>
<thead>
<tr>
<th>Contextual factor</th>
<th>Data collection method</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Physiological factors</strong></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>Self-report [43,44]</td>
</tr>
<tr>
<td>Sex</td>
<td>Self-report [36,43]</td>
</tr>
<tr>
<td>Body weight</td>
<td>Fitbit [16] and self-report [43]</td>
</tr>
<tr>
<td>BMI</td>
<td>Self-report [44]</td>
</tr>
<tr>
<td>Body temperature</td>
<td>Diary [16]</td>
</tr>
<tr>
<td>Heart rate</td>
<td>Fitbit [35,44] and MS Band [43]</td>
</tr>
<tr>
<td>Menstrual cycle</td>
<td>Diary [16]</td>
</tr>
<tr>
<td>Calorie in and out</td>
<td>Fitbit [16] and MS Band [43]</td>
</tr>
<tr>
<td>Activity calorie</td>
<td>Fitbit [16]</td>
</tr>
<tr>
<td><strong>Psychological factors</strong></td>
<td></td>
</tr>
<tr>
<td>Stress</td>
<td>Diary [16]</td>
</tr>
<tr>
<td>Mood</td>
<td>Diary [16] and SleepApp [19]</td>
</tr>
<tr>
<td>Tiredness</td>
<td>Diary [16]</td>
</tr>
<tr>
<td>Dream</td>
<td>Diary [16]</td>
</tr>
<tr>
<td>Sleep quality the previous night</td>
<td>SleepAsAndroid [20] and MS Band [43]</td>
</tr>
<tr>
<td>Cognitive performance</td>
<td>Keystroke time [34] and click time [34]</td>
</tr>
<tr>
<td><strong>Behavioral factors</strong></td>
<td></td>
</tr>
<tr>
<td>Steps</td>
<td>Fitbit [16,37] and MS Band [43]</td>
</tr>
<tr>
<td>Distance walked</td>
<td>Fitbit [37]</td>
</tr>
<tr>
<td>Active time</td>
<td>Fitbit [16,37]</td>
</tr>
<tr>
<td>Exercise</td>
<td>SleepAsAndroid [20], MS Band [43], Polar [40], Garmin [42], and SleepApp [19]</td>
</tr>
<tr>
<td>Coffee</td>
<td>Diary [16], SleepAsAndroid [20], and SleepApp [19]</td>
</tr>
<tr>
<td>Alcohol</td>
<td>Diary [16], SleepAsAndroid [20], and SleepApp [19]</td>
</tr>
<tr>
<td>Tobacco</td>
<td>Self-report [44] and SleepApp [19]</td>
</tr>
<tr>
<td>Electronic device use</td>
<td>App use time (total and different app categories) [31], diary [16], Bing search logs [43], SleepApp [19], and campus network [36]</td>
</tr>
<tr>
<td>Nap</td>
<td>Diary [16], SleepAsAndroid [20], and SleepApp [19]</td>
</tr>
<tr>
<td>Location</td>
<td>Campus Wi-Fi [31] and Cortana [43]</td>
</tr>
<tr>
<td>Social activity</td>
<td>GruMon (location estimation based on Wi-Fi signals) [31], diary [16], and Twitter [43]</td>
</tr>
<tr>
<td>Mealtime</td>
<td>Diary [16], smartphone camera [42], SleepApp [19], and campus smart card [36]</td>
</tr>
<tr>
<td>Waketime</td>
<td>SleepAsAndroid [20]</td>
</tr>
<tr>
<td>Bedtime</td>
<td>Fitbit [37], IoT sensor [42], and SleepApp [19]</td>
</tr>
<tr>
<td><strong>Environmental factors</strong></td>
<td></td>
</tr>
<tr>
<td>Ambient temperature</td>
<td>Diary [16] and IoT sensor [42]</td>
</tr>
<tr>
<td>Ambient humidity</td>
<td>Diary [16] and IoT sensor [42]</td>
</tr>
<tr>
<td>Ambient light</td>
<td>Diary [16] and SleepAsAndroid [20]</td>
</tr>
<tr>
<td>Ambient noise</td>
<td>SleepAsAndroid [20]</td>
</tr>
<tr>
<td>Day of week</td>
<td>MS Band [43]</td>
</tr>
</tbody>
</table>

IoT: internet of things.

We found that 13 (93%) of the 14 reviewed studies conducted their own data collection experiments [16,31,33,37,38,43,44] in free-living conditions. In these studies, sleep data were recorded in participants’ usual sleep environments (eg, homes...
and caregiving facilities), whereas contextual factors were recorded while participants were at schools, universities, workplaces, or sports centers. In contrast, only 1 study used an existing data set [35], which can be accessed over the web [45]. Data sharing is not yet a common practice in the field, and the number of public data sets is limited.

Knowledge Discovery in Sleep Tracking (RQ3)

Data Preprocessing

All the reviewed studies used data sets that were collected in free-living environments. Data collection “in the wild” increases the ecological validity of the studies but at the sacrifice of data quality. The first step in the knowledge discovery process is to deal with missing, wrong, and duplicate data. Although there are many methods for data cleaning in the literature, the methods adopted in the reviewed publications are extremely simple and straightforward. Most of the studies (5/14, 36%) simply excluded records that contain missing values (eg, sleep logs with missing fields or sleep duration of 0 minutes) [16,19,37] or excluded users who do not contribute sufficient data (eg, fewer than 30 sleep records) [35,36]. One study excluded a certain data source (eg, search engine interactions originating from mobile devices) to avoid causing distortion to the data distribution [34]. Similarly, data out of logical ranges were removed. Users aged <10 years or >100 years, with weight <22.7 kg or >112.5 kg, or with height <127 cm or >457.2 cm were excluded in the study by Farajtabar et al [43]. Extremely short (<0.5 or 4 hours) and long (>12 hours) sleep records were removed in the studies by Althoff et al [34] and Farajtabar et al [43]. Sleep entries with bedtime between 7:00 AM and 7:00 PM were removed in the study by Liang et al [33]. Exercise time is another criterion for filtering out potentially erroneous data records. For example, exercise events <5 or >180 minutes were removed in the study by Farajtabar et al [43]. Exercises with calorie consumption per hour <50 or >2000 calories or with a duration of <10 minutes were excluded in the study by Liu et al [40]. In addition, data records with steps <1000 and those with a sedentary time of 0 minute were removed in the study by Liang et al [16].

Time stamps are another focus in data preprocessing. The data collection in the study by Ravichandran et al [19] primarily relied on users’ manual input in SleepApp and thus had a higher risk of human errors. Consequently, all logs with aberrant timestamps were removed. In addition, 12 hours were added to or subtracted from the recorded bedtime or wake-up time where the users might have forgotten to toggle the AM and PM switch on the app. Dealing with timestamps involves not only data cleaning but also temporal matching among multiple data sources [42] as well as data type conversion (eg, 18:30 to 1830) [16,37]. Other types of data preprocessing included selecting users with larger variations in sleep and exercise [38], removing redundant entries [19], and resampling the raw data (eg, the photoplethysmography-derived heart rate time series was aggregated every 3 minutes to achieve a constant sampling rate [38]).

Some knowledge discovery processes that rely on machine learning or data mining techniques may require a feature engineering process instead of directly using the cleaned data as input. For example, several studies have involved the construction of secondary features from the cleaned data [37,38,40]. Features were normalized to have a mean and SD equal to 0 and 1 [42] or normalized over another feature (eg, exercise intensity features were normalized by dividing the basal metabolic rate [38]). Dimension reduction (eg, principal component analysis) was applied to reduce the number of input features to avoid the adverse effect of the “curse of dimension” [31].

Data Mining

The selection of the data mining method depends on the purpose of the studies and, to a lesser degree, on the size of the available data set. Table 4 provides a summary of the data mining methods and the specific techniques or algorithms used in the reviewed studies. We also listed the independent variables (or input) and dependent variables (or output) of the constructed models. Correlation analysis, regression analysis, and rule induction are the most used methods for finding meaningful associations between contextual factors and sleep quality metrics. In total, 3 correlation analysis techniques, Pearson correlation, Spearman correlation, and repeated measure correlation, were applied to examine the strength of the pairwise linear relationships between sleep and contextual factors [16,19,20]. Similarly, various regression analysis methods have been used, ranging from simple linear regression to linear mixed effects regression to piecewise fixed effects regression [34,35,43]. Least square estimation was the most popular technique for parameter estimation in regression analysis and was used in the studies by Althoff et al [34] and Farajtabar et al [43]. The study by Faust et al [35] provided no information but is highly likely to use the same technique. It is worth noting that the Pearson correlation coefficient is equivalent to the standardized slope of a simple linear regression line.
Table 4. Summary of the data mining methods used in the reviewed studies.

<table>
<thead>
<tr>
<th>Data mining method and techniques or algorithms</th>
<th>Data size</th>
<th>Independent variable</th>
<th>Dependent variable</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Correlation analysis</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pearson correlation [20]</td>
<td>Preliminary study: 24 users over 20 days; final study: 19 users over 21 days</td>
<td>TST&lt;sup&gt;a&lt;/sup&gt; and contextual factors</td>
<td>SOL&lt;sup&gt;b&lt;/sup&gt;, NAWK&lt;sup&gt;c&lt;/sup&gt;, and sleep rating</td>
</tr>
<tr>
<td>Spearman correlation [16]</td>
<td>12 users over 2 weeks</td>
<td>Contextual factors</td>
<td>TST, WASO&lt;sup&gt;d&lt;/sup&gt;, NAWK, SOL, and SE&lt;sup&gt;e&lt;/sup&gt;</td>
</tr>
<tr>
<td>Repeated measure correlation [19]</td>
<td>10 users over 2 weeks</td>
<td>Bedtime, TIB&lt;sup&gt;f&lt;/sup&gt;, and contextual factors</td>
<td>SE, SOL, NAWK, restlessness, TIB, and LSEQ&lt;sup&gt;g&lt;/sup&gt;</td>
</tr>
<tr>
<td><strong>Regression analysis</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Piecewise fixed effects regression [34]</td>
<td>31,793 users over 18 months; all American users</td>
<td>Time of day, time after waking up, and sleep duration</td>
<td>Cognitive performance</td>
</tr>
<tr>
<td>Simple linear regression [43]</td>
<td>Approximately 20,000 users over 4 months</td>
<td>Contextual factors</td>
<td>SOL, NAWK, and SE</td>
</tr>
<tr>
<td>Linear mixed effects model [35]</td>
<td>557 users over 1 year</td>
<td>Bedtime regularity</td>
<td>Resting heart rate</td>
</tr>
<tr>
<td><strong>Rule induction</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A priori algorithm [33]</td>
<td>1 user over 180 days; 4 users over 2 weeks</td>
<td>Contextual factors</td>
<td>SE</td>
</tr>
<tr>
<td>Learn from Examples using Rough Sets [44]</td>
<td>280 users over 1 month; only the data of males were used</td>
<td>Contextual factors</td>
<td>Sleep ratio</td>
</tr>
<tr>
<td>Event mining (+causal inference) [42]</td>
<td>1 user over 800 days</td>
<td>Contextual factors</td>
<td>SOL, WASO, NAWK, and SE</td>
</tr>
<tr>
<td><strong>Causal inference</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stratified propensity score analysis [43]</td>
<td>Approximately 20,000 users over 4 months</td>
<td>Contextual factors</td>
<td>SOL, NAWK, and SE</td>
</tr>
<tr>
<td>Bayesian network analysis [36]</td>
<td>5200 users over 6 months</td>
<td>Contextual factors and bedtime</td>
<td>Contextual factors and bedtime</td>
</tr>
<tr>
<td><strong>Time series analysis</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Anomaly detection [37]</td>
<td>1 user over 35 days</td>
<td>Fribit measured intra-day time series, TST, WASO, NAWK, and bedtime</td>
<td>Permutation entropy of sleep time series</td>
</tr>
<tr>
<td>SAX&lt;sup&gt;h&lt;/sup&gt;-based motif matching and principle optimization [38]</td>
<td>100 users over 10 weeks</td>
<td>Heart rate time series data</td>
<td>PSQI&lt;sup&gt;i&lt;/sup&gt;</td>
</tr>
<tr>
<td><strong>Statistical test</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unpaired 2-samples Wilcoxon test [40]</td>
<td>271 users over 8 months</td>
<td>Contextual factors</td>
<td>Statistical differences between good and poor sleep</td>
</tr>
<tr>
<td><strong>Decision tree</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>J4.8 Classifier [31]</td>
<td>400 users over 15 months</td>
<td>Contextual factors</td>
<td>PSQI</td>
</tr>
</tbody>
</table>

<sup>a</sup>TST: total sleep time.
<sup>b</sup>SOL: sleep onset latency.
<sup>c</sup>NAWK: number of awakenings.
<sup>d</sup>WASO: wake after sleep onset.
<sup>e</sup>SE: sleep efficiency.
<sup>f</sup>TIB: time in bed.
<sup>g</sup>LSEQ: Leeds Sleep Evaluation Questionnaire.
<sup>h</sup>SAX: Symbolic Aggregate Approximation.
<sup>i</sup>PSQI: Pittsburgh Sleep Quality Index.
Although correlation analysis and regression analysis (except piecewise constant approximation) capture the relationships between sleep and contextual factors in the entire sampling range, the piecewise regression in the study by Althoff et al [34] shared some resemblance with rule induction methods that capture the relationship between sleep and contextual factors within a constrained range. However, in contrast to piecewise regression, which quantifies the covariance between 2 variables in each partitioned segment, rule induction methods focus on extracting frequent patterns in the data sets that characterize the co-occurrence of 2 variables when their values fall into the corresponding ranges specified in a rule. Moreover, rule induction methods are usually robust to missing data. As the rule induction methods were originally developed to analyze categorical data, numerical data need to be converted to categorical data through a discretization step before rule induction methods can be applied. There are 4 discretization methods used in the reviewed studies: equal size discretization [33,44], equal frequency discretization [33], k-means clustering discretization [33], and discretization with heuristically defined cutoffs [42]. Association rules mining is a popular rule induction method that has been widely used in traditional medical and health informatics applications; however, it has only been used in 1 study among all the studies we reviewed [33]. In that study, the apriori algorithm was applied for rule induction. The quality of the induced association rules was validated by higher local correlation coefficients (ie, the Pearson correlation coefficient when the variables fall into the ranges specified in a rule) than the global correlation coefficients (ie, the Pearson correlation coefficient between 2 variables within the entire sampling range). To better handle the potential inconsistency (eg, conflicting records) in the data set, Rock-Hyun et al [44] applied another rule induction algorithm named learning from examples using rough sets. The global covering algorithm computes the lower and upper approximations of all the target sleep quality metrics (eg, sleep ratio="good") if the input data set contains conflicting records. The quality of the induced rules was assessed based on the predictive accuracy of the target sleep metrics. Although association rules mining and learning from examples using rough sets capture only the parallel co-occurrence of 2 items (ie, when the values of 2 variables fall into the corresponding ranges specified by a rule), event mining can also capture the co-occurrence of 2 items with a time lag (ie, the temporal sequence when the 2 items occur) [46]. To a certain degree, event mining resembles sequential pattern mining [47]; however, this characteristic was not used in the study by Upadhyay et al [42].

Causal inference is a powerful approach to reduce potential bias in the identified relationships between sleep and contextual factors because of observed confounding factors. This method is likely to outperform simple correlation analysis or rule induction–based methods. In the study by Farajtabar et al [43], stratified propensity score analysis was performed to isolate the effects of potential confounding factors. A similar technique was used in the study by Upadhyay [42] to enhance the quality of the induced rules by accommodating confounding factors. In addition, the Bayesian network was applied to explore the relationship between sleep schedules and behavioral factors [36]. Statistical tests and decision trees were also used in the existing literature, but only in 1 study each. The unpaired 2-samples Wilcoxon test was applied to identify significant differences in a set of selected contextual factors between good and poor sleepers [40]. Despite its simplicity, this method does not generate quantitative relationships between the contextual factors and sleep quality. In contrast, decision trees were used in the study by Jayarajah et al [31] to predict sleep quality using contextual factors as input features.

In addition to the abovementioned methods, time series analysis was also used but only in 2 studies [37,38]. Dimension reduction and anomaly detection were combined to identify aberrant sleep recordings while counting in personal sleep baseline in the study by Liang et al [37]. Feng and Narayanan [38] introduced a method to discover motifs in heart rate time series, which were signal patterns that appeared most frequently during sleep [38]. They then used these motifs as features to predict sleep quality. In contrast, although the study by Upadhyay et al [42] adopted a streaming data perspective, it did not incorporate any formal time series analysis technique [39].

**Knowledge Discovered**

The knowledge discovery process in the reviewed studies identified interesting associations both at the cohort level and the individual level. First, significant associations were found among the sleep quality metrics. Late bedtime was associated with a higher permutation entropy of the Fitbit measured sleep time series (indicating a higher chance of aberrancy) [37]. Bedtime deviation was correlated to longer SOL [19]. In addition, sleep duration was positively associated with subjective sleep satisfaction [19,20].

Regarding the relationship between sleep quality and contextual factors, exercise was the most identified association factor [33,40], but the relationship between exercise and sleep was complex [40,43]. First, not all exercise features have a predictive power of sleep quality. For example, Liu et al [40] found that exercise duration, relative calories consumption, and exercise timing could be used as predictors of sleep quality, but exercise intensity was not significantly associated with sleep quality. Second, exercise may be positively associated with some sleep quality metrics but negatively associated with others. For example, exercise before bed may be linked to shorter SOL and higher SE [43], and exercise seems to improve SOL the most among all the sleep quality metrics [42]. However, the results diverged as different types of exercises were considered. Taking more steps meant fewer awakenings, whereas running and burning more calories were correlated with more awakenings [43]. Moreover, longer exercise duration (eg, >100 minutes) may be associated with good sleep for some users but poor sleep for others [40]. Furthermore, confounding factors may modulate the relationship between sleep and exercise. With causal inference, it was found that pleasant ambient temperature at bedtime significantly strengthened the relationship between exercise and sleep, whereas having a poor sleep the previous night detracted from the beneficial effects of exercise [42].

Digital device use is another important factor that correlates with sleep quality and sleep schedule. No web searches before bed correlated with shorter SOL and higher SE, whereas web...
searches before bed correlated with more awakenings [43]. The association between app use and sleep quality was modulated by the frequency and timing of use [31]. In particular, low social app use was associated with good sleep, and more app use correlated with good sleep if used for >4 hours before sleep. Reading and gaming app use within 1 hour before bedtime correlated with poor sleep. A strong connection between internet surfing habits and bedtime was identified by Guo et al [36]. Video lovers tended to go to bed later than game fans. Going to bed late, in turn, has negative consequences. Deviations from usual bedtime may result in a higher resting heart rate during sleep [35]. Students who went to bed late were more likely to have a poor academic performance [36]. Late bedtime (in relation to one’s circadian cycle) reduced cognitive performance the next day, whereas early bedtime did not have the same negative effect [34]. In contrast, having a sufficient sleep was important for maintaining normal cognitive performance [34].

As expected, caffeine and alcohol consumption were significant association factors. Consuming caffeine late in the day was a universal negative factor in subjective sleep ratings [20]. Alcohol consumption was positively correlated with SE and wake-up freshness and was negatively correlated with wake after sleep onset and number of awakenings for some users but not all users [16].

Not just personal activities or substance consumption associated with sleep, but places visited before bedtime and social life also play a role. One study found that students who spent more time with friends had better sleep quality than those who stayed alone on campus most of the time [31]. In addition, if students spent most of their time outside campus, good quality sleep was found for those who spent <15% of their time being alone. Another study tracked users’ location during the day and stated that users took longer to fall asleep if they visited food-related or bank-related locations close to bedtime [43]. In addition, sleep quality may vary depending on the environment in which sleep takes place. The most common relationship identified for many users by Daskalova et al [20] was the pair of noisiness and number of awakenings [16]. Temperature was positively associated with all sleep metrics except for SOL [42].

Challenges and Opportunities (RQ4)

Knowledge discovery in sleep tracking is the process of extracting nonobvious hidden knowledge from self-tracking sleep data and other available contextual information. Preparing a data set of a sufficient size is the first step in this process. Almost all the reviewed studies (13/14, 93%) conducted original data collection experiments using noninvasive wearable and mobile sensors. The existing literature highlighted several challenges of data collection in sleep tracking. First, the absence of an objective, quantifiable, and universal definition of good sleep places a big challenge in annotating the collected sleep data [16,19]. Without a well-annotated data set, it is not feasible to apply supervised data mining techniques, and the absence of ground truth impedes the unbiased evaluation of the knowledge discovery process. Second, some contextual factors are considered difficult to quantify. These factors include digital device use, caffeine and alcohol consumption, and social interaction [16], to name but a few. The timing of data logging may also influence the results [20]. For example, users were advised to avoid using digital devices 2 hours before bedtime but had to log on to their smartphones to submit daily data at the end of the day. Third, existing passive sensing methods may have strong limitations [34]. For example, some studies (2/14, 14%) assume that users check their smartphone right before bedtime and immediately after waking up [31,36] and thus may miss out on users who have no such habits. Consumer wearables may have limited accuracy in measuring sleep stages and other factors [7], but the issue of data quality was not considered in the reviewed studies [35].

Moreover, interpreting the knowledge discovery outcome is not always straightforward. Correlation analysis essentially captures the covariance of 2 variables. Users with regular sleep and daily life routines may end up with no significant correlations found because of the lack of variability in their data. However, users may misinterpret this as having no relationship [16]. Rule induction methods usually generate a large number of rules, but not all of them are useful. Long rules with too many factors in the antecedent, despite of being explainable, provide no actionable insights because of their complexity (eg, “IF 17.85 < BMI < 25.21 AND Smoking is Yes AND 61.81 < Normal_Avg_HR < 79.0 AND 0 < Normal_Awake <19.0 AND 1.5 < Normal_Really_Awake < 24.00 AND 1.5 < High_Asleep < 606.5 AND 1.5 < High_Awake < 155.0 AND 0.5 < High_Really_Awake < 175.5 THEN Sleep Quality Status is ‘Bad’ with support 8”) [44]. In contrast, short association rules may be more comprehensible (eg, “minutes very active={33; 38}=> good sleep or steps={18,658; 20,263}=> good sleep” [33]). However, heuristic discretization without a semantic meaning may impede understandability [20].

Despite the challenges, the reviewed studies highlighted several opportunities for future research. In total, 3 studies suggested considering more contextual factors in addition to the ones already studied, such as emotion, diet, productivity, and chronotypes [31,34,36,42]. Acknowledging that the correlations at a cohort level may be weak [31], argues for an individual-centric approach to identifying the most important contextual factors for each user. Along the same line [43], it was pointed out that building predictive models within similar user groups is more practical. They proposed a hierarchical modeling scheme with a top layer containing population parameters and lower layers personalized to individual users. Similar user profiling and segmented modeling proposals were presented in the studies by Liang et al [33] and Farajtabar et al [43].

Discussion

Principal Findings

Sleep tracking using consumer wearable devices and mobile apps has attracted remarkable attention from the research community. However, sleep tracking studies have focused on developing sleep tracking technologies for accurately measuring sleep per se, and little attention has been directed to the extraction of patterns and insights from these data. To the best of our knowledge, this scoping review is the first to map the
existing literature from a knowledge discovery perspective in sleep tracking.

Our analysis results showed that the number of publications on the topic of interest has slightly increased over the years but is still low, probably because the data-driven scheme has not been fully embraced in personal informatics. Nonetheless, we found that the existing literature covered all 4 levels of analytics, as presented in Table 1. Most of the 14 studies that we reviewed applied simple correlation analysis, regression analysis, and rule induction methods to discover the associations between sleep and other aspects of life. Although most consumer sleep tracking technologies allow users to visually inspect their sleep data (which is descriptive in nature), the reviewed studies demonstrated the feasibility of diagnostic analysis with a flux of sleep and contextual data. Although correlation does not necessarily indicate causality, a combination of association analysis and causal inference—as was done in the study by Upadhyay et al [42]—may help users narrow down the scope of possible modifiable factors that are likely to affect their sleep quality. Machine learning and data mining techniques were only used in a few studies for anomaly detection (which is diagnostic) [37] or sleep quality prediction (which is predictive) [31,43]. In total, 2 studies developed computational models to generate personalized recommendations for better sleep and showed promise in prescriptive analysis of sleep tracking [20,42]. The most used sleep metrics among the reviewed studies were subjective sleep quality, SE, SOL, and time at lights off. Exercise, digital device use, places visited during the day and before bedtime, and sleep environment are the major factors that significantly correlate with various dimensions of sleep quality.

Taken together, there are a few key challenges that are relevant to the findings. On the one hand, it is nontrivial to collect high-quality data in naturalistic settings. Challenges include how to motivate users to overcome tracking fatigue, how to enhance the reliability of consumer wearables and apps, and how to quantify and automate the collection of contextual information to represent the current challenges surrounding the collection of sleep tracking data sets. On the other hand, how to extract hidden knowledge from data, how to accommodate commonness and individuality, and how to interpret data mining results are topics for future studies.

**Nuance in Handling Within-Individual Variation**

The selection of appropriate data mining methods relies on a correct understanding of the nature of the sleep tracking data set. Researchers often conduct longitudinal data collection experiments that involve the collection of multiple measurements of the same variables (eg, sleep quality, exercise, and ambient light) from each individual user. The data form a hierarchical or clustered structure when aggregated at the cohort level. Caution must be exercised when applying traditional analytic and modeling techniques developed for single-level data, as hierarchical data are likely to violate the assumption of independent errors of those techniques. In particular, although a hierarchical data set offers the benefit of a larger amount of data, the within-individual variation at the individual level needs to be addressed carefully through multilevel analysis and modeling.

In a multilevel analysis framework, the repeated measures are clustered within the level of an individual, and each individual is treated as a cluster unit. Depending on whether the analysis of one cluster involves pooling the data of other clusters, there are 3 approaches to analyzing a hierarchical data set: complete pooling, no pooling, and partial pooling. Complete pooling completely ignores the variation between individual users and treats all samples as being drawn from the same population. A dominant portion of the studies reviewed in this work [16,31,33,34,36,38,40,43,44] adopted this approach. Nonetheless, this approach is undesirable, as it violates the assumption of independence. The results could have been distorted when the between-individual variation was high. At the other end of the spectrum lies the no pooling approach, where the analysis of the relationship between sleep and contextual factors was performed only on the data of each individual user without considering data from other users. Daskalova et al [20] Upadhyay et al [42] embraced an N-of-1 design and correspondingly adopted the no pooling approach to analyze the collected data. At the surface, this approach is plausible for fully handling the within-individual variation. However, it bears the risk of overstating the variation between individual users because of potential overfitting when the number of samples from individual users is small. Partial pooling or multilevel modeling compromises between pooled and unpooled estimates, with the relative weights of pooling determined by the sample size of each individual user and the variation within and between individuals. Multilevel modeling automatically adjusts the degree of pooling with a “soft constraint,” which ensures strong pooling for users with fewer records and weak pooling for users with abundant records in the data set [32]. We found that only Ravichandran et al [19] and Faust et al [35] used the multilevel modeling approach and explicitly considered the within-individual variation.

Most reviewed studies (8/14, 57%) seem to have relied on the undue assumption of an independent and identically distributed data set. As a result, some studies (2/14, 14%) found mixed or even conflicting results on the relationships between sleep and contextual factors at the cohort level [40,44] and, consequently, generated no valuable insights. Studies using an N-of-1 design are interesting exceptions. In these studies, analysis was conducted on each user’s data, thus eliminating the effect at the cohort level. However, the robustness and generalizability of the findings are questionable. Even in studies with an N-of-1 design, it may still be helpful to partially pool some samples from the population to increase the reliability of the model parameter estimates. As such, Gelman et al [48] suggested always using multilevel modeling (ie, “random effects”) as a rule of thumb, for example, linear mixed effect model over simple linear regression model and generalized linear mixed model trees [49] over the J4.8 classifier.

**Limitations of the Study**

There is room for improvement in several aspects of this study. First, because of the limitations inherent in scoping reviews, this study is exploratory and primarily qualitative in nature.
Limited by the review methodology, we were unable to generate a quantitative “summary of findings,” as required for systematic reviews or meta-analyses. Second, our method is nonstandard in a sense that we performed prescreening on the items identified in the ScienceDirect database before importing all entries into Rayyan. Although we made an effort to ensure that the removed items were not relevant, we cannot rule out the possibility of missing publications that should have been included. Third, we did not conduct critical appraisal on the quality of the selected papers or perform a risk of bias assessment, which may have led to potential bias in the selection and interpretation of the papers. Despite these limitations, this review provides a well-scope summary of existing research and could lay the groundwork for future systematic reviews. The research gaps that we identified can be used to inform future research agendas.

Conclusions

This scoping review built an understanding of the scope and nature of existing literature on knowledge discovery in ubiquitous and personal sleep tracking. To the best of our knowledge, this is the first review that exclusively focused on the knowledge discovery aspect of self-tracking in the realm of sleep health. In total, 14 studies were included in the review based on the exclusion criteria. We found that the existing literature covered all 4 levels of the analytics framework in health informatics. However, half (7/14, 50%) of the studies have only applied simple correlation analysis and regression analysis, aiming to discover significant associations between sleep and available contextual information. Machine learning and data mining techniques have not yet been widely used, probably because of the lack of large and quality data sets. Exercise, digital device use, places visited during the day and before bedtime, and sleep environment were the most identified factors associated with sleep quality. We identified key challenges surrounding the collection of high-quality sleep tracking data sets with consumer-grade sensors and in naturalistic settings as well as the extraction of hidden knowledge that could be translated into actionable insights and personalized behavior interventions. We highlight that future research should develop data analytics techniques and prediction models that properly handle the within-individual variation and between-individual variation in sleep tracking data sets. We hope that this scoping review could lay the groundwork for future research on ubiquitous and personal sleep tracking.

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Authors’ Contributions

ZL contributed to study conception. ZL and NHH contributed to study design, analysis and interpretation of results, and manuscript drafting and revision. NHH collected the data. All authors have reviewed the results and approved the final version of the manuscript.

Conflicts of Interest

None declared.

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Abbreviations

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RQ: research question
SE: sleep efficiency
SOL: sleep onset latency
Digital Technologies for Women’s Pelvic Floor Muscle Training to Manage Urinary Incontinence Across Their Life Course: Scoping Review

Stephanie J Woodley¹, BPhy, MSc, PhD; Brittany Moller¹, BSc (Hons); Alys R Clark², BA, MMathSc, PhD; Melanie D Bussey³, BPE, MSc, PhD; Bahram Sangelaji¹, PT, PhD; Meredith Perry³, BPhy, MManipTh, PhD; Jennifer Kruger³, BSc, MSc, PhD

¹Department of Anatomy, School of Biomedical Sciences, University of Otago, Dunedin, New Zealand
²Auckland Bioengineering Institute, University of Auckland, Auckland, New Zealand
³School of Physical Education, Sport and Exercise Sciences, University of Otago, Dunedin, New Zealand
⁴Southern Queensland Rural Health, Brisbane, Australia
⁵School of Physiotherapy, University of Otago, Wellington, New Zealand

Corresponding Author:
Stephanie J Woodley, BPhy, MSc, PhD
Department of Anatomy
School of Biomedical Sciences
University of Otago
270 Great King Street
Dunedin, 9016
New Zealand
Phone: 64 276680828
Email: stephanie.woodley@otago.ac.nz

Abstract

Background: Women with urinary incontinence (UI) may consider using digital technologies (DTs) to guide pelvic floor muscle training (PFMT) to help manage their symptoms. DTs that deliver PFMT programs are readily available, yet uncertainty exists regarding whether they are scientifically valid, appropriate, and culturally relevant and meet the needs of women at specific life stages.

Objective: This scoping review aims to provide a narrative synthesis of DTs used for PFMT to manage UI in women across their life course.

Methods: This scoping review was conducted in accordance with the Joanna Briggs Institute methodological framework. A systematic search of 7 electronic databases was conducted, and primary quantitative and qualitative research and gray literature publications were considered. Studies were eligible if they focused on women with or without UI who had engaged with DTs for PFMT, reported on outcomes related to the use of PFMT DTs for managing UI, or explored users’ experiences of DTs for PFMT. The identified studies were screened for eligibility. Data on the evidence base for and features of PFMT DTs using the Consensus on Exercise Reporting Template for PFMT, PFMT DT outcomes (eg, UI symptoms, quality of life, adherence, and satisfaction), life stage and culture, and the experiences of women and health care providers (facilitators and barriers) were extracted and synthesized by ≥2 independent reviewers.

Results: In total, 89 papers were included (n=45, 51% primary and n=44, 49% supplementary) involving studies from 14 countries. A total of 28 types of DTs were used in 41 primary studies, including mobile apps with or without a portable vaginal biofeedback or accelerometer-based device, a smartphone messaging system, internet-based programs, and videoconferencing. Approximately half (22/41, 54%) of the studies provided evidence for or testing of the DTs, and a similar proportion of PFMT programs were drawn from or adapted from a known evidence base. Although PFMT parameters and program compliance varied, most studies that reported on UI symptoms showed improved outcomes, and women were generally satisfied with this treatment approach. With respect to life stage, pregnancy and the postpartum period were the most common focus, with more evidence needed for women of various age ranges (eg, adolescent and older women), including their cultural context, which is a factor that
is rarely considered. Women’s perceptions and experiences are often considered in the development of DTs, with qualitative data highlighting factors that are usually both facilitators and barriers.

**Conclusions:** DTs are a growing mechanism for delivering PFMT, as evidenced by the recent increase in publications. This review highlighted the heterogeneity in types of DTs, PFMT protocols, the lack of cultural adaptations of most of the DTs reviewed, and a paucity in the consideration of the changing needs of women across their life course.

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**KEYWORDS**

apps; culture; life course; mobile health; mHealth; pelvic floor muscle training; urinary incontinence; women’s health; mobile phone

**Introduction**

**Background**

Pelvic floor muscle (PFM) dysfunction, which most commonly manifests as urinary incontinence (UI), pelvic organ prolapse, and pain, is a major and often unreported problem for women. UI, defined as “any involuntary leakage of urine” [1], affects between 25% and 45% of women worldwide, yet the true prevalence is likely to be higher, with women underreporting UI because of the associated shame and embarrassment [1]. UI substantially affects quality of life (QoL) in relation to both women’s physical and mental health and well-being and also represents a major economic burden (eg, costs associated with routine care and treatment) [2].

PFM training (PFMT), which includes exercises to increase PFM strength and endurance, is recommended as the first choice for managing UI, especially stress UI [1]. PFMT can be undertaken by women to maintain pelvic health by preventing the onset of UI or can cure or improve symptoms and enhance QoL in adult and older women, including during pregnancy and the postpartum period [3,4]. However, despite its effectiveness, approaches to PFMT vary across communities and countries, and maintaining exercise programs, which are often undertaken at home, is difficult [5]. In addition, many women avoid seeking treatment for UI based on the belief that UI is an inevitable consequence of aging or childbirth, or the perception that little can be done to improve symptoms or QoL, or because of limited access to health services [6].

Digital technologies (DTs; such as the World Wide Web; eHealth; and mobile health [mHealth], including SMS text messaging and apps) provide an avenue for women with UI to seek guidance with PFMT and potentially improve their symptoms and QoL [5-8]. To elicit health benefits, women require access to DTs based on the best scientific evidence. However, although the market appears to be flooded with PFMT apps, few have been scientifically validated in terms of content, quality, or appropriateness [9,10]. In addition, knowing whether PFMT delivered via DTs is sound from a clinical perspective is equally important, but there is a lack of information as to whether PFMT in this context is based on contemporary evidence [11]. This is potentially compounded by the notion that few mHealth apps have been developed in collaboration with key stakeholders, such as women experiencing UI or health care professionals [12].

Factors such as age and culture may influence how women engage with PFMT DTs. For example, there is evidence that women are more vulnerable to developing UI at certain stages in life, including (1) young athletic women, particularly those participating in high-impact sports [13]; (2) during and after pregnancy, when one-third of women giving birth for the first time have UI, which may persist for at least 3 months post partum; (3) menopause, where a peak in UI occurs; and (4) older women (UI prevalence ranges from 43% to 77%), particularly those in residential care, where UI is a substantial risk factor for falls [1]. On the basis of this evidence, age-appropriate and specific PFMT programs seem imperative to best cater to women, yet there appears to be a distinct lack of information related to the uptake of DTs to manage UI at different stages in life [11]. Culture, which encompasses particular spiritual, intellectual, and emotional features, including lifestyle, value systems, traditions, and beliefs [14], not only affects how women interact with DTs [15,16] but also shapes their experiences and attitudes toward UI [15-17]. Although it is essential to understand how culture may affect the use of and engagement with PFMT DTs, with reference to UI, it is unclear whether the experiences and needs of women from different cultures or ethnic groups are considered when developing these types of DTs.

**Objectives**

Several systematic reviews have recently been published in this field, mostly focusing on the effectiveness of PFMT DTs in terms of improving symptoms of UI and QoL along with adherence to the prescribed PFMT program [7,8,18-21]. In this context, knowledge of the quality and content of PFMT DTs is also important, as is an understanding of whether such DTs are designed for women across their life course and take into account the cultural contexts and experiences of women and other relevant stakeholders. The main aim of this scoping review was to provide a narrative synthesis of digital health technologies used for women’s PFMT to manage UI. The key objectives of this review were to (1) explore whether PFMT DTs follow best-practice guidelines and describe outcomes related to their use, (2) establish whether DTs have been designed for PFMT at specific stages in life or consider culture, and (3) describe users’ experiences of DTs for PFMT.

**Methods**

This scoping review was conducted in accordance with the Joanna Briggs Institute methodological framework [22] and the
PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) [23]. A protocol was prospectively registered with the Open Science Framework [24].

**Search Strategy**
Following an initial search in PubMed, a systematic search of 7 electronic databases (AMED, CINAHL, Embase, MEDLINE, SPORTDiscus, Scopus, and PsycINFO) was conducted to identify relevant literature (from inception to December 2021). Key search concepts related to (1) DTs (eg, smartphones, cell phones, apps, telemedicine, and mHealth), (2) UI, (3) PFMT or exercise, and (4) key life stages (eg, pregnancy and menopause). Hand searching of reference lists of included articles, as well as citation tracking (eg, Web of Science for the last 5 years), was used to identify additional articles that may have been eligible for screening and inclusion (Multimedia Appendix 1).

**Study Selection Criteria**

**Population**
Studies were included if they (1) focused on women aged ≥14 years with or without UI who were using or had used some form of DT to engage in PFMT, (2) evaluated outcomes related to the use of PFMT DTs for managing UI, or (3) explored users’ experiences of DTs for PFMT. Studies were excluded if the research focus was on women with overactive bladder or enuresis or neurological conditions, they reported collective data for men and women unless the data specific to women could be extracted separately, they used biofeedback devices that were not connected to an app or any other form of eHealth, and they were published in a language other than English for which a translation could not be acquired (eg, through Google Translate).

**Concept**
This review considered studies that explored PFMT delivered via DTs for the management of UI—with a focus on the evidence base for DTs and PFMT—the life course, culture, and users’ experiences. The use of DTs for health (PFMT) is defined as “a broad umbrella term encompassing eHealth (which includes mHealth), as well as emerging areas, such as the use of advanced computing sciences in ‘big data,’ genomics, and artificial intelligence” [25]. In addition to eHealth, other applications such as wearable devices with a digital component (eg, a vaginal biofeedback probe connected to a mobile app), telehealth, and personalized medicine are encompassed within the scope of DTs.

**Context**
Studies that met the previously defined criteria were included to establish the widest coverage of information related to PFMT delivered via DTs for managing UI. This encompassed a large and heterogeneous group of women with or without UI, health care providers (HCPs) or researchers, and other disciplines (eg, IT experts). Any type of health care setting (eg, primary care and community) or discipline (eg, physiotherapy and general practitioners) was considered.

**Study Design**
Research involving quantitative and qualitative study designs and other forms of gray publications, such as opinion pieces, editorials, conference abstracts, theses, and case studies or series, were considered [26].

**Study Selection**
Titles and abstracts were independently screened by 5 authors (AC, BS, JK, MB, and SW) using web-based software (Covidence systematic review software; Veritas Health Innovation). The full texts were read and assessed by 2 of the 3 authors (BM, BS, and SW), with discrepancies resolved through consensus or discussion with another member of the team.

**Data Extraction and Verification**
A customized template was developed in Microsoft Word (Microsoft Corp) and piloted on 5 of the included studies. Data were independently extracted into the template by 5 authors (MB, AC, JK, BM, BS, and SW), transferred to a Microsoft Excel (Microsoft Corp) spreadsheet, and cross-checked by 2 authors (BS and SW). Any disagreements were resolved through consensus or consultation with a third reviewer when necessary. The data extracted related to general study and participant characteristics included authors; year of publication; country; study aims; sample size; inclusion and exclusion criteria (intervention and comparator groups if relevant); age, gender, and level of education of participants; type of UI; and duration of symptoms.

To address the key objectives of this review, the data outlined in Textbox 1 were extracted.
Data Synthesis

The included studies that shared common author teams or apps were grouped accordingly. Descriptive statistics were used to summarize the data (BM, BS, and SW). With the exception of the study protocols, the methodological quality of the included studies was independently appraised using the relevant Joanna Briggs Institute critical appraisal tools [29] by pairs of reviewers, with a third reviewer consulted to reach a consensus if required.

For qualitative studies or the qualitative components of mixed methods studies, thematic synthesis, with the development of analytical themes driven by our review questions (ie, deductive analysis), was used for data synthesis [30] (MP and SW). The analysis occurred over 3 steps, with the last step designed to present clear implications for HCPs and policy makers. First, coding of text segments from the results and discussion specific to the review objectives was performed from sections of the included articles. Next, the raw codes were grouped and named in an iterative manner to form descriptive themes (grouped by the study’s reported main themes and women’s or clinician’s perceptions of facilitators of and barriers to the use of DTs). Finally, analytical themes were generated from descriptive themes, and these analytical themes extended the synthesis beyond the conclusions of the included articles. Data were grouped for both barriers and facilitators under the headings of interactions between users and eHealth, interactions between users and PFMT exercises, and interactions between PFMT exercises and eHealth [31,32]. Although other tangential themes were generated, we presented the themes that were most coherently related to the study objectives.

Deviations From the Protocol

Owing to the large number of papers retrieved, a decision was made to exclude systematic reviews, meta-analyses, and scoping reviews from the analysis, which represents a deviation from the study protocol. Similarly, because of the number of DTs included in this review, we did not classify the types of DTs using the World Health Organization (WHO) classification [33] or rate the apps using the Mobile App Rating Scale [34].

Results

Search Results and Characteristics of the Included Studies

From the 7444 records screened for titles and abstracts, and after the removal of duplicates, 288 (3.87%) full-text reports were reviewed (Figure 1). A total of 89 papers met the inclusion criteria, of which 45 (51%) were classified as primary papers, with the other 44 (49%) considered supplementary papers (Table S1 in Multimedia Appendix 2 [5,6,11,12,31,35-118]; Table S2 in Multimedia Appendix 2 presents the inclusion and exclusion criteria for the included studies [5,6,11,12,31,35-118]). Of the 45 primary studies, many were randomized controlled trials (RCTs; n=13, 29%), with various other designs including cross-sectional studies (n=7, 16%); qualitative studies (n=6, 13%); mixed methods studies combining either RCTs or quasi-experimental trials with qualitative research (n=4, 9%); quasi-experimental studies (n=4, 9%); cohort studies (n=4, 9%); case series (n=4, 9%); and a case report, case-control, and validation study; of these 45 studies, 6 (13%) were study protocols and 2 (4%) were published in a language other than English (Dutch [35] and Portuguese [36]). The supplementary articles consisted of follow-up studies, secondary analyses, associated abstracts reporting a subset of data from the primary article, and author comments and letters to the editor (eg, [89,90,92-99,102-106,108-118]). Publications in this area have increased rapidly since the 2010s, with most protocols registered since 2019 (Figure 2). The methodological quality was rated for 84% (38/45) of the primary studies and was predominantly high (15, 39%) or fair (14, 37%), with 24% (9/38) considered poor (Multimedia Appendix 3 [5,6,36-41,43-46,48-51,53,57-59,61-77,80]).

Key methodological areas for consideration included blinding of participants, therapists, and outcome assessors; measuring...
outcomes in a valid and reliable way and identifying confounding factors (cross-sectional studies); and consecutive recruitment of participants (case series), although aspects such as double-blinding are recognized as problematic in pragmatic and clinical trials.

**Figure 1.** PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) study flow diagram—search for papers related to digital technologies (DTs) and pelvic floor muscle training (PFMT) for women.

**Figure 2.** Publications included in this review presented by year of publication. RCT: randomized controlled trial.
The studies originated in 14 countries, primarily from Europe (9/45, 20% from Sweden; 7/45, 16% from the Netherlands; 3/45, 7% from Spain; and 1/45, 2% from Germany), as well as the United States (6/45, 13%), the United Kingdom (4/45, 9%), Brazil (4/45, 9%), China (4/45, 9%, including Hong Kong), Australasia (4/45, 9%), Canada (1/45, 2%), Japan (1/45, 2%), and Malaysia (1/45, 2%). A total of 47% (21/45) of the studies had a total sample size of <50, 9% (4/45) recruited between 50 and 100 participants, and 44% (20/45) of the studies sampled >100 participants (2/20, 10% of which analyzed data from a sample of >10,000 women; Multimedia Appendix 3).

### Participant Characteristics

#### Age

The age of the participants ranged from 18 to 98 years, with approximately 35% of studies (16/45, 36%) including women in their 40s or 50s as the average age. The level of education of the recruited participants was stated for just over half (24/45, 53%) of the primary studies. Among these, most women in each study were shown to be educated at the university level.

#### UI in the Included Studies

Studies mostly recruited women with stress UI only (17/45, 38%) [5,6,37-51], whereas 7% (3/45) of the studies included those with stress and mixed UI if stress symptoms were predominant [52-54], and 24% (11/45) included a mixture of stress, urge, and mixed UI types [55-65]. In total, 11% (5/45) of the studies included healthy (continent) and incontinent participants [66-70], and 11% (5/45) did not clearly specify the UI type [71-75], and this was irrelevant in 7% (3/45) [36,70,80]. Only 2% (1/45) of the studies [76], a case study, looked at urge UI only. A total of 20% (9/45) of the studies documented the duration of women’s UI symptoms before their inclusion in the study. Of these, Asklund et al [5] required participants to have had symptoms for at least 6 months as part of their inclusion criteria. The remaining 18% (8/45) of the studies [38,40,43,46,51,61,64,65] showed variable durations, ranging from <3 months to 26 years (Multimedia Appendix 3).

#### Stage in Life

A total of 17 (38%) of the 45 studies reported life stage parameters: 29% (5/17) recruited women in the postpartum period [67-69,75,77]; 18% (3/17) recruited pregnant women [47,51,60]; 12% (2/17) included both pregnant and postpartum women [52,66]; 6% (1/17) included postmenopausal women [59]; and 24% (4/17) reported including a mixture of premenopausal, perimenopausal, postmenopausal, lactating, and postpartum participants [45,46,58,62]. A case study [76] included women reported as parous and Campbell et al [42] recruited athletic women for their RCT.

### Cultural Context

Some studies developed the DTs for use by women in their specific countries (eg, Sweden [5], Japan [68], and Germany [70]), and the Tat has been translated into a number of different languages [56,63,78].

One group conducted a systematic review to explore variables that may influence adherence to PFMT DTs, which led to the development of the iPelvis app [11,57]. The authors emphasized the importance of considering ethnicity as part of a woman’s individuality, and as such, the avatar character within the iPelvis app can be ethnically matched to the woman by altering features such as skin color, the flag of the country, and cultural costumes, as well as age and stage in life (eg, pregnant or older adult). This concept was supported by Han et al [72], who stated that the information in apps needs to be formatted in a culturally relevant way to ensure that it is effective. The importance of ongoing research to evaluate apps in different and diverse cultural contexts was acknowledged in 7% (3/45) of the studies [72,73,79].

#### DTs in the Included Studies

### Overview

Among the 45 primary studies, data related to DTs and PFMT were not extracted from 4 (9%)—1 (25%) [55] analyzed data collected from 3 previous RCTs [5,6,64], and 3 (75%) qualitative studies [46,77,80] took a broad approach without focusing on a specific technology for the delivery of PFMT. Therefore, the data and information in the following sections were derived from 91% (41/45) of the studies, some of which used the same DTs (eg, Tat, Leva, and Pen Yi Kang: Table 1).

https://mhealth.jmir.org/2023/1/e44929
Table 1. Summary of digital technologies (DTs) and their features.

<table>
<thead>
<tr>
<th>Study</th>
<th>DT Description</th>
<th>BTraining or support in use of DT</th>
<th>Gamification</th>
<th>Self-monitoring</th>
<th>R and R</th>
<th>Social media features</th>
<th>Mobility requirement(s)</th>
<th>EF^a</th>
<th>DE^b</th>
<th>EF^c</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anglès-Acedo et al [37,38]</td>
<td>Mobile app—WOMEN UP</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>NI</td>
<td>Internet; Bluetooth</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes;</td>
</tr>
<tr>
<td>Araujo et al [39]</td>
<td>Mobile app—Diário Saúde</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>No</td>
<td>Internet</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Asklund et al [5]; Asklund and Samuelsson [66]; Nystöm et al [73]; Rygh et al [63]; Samuelsson et al [50]</td>
<td>Mobile app—Tät</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>No</td>
<td>Internet</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Wadensten et al [64]</td>
<td>Mobile app—Tät II</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>No</td>
<td>Internet</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Bokne et al [41]</td>
<td>Internet-based program—Tät</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>No</td>
<td>No; no</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Firet et al [56]</td>
<td>Internet-based program—Tät</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>NI</td>
<td>Internet</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Sjöström et al [6]</td>
<td>Internet-based program—Tät</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>No</td>
<td>Internet; Bluetooth</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Barbato et al [40]</td>
<td>Internet-based program</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>No</td>
<td>Internet</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Campbell et al [42]</td>
<td>Mobile app—Squeezy App</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>No</td>
<td>Internet; Bluetooth</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Robson [74]</td>
<td>Mobile app—Squeezy App</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>No</td>
<td>Internet; Bluetooth</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Carrón Pérez et al [43]</td>
<td>Telehabilitation device and vaginal probe</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>NI</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Coggins et al [44]</td>
<td>Mobile app and vaginal device—Elvie</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>NI</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Conlan et al [45]</td>
<td>Telehealth</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>NI</td>
<td>Internet</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Cornelius [71]</td>
<td>Mobile app and vaginal probe—PeriCoach</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>NI</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Shelly [76]</td>
<td>Mobile app and vaginal probe—PeriCoach</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>NI</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Smith [53]</td>
<td>Mobile app and vaginal probe—PeriCoach</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>NI</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Dufour et al [67]</td>
<td>Mobile app and vaginal device—iBall</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>NI</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Goode et al [58]</td>
<td>Web-based—My-HealththeBladder</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>Yes</td>
<td>Internet</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Han et al [72]</td>
<td>Mobile app—Bwom</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>NI</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Hui et al [59]</td>
<td>Telemedicine continence program (video-conferencing)</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>No</td>
<td>No; no</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Jaffar et al [60]</td>
<td>Mobile app—KEPT-app</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>NI</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Kinouchi and Ohashi [68]</td>
<td>Smartphone-based reminder system</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes;</td>
<td>NI</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
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<tr>
<td>Woodley et al</td>
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</table>
Types of DTs (Consensus on Exercise Reporting Template for PFMT Item 1)

A total of 28 types of DTs were used across the 41 studies. Just over 40% (12/28, 43%) of these were solely mobile apps, 4% (1/28) trialed a smartphone-based messaging system, 11% (3/28) were internet-based programs, and 7% (2/28) were dedicated to videoconferencing. A total of 32% (9/28) of the technologies involved the use of a portable vaginal biofeedback or accelerometer-based device [36-38,43,44,48,49,53,54,62,67,71,76] that provided real-time feedback transmitted via Bluetooth to a mobile app or, in one instance, to a computer application [43]. In addition to the vaginal device, electromyographic data were integrated from surface electrodes attached to the abdominal muscles [37,38] or PFMs [36].
**Evidence Base or Previous Testing of DTs**

A total of 54% (22/41) of the studies provided some evidence base for or testing of the DTs [5,41,50,51,56,58,61,63-66,69,73,74], which had been either undertaken in the development stage or as an iterative process (eg, Tåt) or was one of the specific purposes of the study [11,36-38,47,48,60,75]. Some studies (4/41, 10%) implemented a design framework (eg, Reach, Effectiveness, Adoption, Implementation, and Maintenance framework [47] or the Fit Between Individuals, Task, and Technology framework [56]) in their trials. The development of the technologies generally involved collaboration, testing, and input from IT experts (such as hardware or software engineers) and HCPs or researchers with relevant clinical expertise (eg, obstetricians, women’s health physiotherapists, and nurses) and feedback from women, the end users of the product. One app (1/12, 8%) was developed based on 12 key variables identified through a systematic review of the literature [57].

**Capacity to Extract Data**

Approximately 60% of the studies (25/41, 61%) reported the capacity to extract data to monitor women’s progress; approximately 30% did not (12/41, 29%), and this was not indicated in 10% (4/41) of the studies. Data were extracted directly from the DTs in 20% (5/25) [39,43,49,61,65], and in 1 (4%) of the 25 studies, data could be emailed to the researchers via the app [36]. In other studies (19/25, 76%), data were transmitted from an app and stored or accessed on an associated web platform or server [37,38,42,44,47,56-58,68-71,75,76] or uploaded from the app to a cloud-based storage system [51,54,60,62,67]. Of the suite of studies that used Tåt, 11% (1/9) indicated the collection of user statistics from the internet-based program [56], and 22% (2/9) reported that women could voluntarily choose to use the statistics function and submit their user statistics at follow-up [5,64].

**Educational Features (Consensus on Exercise Reporting Template for PFMT Item 10)**

Educational information was incorporated into 61% (25/41) of the studies, with most including a combination of topics such as education about the anatomy and function of the PFMs, PFMT, stress UI, and related lifestyle advice (eg, weight management, physical activity, and fluid management). A total of 2% (1/41) of the studies provided holistic advice on breathing, posture, and movement [40] and used videos to deliver this information, an approach also adopted by another 7% (3/41) of the studies [57,72,81], with another incorporating audio fragments [56]. In a videoconferencing study, education was provided by a nurse specialist across a series of talks rather than being integrated into the technology itself [59]. Of the studies that did not incorporate education, 6% (1/16) involved telerehabilitation [43], and 12% (2/16) were mobile apps [39,68], with 6% (1/16) solely using a smartphone reminder system [68].

**Reinforcements, Reminders, and Self-monitoring (Consensus on Exercise Reporting Template for PFMT Items 5 and 6)**

A variety of reinforcements were used across 59% (24/41) of the studies, but the most common was the provision of visual (eg, graphics) or audiovisual feedback to guide women on the performance of PFMT, with the inclusion of voice [52,57] or sound [47] commands or accompanying music [39]. Goode et al [58] included storytelling; another study had an exercise module with a timer and score board [60].

In just over 50% (21/41, 51%) of the studies, reminder systems were incorporated into or complemented the DTs. In most cases (13/21, 62%), the reminders were customizable and were set by the women; in 24% (5/21) of the studies, push notifications were sent by the researcher or HCPs [21,47,52,60,68], and in 14% (3/21) of the studies, women were emailed a reminder (internet-based programs) [6,56,58].

Self-monitoring was a feature in 61% (25/41) of the studies. Apps commonly enabled tracking of exercise progress by women, including a statistical function (eg, Tåt) or graphs or the capacity to record exercise adherence over time (eg, number and level of exercises). This function was also available through a web portal [37,38,76], or training diaries were completed and sent via email [6]. Some technologies also included a bladder diary [58,60,71] to monitor urinary symptoms.

**Social Media and Gamification**

In total, 7% (2/28) of the DTs had the capacity for social media forums: the iPelvis, which included a website and Facebook page [11,57], and the iBall [67], which enabled women to connect with others in a web-based community (but it was disabled for the purpose of the study, as it was only available in Chinese).

A total of 21% (6/28) of the DTs incorporated gamification [36-38,48,57,67], which, with 1 exception [57], was used in conjunction with biofeedback. Descriptions of gamification included “serious games” [37,38], games or activities (eg, weight lifting room and flying arena) [67], and gaming and virtual reality mediated by a comic character [11,57] or a cyclist [36] with built-in scoring systems.

**Technical Support**

A total of 32% (13/41) of the studies offered instructions (eg, handouts and instructions via email) on how to download and install the app or use and effectively care for the equipment (eg, vaginal probes) [5,47,49,51,53,54,57,60,61,64,67-69].

Follow-up technical support was offered in 15% (6/41) of the studies by a research assistant [6,47,51,54,56,60] using encrypted email or via the app. A total of 10% (4/41) of the studies included in-person sessions with supervision or testing of the technology [36,43,62,76] by physiotherapists [36,43,76] or an unspecified individual [62].

**PFMT in the Included Studies**

**Evidence Base**

Just over half (21/41, 51%) of the studies provided some evidence base for the PFMT program that was being delivered via the DTs; in the remaining studies, this was not indicated or was unclear. Evidence for PFMT varied, ranging from existing programs tested in RCTs, including the seminal publication by Bø et al [119] and others later (eg, the *Group Rehabilitation Or Individual Physiotherapy for Urinary Incontinence in Aging"*)
Women [GROUP] trial [120]), to expert opinion [121], guidelines (eg, the National Institute for Health and Care Excellence) [122], and the Dutch clinical practice guidelines for the physiotherapy management of stress UI [123], with enhancements made based on feedback from clinicians, women, and researchers (eg, Tät).

**Delivery of PFMT (Consensus on Exercise Reporting Template for PFMT Items 1, 2, 3, 4, and 12)**

On the whole, women engaged with the DTs at home on an individual basis, with 22% (9/41) of the studies including exercise both at home and in a clinical setting [39,42,43,51,52,57,62,76] or community center [59] (Table 2; please note that, in some cases, the same DT was used across multiple studies). In 10% (4/41) of the studies, women also attended supervised group sessions once a week to undertake PFMT via teleconferencing [59], in person [52,57] with a maximum of 4 women per group [52], or specific to one of the study arms (app plus physiotherapy group) [57]. In the study by Pla et al [49], Skype was the medium for supervision of group-based hypopressive abdominal exercises 3 times per week (5-9 women per group), with women also receiving monthly individual videoconferencing sessions to check progress.

In addition to the 10% (4/41) of studies that provided supervision for women in a group setting [49,52,57,59], 34% (14/41) supported women on an individual basis. Examples included confirming a PFM contraction or PFMT practice [39,51] and checking women’s adherence to the program [39]; providing a set number of supervised sessions over the duration of the program (which ranged between 1 and 12) either in person [42,76] or remotely via email [6,41], phone call [54], or videoconferencing [45]; and more intense supervision, such as five 30-minute sessions over 2 weeks [43] and daily sessions 5 days per week [62]. If women required extra support with PFMT-related content, this was offered through email [45,49,56] or the chat function on an app [54], with Anglès-Acedo et al [37,38] noting that their web platform enabled “personalised supervision.”

Details of the personnel providing supervision or support for PFMT were reported in 18 studies, with 8 (44%) referring to a physiotherapist [49,57] who was specialized in women’s or pelvic health [39,42,43,45,52,76]. In others, a nurse specialist [59], therapist [37,38], urogynecologist [61], urotherapist [6,41], general practitioner [56], trained researcher [51], trained research assistant [62], or trained study staff member [54] provided supervision or support.
<table>
<thead>
<tr>
<th>Studya</th>
<th>DTb</th>
<th>PFMT evidence base</th>
<th>Individual or group PFMT and setting</th>
<th>Supervision of PFMT and qualifications</th>
<th>Confirmation of voluntary PFM contraction</th>
<th>PFMT parameters</th>
<th>Duration of program</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anglés-Acedo et al [37,38]</td>
<td>Mobile app—WOMEN UP</td>
<td>NId</td>
<td>Individual; home</td>
<td>Web platform; therapist</td>
<td>Biofeedback</td>
<td>NI</td>
<td>3 months</td>
</tr>
<tr>
<td>Araujo et al [39]</td>
<td>Mobile app—Diário Saúde</td>
<td>NI</td>
<td>Individual; home and clinic</td>
<td>In person, monthly; specialist women’s health physiotherapist</td>
<td>Digital assessment; specialist physiotherapist</td>
<td>8-second hold, 8-second relaxation followed by 3 phasic contractions 8 times, 2 times per day (sitting, lying down, or standing)</td>
<td>3 months</td>
</tr>
<tr>
<td>Asklund et al [5]; Asklund and Samuelsson [66]; Nyström et al [73]; Rygh et al [63]; Samuelsson et al [50]</td>
<td>Mobile app—Tät</td>
<td>Yes</td>
<td>Individual; home</td>
<td>No; —</td>
<td>No</td>
<td>Progressive PFMT (6 basic and 6 advanced levels), different combinations and repetitions of PFM contractions (strength and endurance, quick contractions, and the “knack”); advanced phase incorporates different positions (standing, lifting, and walking); strengthening: from a 5-second hold, 5-second relaxation 2 times (basic) to a 7-second hold, 7-second relaxation 40 times (advanced); endurance: from a 14-second hold once (basic) to a 59-second hold, 59-second relaxation 2 times (advanced); quick: from a 3-second hold, 3-second relaxation 5 times (end of the basic phase) to a 3-second hold, 3-second relaxation 20 times (advanced) 3 times daily</td>
<td>3 months</td>
</tr>
<tr>
<td>Wadensten et al [64]</td>
<td>Mobile app—Tät II</td>
<td>Yes</td>
<td>Individual; home</td>
<td>No; —</td>
<td>No</td>
<td>Progressive, 4 different PFM exercises are included across 8 modules based on the Tät [5], from 3 times per day for 2 minutes (module 1) to 3 times per day for 3-4 minutes (module 4) and 3 times per day for 12 minutes (module 8)</td>
<td>15 weeks</td>
</tr>
<tr>
<td>Bokne et al [41]; Sjöström et al [6]</td>
<td>Internet-based program—Tät</td>
<td>Yes</td>
<td>Individual; home</td>
<td>Email once per week plus support as needed; urotherapist</td>
<td>No</td>
<td>Progressive, tailored (in part) program with 8 levels, including the “knack”; strength: hold maximal contractions for 8 seconds, 8-10 repetitions, 3 times per day; endurance: hold submaximal contractions for 15-90 seconds, 1 repetition, 3 times per day; quick contractions: hold for 3 seconds, 8-10 repetitions, 2-3 times per day</td>
<td>3 months</td>
</tr>
<tr>
<td>Firet et al [56]</td>
<td>Internet-based program—Tät</td>
<td>Yes</td>
<td>Individual; home</td>
<td>Email support as needed; GPb in training or researcher</td>
<td>No</td>
<td>Progressive, 4 different PFM exercises are included across 8 modules based on the Tät [5], from 3 times per day for 2 minutes (module 1) to 3 times per day for 3-4 minutes (module 4) and 3 times per day for 12 minutes (module 8)</td>
<td>3 months</td>
</tr>
<tr>
<td>Barbato et al [40]</td>
<td>Internet-based program</td>
<td>NI</td>
<td>Individual; home</td>
<td>No; —</td>
<td>No</td>
<td>“Self-paced” PFMT, 10-15 minutes daily</td>
<td>3 weeks</td>
</tr>
<tr>
<td>Study</td>
<td>DT</td>
<td>PFMT evidence base</td>
<td>PFMT or group PFMT and setting</td>
<td>Supervision of PFMT and qualifications</td>
<td>Confirmation of voluntary PFMT contraction</td>
<td>PFMT parameters</td>
<td>Duration of program</td>
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<tr>
<td>Campbell et al [42]</td>
<td>Mobile app—Squeez App</td>
<td>NI</td>
<td>Individual; home and clinic</td>
<td>In person, ≤7 appointments (45-60 minutes) over 6 months depending on women’s needs; specialist pelvic health physiotherapist</td>
<td>Digital assessment (crotch lying) and specialist physiotherapist; biofeedback (standing)</td>
<td>Progressive, tailored PFMT (in different functional positions) for strength, power, endurance, and relaxation, and the “knack”; no specific details of the PFMT program</td>
<td>Phase 2: 6 months</td>
</tr>
<tr>
<td>Robson [74]</td>
<td>Mobile app—Squeez App</td>
<td>NI</td>
<td>Individual; home</td>
<td>—</td>
<td>—</td>
<td>NI</td>
<td>Survey, open for 3 months</td>
</tr>
<tr>
<td>Carrón Pérez et al [43]</td>
<td>Telerehabilitation device and vaginal probe</td>
<td>NI</td>
<td>Individual; home and clinic</td>
<td>In person, 5 times for 30 minutes over 2 weeks plus monthly follow-up; pelvic floor expert physiotherapist</td>
<td>Biofeedback</td>
<td>PFMT: five 30-minute sessions in the clinic (over 2 weeks) plus home exercise program; daily</td>
<td>3 months</td>
</tr>
<tr>
<td>Coggins et al [44]</td>
<td>Mobile app and vaginal device—Elvie</td>
<td>NI</td>
<td>Individual; home</td>
<td>No</td>
<td>Biofeedback</td>
<td>NI</td>
<td>NI</td>
</tr>
<tr>
<td>Conlan et al [45]</td>
<td>Telehealth</td>
<td>NI</td>
<td>Individual; home</td>
<td>In person, initial 1-hour session plus email support over 6 weeks; continence physiotherapist</td>
<td>—</td>
<td>Individualized PFMT</td>
<td>6 weeks</td>
</tr>
<tr>
<td>Cornelius [71]</td>
<td>Mobile app and vaginal probe—PeriCoach</td>
<td>NI</td>
<td>Individual; home</td>
<td>NI; pelvic floor clinicians (for some participants)</td>
<td>Digital palpation; biofeedback</td>
<td>Dosage; contraction, relaxation 5 times for 5 seconds, 10 repetitions, 4 times per day, 5 times per week</td>
<td>8 weeks</td>
</tr>
<tr>
<td>Shelly [76]</td>
<td>Mobile app and vaginal probe—PeriCoach</td>
<td>NI</td>
<td>Individual; home and clinic</td>
<td>In person, 6 sessions over 8 weeks; pelvic floor physiotherapy specialist</td>
<td>Digital assessment and specialist physiotherapist; biofeedback</td>
<td>Progressive, tailored, starting with contraction, relaxation 3 times for 8 seconds, 8 repetitions (20-25 repetitions per day; week 1); 5 times for 7 seconds, 8 repetitions (40-50 repetitions per day; week 2); 6 times for 3 seconds, 15 repetitions (week 5); 10 times for 3 seconds, 15 repetitions (week 8); supine, then standing; functional training with forward bending and during ADLs; 2 times per day, 5 times per week</td>
<td>8 weeks</td>
</tr>
<tr>
<td>Smith [53]</td>
<td>Mobile app and vaginal probe—PeriCoach</td>
<td>NI</td>
<td>Individual; home</td>
<td>NI; NI</td>
<td>NI</td>
<td>NI</td>
<td>20 weeks</td>
</tr>
<tr>
<td>Dufour et al [67]</td>
<td>Mobile app and vaginal device—iBall</td>
<td>Yes</td>
<td>Individual; home</td>
<td>No; —</td>
<td>Digital palpation; specialist pelvic health practitioner</td>
<td>3 times, 10 sets of 10 exercises 3-4 times per week</td>
<td>16 weeks</td>
</tr>
<tr>
<td>Goode et al [58]</td>
<td>Web-based—My-HealtheBladder</td>
<td>Yes</td>
<td>Individual; home</td>
<td>No; —</td>
<td>No</td>
<td>Progressive, from contraction, relaxation 2 times for 4 seconds (week 1) to 5 times for 5 seconds (week 4), 9 times for 9 seconds, and 10 times for 10 seconds (week 8) plus bladder control strategies</td>
<td>8 weeks</td>
</tr>
<tr>
<td>Study b</td>
<td>DT b</td>
<td>PFMT evidence base</td>
<td>Individual or group PFMT and setting</td>
<td>Supervision of PFMT and qualifications</td>
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<tr>
<td>Han et al [72]</td>
<td>Mobile app—Bwom</td>
<td>NI</td>
<td>Individual; home</td>
<td>No; N/A m</td>
<td>No</td>
<td>Progressive, “personalized” exercise plans, each with 6-12 exercises, with a new exercise each week</td>
<td>2 weeks</td>
</tr>
<tr>
<td>Hui et al [59]</td>
<td>Videoconferencing</td>
<td>NI</td>
<td>Individual and group; home and community center</td>
<td>Weekly videoconferencing; nurse specialist assisted by a research assistant (registered nurse)</td>
<td>Digital assessment and nurse specialist; biofeedback</td>
<td>1 videoconferencing session per week</td>
<td>8 weeks</td>
</tr>
<tr>
<td>Jaffar et al [60]</td>
<td>Mobile app—KEPT a-app</td>
<td>Yes</td>
<td>Individual; home and clinic</td>
<td>No; —</td>
<td>No</td>
<td>Progressive, 3 training skills and modes (different positions): beginner (2-second hold), intermediate (6-second hold), and advanced (10-second hold); 10 repetitions, 3 times per day; adherence phase: once they can perform PFMT confidently, maintain 10 cycles, 3 times per day</td>
<td>At least 16 weeks o</td>
</tr>
<tr>
<td>Kinouchi and Ohashi [68]</td>
<td>Smartphone-based messaging system</td>
<td>Yes</td>
<td>Individual; home</td>
<td>No; —</td>
<td>No</td>
<td>Hold 3-6 seconds, 3 sets of 6 contractions per day; different positions (standing, bent-knee lying, and 4-point kneeling)</td>
<td>8 weeks</td>
</tr>
<tr>
<td>Fischer Blosfield et al [57]</td>
<td>Mobile app—iPelvis</td>
<td>Yes</td>
<td>Individual and group; home and clinic (depending on study group allocation) p</td>
<td>12 sessions once a week, in person, in a group; physiotherapist</td>
<td>All participants had “physical examination”; women who had difficulty contracting PFMT had a vaginal examination, with instruction</td>
<td>App+physiotherapy: PFMT in a group once per week plus app at home</td>
<td>3 months p</td>
</tr>
<tr>
<td>Moossdorf-Steinhauser et al [52]</td>
<td>Mobile app—iPelvis (in conjunction with the Motherfit program)</td>
<td>Yes</td>
<td>Individual and group; home and clinic</td>
<td>8 sessions in person (60 minutes) in a group (maximum of 4 women); specialist pelvic physiotherapist</td>
<td>Observation and digital assessment, supine; pelvic specialist physiotherapist</td>
<td>Progressive group program, including strength and endurance, speed, and functional exercises, and the “knack”; NI if the home program was the same; build up to 8-12 contractions, 6-8-second hold plus 3-4 fast contractions; strength and endurance: 3 times per day, daily (minimum of 3-4 times week); different positions (lying down, sitting, kneeling, and standing); after 6 months of training; maintenance 2 times per week; speed: fast repetitions, build up to 10 sets of 3 quick contractions and 10 sets of 5 quick contractions 3 times per day</td>
<td>8 weeks, continuing past 6 months of home training</td>
</tr>
<tr>
<td>Li et al [69]</td>
<td>Mobile app and audio guidance—Pen Yi Kang</td>
<td>NI</td>
<td>Individual; home</td>
<td>No; —</td>
<td>Digital assessment; experienced physiotherapist</td>
<td>NI</td>
<td>6 weeks</td>
</tr>
<tr>
<td>Study&lt;sup&gt;a&lt;/sup&gt;</td>
<td>DT&lt;sup&gt;b&lt;/sup&gt;</td>
<td>PFMT evidence base</td>
<td>Individual or group PFMT and setting</td>
<td>Supervision of PFMT and qualifications</td>
<td>Confirmation of voluntary PFMT contraction</td>
<td>PFMT parameters</td>
<td>Duration of program</td>
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<tr>
<td>Wang et al [51]</td>
<td>Mobile app and audio guidance—Pen Yi Kang</td>
<td>NI</td>
<td>Individual; home</td>
<td>In-person initial 45-minute session plus phone contact once a month; trained researcher</td>
<td>Digital palpation; surface EMG, supine, and hips and knees bent</td>
<td>Progressive, different positions (sitting, standing, and lying down); 3-second hold, 2–6-second relaxation for 15 minutes, 2 times per day or 150 contractions per day</td>
<td>3 months</td>
</tr>
<tr>
<td>Li et al [47]</td>
<td>Mobile app—UIW&lt;sup&gt;f&lt;/sup&gt;</td>
<td>Yes</td>
<td>Individual; home</td>
<td>No; —</td>
<td>Perineum palpation, supine, and surface EMG in lithotomy position; experienced obstetrician</td>
<td>Adapted from Tät [5]; progressive, 2 basic and 4 advanced levels, including different combinations and repetitions of 4 commonly used contraction types: test contraction, strength contraction, endurance contraction, and quick contraction; up to each woman to determine use (frequency and duration)</td>
<td>8 weeks</td>
</tr>
<tr>
<td>Loohuis et al [61]</td>
<td>Mobile app—URinControl</td>
<td>Yes</td>
<td>Individual; home</td>
<td>No; —</td>
<td>Assessed according to the ICS&lt;sup&gt;s&lt;/sup&gt;; urogynecologist</td>
<td>Progressive program, directed to appropriate part of the app to start training; no further information provided</td>
<td>4 months</td>
</tr>
<tr>
<td>Wessels et al [65]</td>
<td>Mobile app—URinControl</td>
<td>Yes</td>
<td>Individual; home</td>
<td>No; —</td>
<td>No</td>
<td>Progressive program, directed to appropriate part of the app to start training; no further information provided</td>
<td>—</td>
</tr>
<tr>
<td>Moretti [36]</td>
<td>Mobile app, vaginal probe, and surface electrodes—MyoPelvic</td>
<td>Yes</td>
<td>— —</td>
<td>Biofeedback, maximal voluntary contraction, and supine; researcher</td>
<td>Phasic fibers: contract &lt;4 seconds, relax for twice the duration of the contraction, 12 repetitions maximum (as dictated by the game); tonic (slow) fibers: contract 4-10 seconds, relax for the same duration, 12 repetitions maximum (as dictated by the game); 1-2-minute rest between games recommended but not enforced; muscle coordination training (not specified)</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td>Pedofsky et al [48]</td>
<td>Mobile app and intravaginal pressure sensor array—FemFit</td>
<td>Yes</td>
<td>— —</td>
<td>—</td>
<td>Progressive, graduated exercise; no further information provided</td>
<td>12 weeks</td>
<td></td>
</tr>
<tr>
<td>Pla et al [49]</td>
<td>Mobile app and vaginal device—Birdi</td>
<td>NI</td>
<td>Individual and group; home</td>
<td>Videoconferencing; 2 initial individual sessions 3 times per week in a group and monthly individual session plus email or phone support; physiotherapist</td>
<td>Measured by the device</td>
<td>Daily PFMT, tailored</td>
<td>2 months</td>
</tr>
<tr>
<td>Pulliam et al [62]</td>
<td>Mobile app and vaginal insert—Leva Pelvic Digital Health System</td>
<td>NI</td>
<td>Individual; home and clinic</td>
<td>In person, once a day, 5 times per week over 6 weeks; trained research assistant</td>
<td>Accelerometer-based system</td>
<td>15-second PFM contraction 5 times, 15-second relaxation, 2 times per day in standing position</td>
<td>6 weeks</td>
</tr>
<tr>
<td>Weinstein et al [54]</td>
<td>Mobile app and vaginal insert—Leva Pelvic Digital Health System</td>
<td>NI</td>
<td>Individual; home</td>
<td>3 phone calls in first 2 weeks plus support via the chat function; trained study staff</td>
<td>No</td>
<td>5 cycles of squeeze and lift, and 15 seconds of rest for 15 seconds each, 2.5 minutes 3 times per day</td>
<td>8 weeks</td>
</tr>
</tbody>
</table>
Content of PFMT (Consensus on Exercise Reporting Template for PFMT Items 7, 8, 9, 13, 14, and 15)

Confirmation of a voluntary PFM contraction was undertaken in just under half (19/41, 46%) of the studies and was either not included in the study design in 41% (17/41) of the studies or not indicated or appropriate (5/41, 12%). Confirmation was obtained through digital assessment [39,57,61,69], which was also used to teach a correct contraction or relaxation of the PFM [52,67]; biofeedback or the digital device [36-38,43,44,49,62]; or a combination of both [42,47,51,59,71,76]. Digital assessment was undertaken by a specialized HCP, although it was not indicated who performed this procedure in 7% (3/41) of the studies [51,57,71]. In the RCTs that used digital assessment, this was provided to all women across all the study groups.

A total of 49% (20/41) of the studies offered PFMT programs that were progressive in terms of content or position. Although most programs were generic, 10% (2/20) were tailored to the individual by provision of supervision [49,76], and another 15% (3/20) provided some indication or tailoring of the starting level for PFMT [61,64,72].

The details of the PFMT content were not indicated in 34% (14/41) of the studies, whereas the rest used a combination of strength, endurance, and power exercises; relaxation; or a combination of these. Direct PFMT, together with functional PFMT (eg, the “knack”), was included in 29% (12/41) of the studies [5,6,41,42,50,52,57,63,64,73,76,78], and it is likely to have been integrated into another 5% (2/41) of the studies that were based on the Tät [47,56].

Of the 19 studies that provided details about the prescribed dose, 14 (74%) recommended PFMT 3 times a day [5,6,41,47,50,52,54,56,60,63,64,68,73,78], 4 (21%) recommended PFMT twice a day [39,51,62,76], and 1 (5%) recommended it 4 times a day [71]. The most common program duration was 3 months (17/41, 41% of the studies) [5,6,37-39,41,43,50,51,56,57,63,66,73-75,84], followed by 2 months [47,49,52,54,58,59,68,71,76], with others spanning 2 to 6 weeks [40,45,62,69,72] or >15 weeks up to 6 months [42,53,60,61,64,67] to 1 year [70]. It should be noted that women in the study by Moossdorff-Steinhauser et al [52] continued exercising at home for at least 6 months after the end of the 8-week group exercise PFMT, and the 16 weeks specified by Jaffar et al [60] were the minimum program duration.

Adverse Events (Consensus on Exercise Reporting Template for PFMT Item 11)

A total of 20% (8/41) of the studies documented adverse events [6,36,37,43,52,54,62,64]. Adverse effects were reported in 12% (5/41) of the studies, none of which were deemed serious. Some examples include vaginal discomfort, infection, or allergic reactions related to the use of the vaginal device [37,43]; lower abdominal pain related to PFMT [6]; and increased spontaneous urine leakage [64].
Treatment Fidelity (Consensus on Exercise Reporting Template for PFMT Item 16)

A total of 5% (2/41) of the studies, both of which were protocols [47,60], assessed the implementation of the intervention. The methods used included monitoring participant activity and training time through the app [60], tracking technical support provided, consultation support, and reminders sent to women who had not used the app over the previous week [47].

UI Outcomes

UI outcomes following DTs were presented in 56% (23/41) of the studies (Table S1 in Multimedia Appendix 4 [5,6,39-41,43-44,45-49,51,53,57-59,61-64,67,68,73,76]), with improvements reported across measures in all but 1 study (within groups; 22/23, 96% [68]). All studies (23/23, 100%) analyzed changes in UI symptoms and severity or general or UI-specific QoL, as measured through self-reported questionnaires, UI episode frequency, pad weight tests, or UI aid use.

Adherence to the Program

A total of 61% (25/41) of the studies indicated methods for evaluating adherence, with some (9/25, 36%) using more than one approach (Table S2 in Multimedia Appendix 4 [5,6,37,39,41-44,47,50-52,54,56,58,60,61,63,64,67-69,71,73,74]). In total, 72% (18/25) of the studies gathered data from the DTs themselves [5,37,39,42,43,47,51,52,54,56,58,60,61,64,67-69,79], 48% (12/25) used self-report via email [6] or a web- or app-based questionnaire [5,41,44,50-52,61,63,64,74,79], and 4% (1/26) included in-person appointments [42].

A total of 68% (17/25) of the studies provided data following completion of the program. Women in 76.4% (13/17, 50%) of these studies provided a self-report of adherence to the prescribed PFMT, which was measured and reported in a variety of ways—visual analogue scale [39], validated questionnaire to assess efficacy [51], number of exercises completed over specified time points (eg, in the last month or last week, daily, weekly, or monthly) [5,41,44,50,58,63,74,79], or percentage of women who performed PFMT [37,68] or adhered to the program [58] or some of the program [85]. Self-reported daily PFMT for women using DTs ranged from 23.4% to 41% over 3 months [5,63].

Performance of PFMT was also captured via the DTs in some studies (9/25, 36%), including measures of how often the app was used (eg, never, once a week, and >3 times per week) [50,61,63,64,69], mean number of exercises performed per day (1.6 [5]), median number of days PFMT was performed per week (4.9 [43]), and percentage of women who completed at least 75% of the study requirements for the program (14.4% [85]).

Two studies compared adherence to the DTs with a control group. Adherence was significantly higher (P<.001) in the group using the DTs at 1, 2, and 3 months [39], but there was no difference (P=.40) reported between the groups in the study by Carrión Pérez et al [43].

Satisfaction With DTs and Outcomes

A total of 63% (17/41) of the studies considered satisfaction with the DTs, including reporting on experiences with specific aspects (eg, PFMT, exercise logs, reminder features, and ease of accessing videos or instructions) [5,36,37,39,40,44,45,52,54,59,60,62,64,67,72,74,75] (Table S2 in Multimedia Appendix 4). Although a range of different outcome measures was used, it appears that most participants were satisfied with the DTs and would recommend them to others. An exception was the study by DuFour et al [67], in which only 18.2% (2/11) of the women would recommend the mHealth device or consider using it again; however, this response increased to 63.6% (7/11) if the device were to be modified.

Satisfaction with the program as a whole, or self-reported improvement, was reported in 27% (11/41) of the studies [5,6,40,43,44,49,52,54,58,64,71]. Responses varied with respect to overall satisfaction, ranging from not satisfied (6% in the study by Goode et al [58] and 33% in the study by Wadensten et al [64]) to somewhat satisfied (75% in the study by Goode et al [58]) and completely satisfied and symptom-free (7% in the study by Wadensten et al [64]). Although satisfaction in the study by Sjöström et al [6] was higher in the intervention (app) group at 4 months, there was no significant difference at the 1- and 2-year follow-ups; no difference between groups was reported by Carrión Pérez et al [43]. Self-reported improvement in symptoms was variable, with <25% of the women in 18% (2/11) of the studies [40,44] reporting that they were much or very much better (10.3%–23.5%) with respect to symptoms, but more women (55.7%) reported the same for self-perceived improvement in PFM strength [5].

Qualitative Synthesis: Experiences of Women and HCPs

The summary data from the completed qualitative or mixed methods studies (11/45, 24%) are presented in Multimedia Appendix 5 [31,38,42,46-48,65,67,77,78,80,86,87]. In almost all the studies, the same factors were presented as both facilitators and barriers. This demonstrates that preference for or against any given DT may be related to the individual and that personal preferences can change over time.

The results demonstrated some overarching facilitators. Participants liked the anonymity that DTs provide for the treatment of UI symptoms [31,38,46,65,86,87]. Several studies (6/11, 55%) discussed that UI is still considered a socially “taboo subject,” a topic that women can find difficult to acknowledge to themselves, let alone discuss with an HCP [31,65,77,80,86,87]. Being judged or feeling embarrassed to discuss UI was a common finding, and the opportunity to access DTs provided women with a viable, accessible, and potentially less time-consuming alternative means of seeking support [31,38,46,48,65,77,78,80,86,87]. Furthermore, the ability to use an app in the convenience of their own environment facilitated empowerment, confidence, and self-efficacy regarding the ability to manage their UI symptoms with PFMT exercises [31,38,46,48,65,77,78,86,87].

All studies (11/11, 100%) demonstrated that the knowledge content across the various apps was helpful. Knowledge included gaining a better understanding of the causes of UI, where PFMs are and what is their function, and the fact that UI is a common problem. In total, 18% (2/11) of the studies [65,87] reported
DTs were considered successful by participants if an improvement in UI symptoms was observed [31,67,78,86,87]. Participants were reported to be more adherent when UI symptoms were more severe [31,86,87] and less adherent to PFMT as UI symptoms improved [31,65,78,86,87]. However, other personal and technological factors also influenced adherence to the various PFMT programs and, thus, UI symptom outcomes. These included the needs of other family members, especially for new mothers; concomitant health issues; and other life events [31,65,78,80,86,87].

Establishing a routine; the use of reminders, journals, and diaries; and family support went some way toward mitigating these barriers [31,46,77,86,87]. Although some HCPs expressed concerns about the ability of older women to use DTs [80], the studies in this review suggest that the competing time pressures experienced by women with young families, especially if they were working, were more of a barrier [31,65,67,87]. Culture was not discussed in any of the studies, so it is unclear whether the same facilitators and barriers apply across all cultures and ethnic groups.

Another common finding across the studies was concern about the ability to “correctly” contract the PFMs. Although the concept of an internal exam to determine a “correct” contraction was not always appealing [65], being unsure of whether the exercises were being performed correctly was a barrier to adherence [31,46,65,77,80,86,87]. Consequently, several studies (8/11, 73%) [31,46,48,65,77,80,86,87] suggested that engagement with HCPs, perhaps for an initial assessment and then for progression at a later point in time, was an important facilitator. Other studies found that HCP consultations were required to support adherence and provide encouragement and progression of PFMT in addition to the benefits of DTs [31,86]. Both consultations with HCPs and DTs (if from a recognized institution, such as a university) reassured participants that the information they received and the PFMT program they were trying were from a credible source [31,77].

As per the results in Multimedia Appendix 5, technology that was easy to set up, insert (if applicable), comfortable, and portable was more acceptable to participants [31,38,46,48,67,77,78,87].

**Discussion**

### Principal Findings

This systematic scoping review was undertaken to explore the range and features of DTs available for managing UI. Specifically, we sought to determine whether the PFMT embedded in DTs follows best-practice guidelines, is designed for women at specific stages in life, and considers cultural contexts and the experiences of women and other relevant stakeholders.

It is evident that the medium of DT for the conservative management of UI is prevalent and continually expanding, with rapid growth apparent particularly over the last 10 years. In total, 89 studies were included in this scoping review—51% (45/89) were primary studies and 49% (44/89) supplementary papers—which is larger than the number (between 3 and 10 papers) included in several recent narrative and systematic reviews in this field [7,8,18-21,124,125]. This difference likely reflects variations in inclusion and exclusion criteria, which in this study were intentionally broad so as to encompass a range of sources, including qualitative research.

The WHO global strategy on digital health stipulates that DTs should be “people-centred, trust-based, evidence-based, effective, efficient, sustainable, inclusive, equitable and contextualised” [126]. In terms of the evidence-based dimension, it is encouraging that over half of the DTs (22/41, 54%) were developed based on evidential research or testing. The means of achieving this varied across the studies, but most adopted an iterative process of continuous testing, implementation, and refinement. IT input is obviously integral to the development of DTs, but importantly, a number of studies in this review took a user-centered approach by seeking the opinions of women with or without UI and, in some cases, HCPs who may be involved in a woman’s care. Considering users’ opinions, needs, and expectations at all stages of DT design is not only endorsed by the WHO [126] but is also vital in optimizing the usability and acceptability of the DTs and their adaptation to ensure effectiveness in outcomes [127]. Some studies (4/41, 10%) adopted a theoretical user-centered framework to guide the design of the DTs [47,48,56,60], and standardization and use of such frameworks by future developers will assist in continued improvements in the quality of DT apps specifically for PFMT, which could ultimately enhance the conservative management of UI.

Free and commercial PFMT apps are readily available for download from app stores, but only some are clinically sound from a PFMT perspective [128], with many lacking in terms of accuracy, content, quality, and functionality [10,128-130]. Just over half (21/41, 51%) of studies documented that the PFMT programs were drawn or adapted from a known evidence base, which suggests that they are in line with the recommendations of PFMT exercise theory that lead to improvements in UI symptoms [122,131]. However, there was a large variation in the PFMT reported, including the type of exercise, dose, frequency, progression, and supervision, and some PFMT details were often incompletely reported (particularly in abstracts, which is to be expected). In addition to details about PFMT, other items in the Consensus on Exercise Reporting Template for PFMT guidelines [28] were also inconsistently adopted across the studies—less than half incorporated confirmation of a voluntary PFM contraction (19/41, 46%) or reported on adverse events (8/41, 20%) or treatment fidelity (2/41, 5%), whereas just over half used reminder systems available with the DTs (21/41, 51%). From a technological perspective, some of these items, such as reminders (eg, individualized push notifications), and other features, such as social media and gamification (used in 2/28, 7% and 6/28, 21% of the studies, respectively), are suggested to be important in supporting adherence to mHealth [11,132] and are worth considering for future DTs.
As shown across a range of studies, using DTs to deliver PFMT can be effective in improving UI symptoms and QoL. In the 56% (23/41) of the studies that reported outcome measures, improvements were seen across most outcome measures for women using DTs and, in the case of comparison groups, often for those who were receiving PFMT via an alternative method (eg, pamphlet or usual care). Many of the outcome measures were self-reported, which is appropriate, as the lived experience of women is of interest. As the qualitative data show, aspects such as convenience and reduction in symptoms were of most relevance, which reinforces the need for future studies to include qualitative components to determine relevance to the primary end user. Women’s satisfaction with the program as a whole, as documented in 27% (11/41) of the studies, was variable in terms of outcome measures and data but was likely closely connected with UI outcomes. For example, in an RCT [6], the satisfaction of the women using the app was higher than that in the control group (printed PFMT) at 4 months, aligning with a significant improvement in UI symptoms; however, there was no difference between the groups at the 1- and 2-year follow-ups [88], when the effectiveness of the intervention had also waned, as had adherence to the prescribed intervention program. These findings suggest that PFMT delivered via DTs is promising as a first-line conservative management for UI, but more high-quality research, which includes long-term follow-up, is required.

There was heterogeneity in the definitions of adherence used by the studies included in this review and the methods (eg, DTs and web-based questionnaires) and measurements used to monitor this. In addition, reporting of adherence data was variable with little standardization, making comparison difficult. Among the 2 RCTs that measured adherence, in 1 (50%; 21 women), adherence was significantly better in those who used an app in the short term (up to 3 months) [39]. However, no difference was found in UI symptoms between groups, consistent with the findings of the other RCT that compared telehabilitation and control [43]. A known problem with app use is attrition after they have been downloaded. Examples from other areas of health research suggest that approximately 20% to 25% of apps are used only once or infrequently, with use dramatically reducing to <5% over a short period (eg, 8 sessions or 15 days) [132,133]. The self-reported daily PFMT for women using DTs ranged from 24.3% to 41% over 3 months [63,79], but no long-term data were available to determine whether this followed a downward trend. There is a plethora of research that demonstrates that managing a long-term condition with regular commitment to exercise is difficult irrespective of the condition [134,135]. Therefore, factoring this typical type of human behavior into PFMT programs delivered via DT, providing reassuring statements regarding the fact that this is typical, being kind to oneself, and knowing how to start again, would be beneficial.

Other suggested benefits of using remote or app-based technologies to deliver PFMT include helping women overcome their embarrassment about seeking help for UI, improving access to health services in remote or underdeveloped areas, and enhancing cost-effectiveness [46,61,82,136]. Although using DTs in isolation may be beneficial, personal or HCP support is also recommended [11,132]. This approach aligns with best-practice guidelines for effective PFMT [122], with supervision provided to support the behavioral aspect of exercise. In this review, many studies (18/41, 44%) incorporated HCP or researcher support either synchronously (eg, in person or remotely) or asynchronously (eg, email contact), ranging from confirmation of a PFM contraction to constant monitoring of progress across the course of the program. A notable feature from the synthesis of findings from the included qualitative studies was that engagement with an HCP was an important facilitator, not only to support adherence and progression of exercises but also because women valued knowing that they were performing the PFM exercises correctly and expressed concern if they were unsure about their technique [31,46,48,65,77,78,80,86,87]. This concern is valid as inadvertently performing an incorrect PFM contraction, such as the Valsalva maneuver, could result in an increase in intra-abdominal pressure, leading to depression of the levator ani muscle and weakening of the surrounding connective tissues, which may inadvertently increase UI [137].

Interestingly, group-based supervised PFMT (either in person or remotely) was offered in 10% (4/41) of the studies [49,52,57,59]. Although results related to improvements in UI outcomes in these studies were mixed, a recent large RCT has shown that group-based PFMT is not inferior to individually supervised PFMT in older women in the treatment of UI, with both groups also undertaking a home exercise program [138]. It is known that peer support is a key strategy to help with long-term self-management as it can facilitate individual problem-solving and goal setting, which can aid with self-efficacy [139,140]. This indicates that a group-based approach to exercise likely offers further advantages to women, such as enhanced motivation to perform PFMT and reduced stigma and feelings of isolation [141]. Given the large variation in the types and levels of support and supervision currently provided for PFMT delivered via DTs, further information is needed to establish what represents best practice in terms of integrating supervision to optimize women-centered care and UI outcomes.

Culture plays a role in how women interact with DTs [15,16], perceive UI [17,142,143], and engage with PFMT and should be taken into account when designing mHealth interventions to encourage use and enhance motivation [16]. Incorporating cultural characteristics into DTs includes considering not only the user’s needs and preferences related to functionality (eg, color, typeface, and layout) but also more implicit aspects such as values, health beliefs, religion, social practices, and language [144,145]. In this scoping review, most DTs originated in high-income countries such as the United Kingdom and the United States and most likely targeted the dominant culture. This is also exemplified by the finding that only 4% (2/45) of the primary papers were written in a language other than English [35,36]. However, some apps (the Tät in particular) have been translated into a number of different languages, and research teams have also sought user input to refine them further [56,63,78], processes that are some of several different methods to enable cultural relevance [144]. The iPelvis app [11,57] explicitly incorporates culturally relevant elements, and although...
these may be features of other DTs included in this scoping review, they were not described. It cannot be assumed that PFMT DTs developed in one culture and translated for use in another will be successful without consulting the cultural context of the women who will use it [146], meaning that user engagement is successful in its success. Therefore, to meet the remit of inclusive and equitable DTs [126] and reach women in low- and middle-income and remote countries, more understanding is needed of what culturally related insights are required to increase the acceptability of and engagement with these technologies [146].

Many studies (28/45, 62%) did not explicitly document information related to the delivery of PFMT via DTs for women at a specific stage in life. Of those that did, most focused on pregnancy or the postpartum period, a time when UI is highly prevalent, with a risk that it could persist and become a long-term condition in some women [1]. During the childbearing years, women experience competing interests for their energy and time, such as preparing for or caring for their new baby, which means that it is vital that they receive sufficient support to adopt and maintain PFMT [67,147]. Engaging with an HCP in conjunction with using DTs was identified as an important facilitator to support PFM exercise (physical and behavioral aspects) [31,46,48,65,77,78,80,87], and there is evidence demonstrating that starting PFMT in early pregnancy may reduce the risk of UI later in pregnancy or up to 6 months post partum [4]. However, pregnant or postpartum women might not seek help from an HCP as they may feel embarrassed about their UI symptoms [148] or think that UI is a “normal” occurrence before and soon after childbirth [149]. In these instances, DTs provide a convenient tool that can support and motivate women to exercise [11,132] in the comfort of their own environment, facilitating empowerment, confidence, and self-efficacy with PFMT [31,38,46,48,65,77,78,86,87]. An additional avenue for support could be further developing and integrating social media into DTs, enabling pregnant and postpartum women to connect with each other as well as with HCPs. In general, more evidence is required to establish the acceptability, design, development, and effectiveness of PFMT DTs across various age ranges, including both adolescent and older women, to ensure that the programs meet women’s needs and circumstances. However, HCPs should have some confidence integrating DTs for PFMT into their practice as, in partnership with a clinician, this may offer women another tool in the management of UI symptoms.

**Limitations**

As this scoping review included a wide range of studies and a variety of DTs, heterogeneity was evident across many study parameters, including the PFMT programs and UI outcomes, and the duration of the trials was relatively short, demonstrating the need for longer follow-up and high-quality data in this developing field of research. Biofeedback is broadly considered a DT; however, we only included studies that provided feedback to women via an app, meaning that we did not capture valuable data from trials of biofeedback that did not have this feature [150,151]. Many studies were from high-middle–income urban settings, which restricts the diversity of the target populations despite one of the benefits of mHealth being its ability to reach a range of people, including those in remote areas [61,82,136]. This review considered women with stress UI and, therefore, did not explore the impacts of PFMT DTs on other conditions or populations, such as urge UI or pelvic organ prolapse or men. As described previously, owing to the large volume of data, we were unable to implement some elements of our a priori protocol, such as synthesizing data from systematic reviews and rating the quality of the apps used in the included studies. Owing to space limitations, we were only able to present the themes most coherently relevant to the scoping review objectives, and in our synthesis, we did not consider how the quality ratings (high, fair, and poor) influenced the data.

**Conclusions**

Evidence related to PFMT delivered via DTs for the conservative management of UI continues to grow exponentially. The development of DTs specifically for this purpose is increasingly based on evidential research or testing, including the exploration of the perspectives and experiences of women and HCPs. Although large variation exists in the reported PFMT parameters, PFMT delivered via DTs is promising in terms of improving UI symptoms and QoL. To further optimize UI outcomes and promote long-term adaptation of PFMT, incorporating technological features such as reminders, social media, and gamification, together with other facilitators such as support from HCPs, could be beneficial for women with UI. A greater understanding is required of how women from different cultures and stages in life regard the acceptability, design, development, and effectiveness of PFMT DTs. This is essential to ensure that the quality and content are appropriate and inclusive so that all women and clinicians can have confidence in using these technologies.

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**Authors’ Contributions**

SJW, MDB, ARC, and JK were responsible for the conceptualization and design of this study. BS developed the search strategy and performed the database searches. Literature screening, data extraction, and quality ratings were completed by MDB, ARC, JK, BM, BS, and SJW; data synthesis and analyses were performed by BM, BS, MAP, and SJW. SJW drafted the manuscript with contributions from BM and MAP. All authors critically revised and approved the final manuscript.
Conflicts of Interest

JK is the chief executive officer of Junofem, which has developed FemFit, one of the apps reviewed in this study. She had no role in the data extraction or analyses of data related to FemFit. The authors have no other conflicts of interest to declare.

Multimedia Appendix 1
Search strategy.
[DOCX File, 40 KB - mhealth_v11i1e44929_app1.docx]

Multimedia Appendix 2
Summary of the included primary and supplementary papers (N=89) and summary of the inclusion and exclusion criteria for the primary and supplementary papers.
[DOCX File, 59 KB - mhealth_v11i1e44929_app2.docx]

Multimedia Appendix 3
Characteristics of the included studies and participants.
[DOCX File, 51 KB - mhealth_v11i1e44929_app3.docx]

Multimedia Appendix 4
Outcomes related to urinary incontinence symptoms and satisfaction with and adherence to the pelvic floor muscle training program delivered via digital technologies.
[DOCX File, 56 KB - mhealth_v11i1e44929_app4.docx]

Multimedia Appendix 5
Summary of main themes and facilitators and barriers from the qualitative studies (N=11).
[DOCX File, 34 KB - mhealth_v11i1e44929_app5.docx]

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**Abbreviations**

DT: digital technology  
GROUP: Group Rehabilitation Or IndividUal Physiotherapy for Urinary Incontinence in Aging Women  
HCP: health care provider  
mHealth: mobile health  
PFM: pelvic floor muscle  
PFMT: pelvic floor muscle training  
PRISMA-ScR: Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews  
QoL: quality of life  
RCT: randomized controlled trial  
UI: urinary incontinence  
WHO: World Health Organization
Parents’ Perceptions of Children’s and Adolescents’ Use of Electronic Devices to Promote Physical Activity: Systematic Review of Qualitative Evidence

María Eugenia Visier-Alfonso¹, PhD; Mairena Sánchez-López², PhD; Beatriz Rodríguez-Martín³, PhD; Abel Ruiz-Hermosa⁴, PhD; Raquel Bartolomé-Gutiérrez⁵, PhD; Irene Sequi-Dominguez⁶, PhD; Vicente Martínez-Vizcaíno⁵,⁶, MD

¹Faculty of Nursing, University of Castilla-La Mancha, Cuenca, Spain
²School of Education, University of Castilla-La Mancha, Ciudad Real, Spain
³Faculty of Occupational Therapy, Logopedics and Nursing, University of Castilla-La Mancha, Toledo, Talavera de la Reina, Spain
⁴Department of Didactics of Musical, Plastic and Body Expression, Faculty of Sports and Sciences, University of Extremadura, Cáceres, Spain
⁵Department of Psychology, University of Castilla-La Mancha, Albacete, Spain
⁶Health and Social Research Center, University of Castilla-La Mancha, Cuenca, Spain

Corresponding Author:
María Eugenia Visier-Alfonso, PhD
Faculty of Nursing
University of Castilla-La Mancha
Camino de Nohales 4
Cuenca, 16071
Spain
Phone: 34 630872012
Email: mariaeugenia.visier@uclm.es

Abstract

Background: The use of physical activity (PA) electronic devices offers a unique opportunity to engage children and adolescents in PA. For this age group (2-17 years), parents play a key role in promoting healthy lifestyles and regulating the use of electronic devices. Therefore, parents’ perceptions of the use of electronic devices for PA in children and adolescents are critical for efficient intervention.

Objective: The aim of this qualitative systematic review was to improve the understanding of parents’ perceptions of the use of electronic devices for PA in children and adolescents.

Methods: A systematic search of electronic databases (Medline/PubMed, SPORTDiscus, Web of Science, Scopus, OpenGrey, and Deep Blue) was conducted. Studies from inception (2010) to May 2022 were identified. Qualitative studies on the perceptions of healthy children’s and adolescents’ (aged 2-17 years) parents regarding PA interventions performed on electronic devices were included according to the Cochrane Qualitative and Implementation Methods Group Guidance Series and the Enhancing Transparency in Reporting the Synthesis of Qualitative Research (ENTREQ) statement. The Joanna Briggs Institute Qualitative Assessment and Review Instrument was used for methodological validity.

Results: In total, 18 studies with 410 parents, mostly mothers, were included. Parents’ perceptions were grouped into 4 categories: usefulness, advantages, general perceptions (electronic devices for health promotion, preferences for real-life PA, and concerns), and acceptability (barriers and facilitators) of electronic devices for PA. Parents perceived electronic devices as useful for increasing PA, learning new skills, and increasing motivation for PA and valued those devices that promoted socialization and family and peer bonding. In terms of general perceptions, parents had positive attitudes toward PA electronic devices; however, they preferred outdoor and real-life PA, especially for preschoolers and children. Concerns, such as physical and psychological harm, addiction, conflicts, and compliance difficulties, were found. Facilitators were identified as ease of use, appropriate feedback, promotion of socialization, and motivational strategies, such as rewards, challenges, and attractiveness. Barriers, such as discomfort, price, and difficulties in using or understanding electronic devices, were also identified. For older children and adolescents, parents were more concerned about high levels of screen time and setting limits on electronic devices and therefore preferred PA electronic devices rather than traditional ones.
Conclusions: Overall, the participants had positive attitudes toward electronic devices for PA and perceived them as an effective way to promote PA in children and adolescents. They also perceived several benefits of using electronic devices, such as health promotion, increased awareness and motivation, and socialization, as well as barriers, facilitators, and age differences. The results of this study could provide researchers with insights into designing more effective, age-appropriate PA electronic devices for children and adolescents and improving adherence to their use.

Trial Registration: PROSPERO CRD42021292340; https://www.crd.york.ac.uk/prospero/display_record.php?RecordID=292340

(Keywords) physical activity; electronic devices; eHealth; parents’ perceptions; children; adolescents; systematic review; qualitative

Introduction

Currently, smartphones, tablets, computers, and apps that run on electronic devices have become part of the everyday life of children and adolescents [1]. Most parents allow their children to use their smartphones to play games or watch videos, and almost all children start handling electronic devices before the age of 1 year [2]. In addition, 73% of parents with children aged 9-11 years say that their children use a computer, 68% say that they use gaming devices, 67% say that they use a smartphone, and 78% say that they use a tablet [1]. There are substantial age differences in the use of electronic devices, and usage increases with age, being higher in adolescents, with most of them reporting using electronic devices daily or almost all the time [3]. Traditionally, research on the use of electronic devices has focused on its association with sleep problems, sedentarism, and overweight/obesity [4]. However, with the growth in technology, the use of eHealth (ie, electronic devices with health-related purposes [5], including physical activity [PA] and fitness apps), has increased [6].

Some advantages of using electronic devices to implement PA interventions are that these programs are more flexible, can be tailored to individual needs, and can be delivered anywhere at any time compared to traditional PA interventions [7]. Moreover, electronic devices might make PA more attractive to children and adolescents [8], as well as having other advantages, such as low cost, empowerment of participants, exposure to new information, increased opportunities for social contact, and new opportunities to access health promotion programs [9]. The potential role of apps in improving PA across children and adolescents has been suggested [10], but evidence of the efficacy of PA apps for this age group is still scarce [10,11]. Thus, more research on electronic devices to promote PA in children and adolescents is needed.

Furthermore, early habits track from childhood through adolescence to adulthood [12], making early childhood a crucial period for the acquisition of habits, such as PA. In addition, parents’ behaviors related to PA have been shown to be associated with their children’s health behaviors [13]. Previous research indicates that PA programs that include families are more effective in increasing PA in children [14,15]. Moreover, a meta-analysis by Hammersley et al [16] suggested that eHealth interventions might be more successful when parents are involved as agents of change. Not only health-related behaviors but also screen time and electronic device access and use depend on the individual’s family [17]. Additionally, parents’ attitudes toward electronic devices are associated with different regulation practices, depending on age and the time spent using electronic devices from childhood through adolescence [18]. All these results recommend parents’ involvement in eHealth interventions [19], with the family being a key intervention target [20]. Finally, from a qualitative perspective, Burrows et al [21] found that most parents are interested in an online eHealth family program and that they feel that important features of the program should be easy to use, engaging, and endorsed by a reputable source and should involve their children directly.

To examine the feasibility of PA interventions delivered through electronic devices, before implementing the interventions, it is critical to understand parents’ perceptions of the interventions because parents’ engagement in these activities is a key factor for their success in children [21] and in the regulation and mediation practices that control electronic device use in adolescents [22]. However, to date, no reviews have focused on parents’ opinions and perceptions of eHealth to promote PA in children and adolescents, although this knowledge might be relevant for the design of both PA electronic devices and effective interventions. The aim of this systematic review of qualitative evidence is to increase the understanding of parents’ perceptions of electronic device–based PA interventions in children and adolescents.

Methods

Overview

This review was conducted according to the Cochrane Qualitative and Implementation Methods Group Guidance Series [23] and the Enhancing Transparency in Reporting the Synthesis of Qualitative Research (ENTREQ) statement [24]. The review protocol was registered in PROSPERO (CRD42021292340).

Eligibility Criteria

Studies were eligible for inclusion if they reported qualitative research analyses of the use of electronic devices for PA in healthy children and adolescents. In this study, electronic devices were defined as tools that can receive, store, process, or send digital information, including computers, tablets, smartphones, smart or electronic watches, and virtual reality devices [25]. Studies using qualitative designs with any of the following data collection procedures were eligible for inclusion: interviews, focus groups, or other qualitative data collection procedures, such as observation. Mixed methods studies were included when quantitative and qualitative data were separately

https://mhealth.jmir.org/2023/11/e44753
reported; however, only data on qualitative analyses were considered. There are different types of electronic devices (ie, activity trackers, video games, smartphone apps) for direct use by children, for use by parents to enhance their children’s PA, or for use by both together.

Studies were excluded if (1) parents were not directly asked; (2) PA interventions referred participants to rehabilitation programs or facilities; (3) populations had developmental disabilities, developmental delays, or cognitive impairment; (4) the electronic device was not designed for use by children or adolescents or for interactive use by parents and children (eg, electronic devices for parents’ use only); and (5) the study was a protocol, review, or meta-synthesis.

**Search Strategy**

Two authors (MVA and ARH) independently identified qualitative studies published from the beginning (in 2010) up to May 2022, reporting parents’ perceptions of PA electronic devices. The research objective was addressed with the question framework PerSPecTIF proposed by Booth et al [26]. Both authors systematically searched Medline/PubMed, SPORTDiscus, Web of Science, and Scopus using a search strategy that combined 5 different concepts: “electronic devices,” “physical activity,” “parents,” “qualitative research,” and “children and adolescents.” The free-text terms and Medical Subject Headings (MeSH) terms used to search were restricted to titles/abstracts. Searches for gray literature (eg, unpublished studies) were conducted using OpenGrey and Deep Blue. In addition, the 2 authors screened the reference lists of the papers included. The complete search strategy is presented in Multimedia Appendix 1.

**Study Selection**

Search terms were entered into each database, and duplicates were removed. The titles and abstracts retrieved were independently assessed for eligibility for inclusion in the review by 2 authors (MVA and ARH) and coded as “yes,” “no,” or “maybe.” The 2 authors were trained regarding study inclusion/exclusion criteria before completing the coding of abstracts. Any disagreements between the 2 authors were resolved through discussion, and if disagreement persisted, a third author (MSL) was consulted.

**Assessment of Methodological Quality**

Papers selected for inclusion were assessed by 2 authors (MVA and MSL) using the 10-item checklist of the Johanna Briggs Institute Qualitative Assessment and Review Instrument (JBI-QARI) [27] for methodological validity prior to inclusion in the review. All items in the checklist were ranked as “yes,” “no,” or “unclear.” Finally, each study was rated overall as “included,” “excluded,” or “seeking further info” [27]. Studies meeting more than 7 items were rated as “included,” studies with items rated as “no” or “unclear” were rated as “seeking further info” and protocols, and corresponding authors were consulted. Studies meeting less than 5 items were rated as “excluded” and removed from the study. Any disagreements between the 2 authors were resolved through discussion, and a third author (BRM) was consulted if disagreement persisted.

**Data Abstraction**

Qualitative data were extracted by 2 independent authors (MVA and MSL). Both authors read the papers and extracted key themes and concepts. These were compared, and any differences were resolved through discussion. The following data were extracted from all eligible papers: authors and context, year of publication, location, paradigmatic approach, method of data collection and analysis, data analysis software, participants’ background, sample size and age, recruitment location and method, study aims, intervention or exposure, and main results.

**Data Analysis and Synthesis**

First, 2 authors (MVA and MSL) read the papers, extracted key themes and proofs (transcriptions of parents’ verbalizations), and generated categories. A third author (BRM) was consulted if discrepancies arose. Differences were solved through discussion until agreement was reached. To identify common themes and analyze meanings, the meta-aggregation approach [28] was used. This process identifies meanings and common themes in qualitative studies using different methodologies and further extracts those meanings into categories that are then synthesized [29]. Next, MVA synthesized the key themes, meanings, and proofs (transcriptions of parents’ verbalizations) into tables.

**Results**

**Study Selection and Characteristics**

The electronic search retrieved 2153 records. After the removal of duplicate studies, 1312 (60.9%) papers were reviewed based on the title and abstract. Following this, the full texts of 43 (3.3%) studies were reviewed; 1 (0.1%) additional study was identified after screening the reference lists of eligible papers. Finally, 18 (41%) eligible papers were included using the selection process shown in Figure 1.
The 18 studies selected were published between 2010 and May 2022 and included 410 parents, mostly mothers, of 2-17-year-old children and adolescents (Tables 1-3). Of the 18 studies, 5 (28%) analyzed preschool children, 7 (39%) analyzed school children, 3 (17%) analyzed adolescents, and 3 (17%) did not provide separate results for children and adolescents. For data collection, 12 (67%) studies [30-41] used focus groups with semistructured interviews, 7 (39%) [20,30,42-46] used individual interviews, and 1 (6%) [41] used nonparticipant observation. Regarding the electronic devices analyzed, 5 (28%) studies [20,30,38,41,42] used smartphone apps, 2 (11%) [37,40] used the Pokémon GO mobile game, 1 (6%) [45] used mobile text messages, 5 (28%) [31-33,39,44] used activity trackers, 4 (22%) [34-36,43] used active video games, and 1 (6%) [46] used virtual reality.
**Table 1. Characteristics of included studies (preschoolers).**

<table>
<thead>
<tr>
<th>Author, country</th>
<th>Method of data collection</th>
<th>Method of analysis (software); paradigmatic approach</th>
<th>Participants’ details (background, age, parents’ details)</th>
<th>Place and methods of recruitment</th>
</tr>
</thead>
</table>
| McCloskey et al [20], United States | Individual semistructured telephonic and face-to-face interviews | Thematic analysis, inductive approach (NVivo v.11, QSR International); N/I | • Background: low-income families in rural areas  
• Age=3-5 years  
• Parents (telephonic interviews): n=29, mean age N/I, 93% (27/29) mothers  
• Parents (face-to-face interviews): n=31, mean age N/I, 77% (24/31) mothers | Purposive sampling (preschool centers, letters) |
| Alexandrou et al [30], Sweden | Focus groups, individual interviews | Thematic analysis, inductive approach; N/I | • Background: socioeconomically diverse district  
• Age=2.5-3 years  
• Somali parents: n=5, mean age 34 (SD 6.6) years; 100% (5/5) mothers  
• Arabic parents: n=4, mean age 31.2 (SD 2) years, 100% (4/4) mothers  
• Swedish parents: n=6, mean age 35.8 (SD 4.7) years, 83% (5/6) mothers | Purposive sampling (health care centers) |
| Costa et al [31], United Kingdom | Focus groups, semistructured interviews | Thematic analysis (NVivo v.9); N/I | • Background: low socioeconomic status  
• Age=2-3 years  
• Asian and White European parents: n=17, mean age 30.36 SD (6.9) years, 100% (17/17) mothers | Purposive sampling (children’s centers) |
| Phillips et al [32], United Kingdom | Focus groups, semistructured interviews | Thematic analysis, inductive approach; N/I | • Background: highly deprived areas  
• Age=3-4 years  
• Parents: n=11, mean age 29 (SD N/I) years, 100% (11/11) mothers | Purposive sampling (children’s centers, nurseries, preschools) |
| Ek et al [42], United States | Individual semistructured interviews | Thematic analysis, inductive approach; N/I | • Background: urban preschools  
• Age=3-4 years  
• Parents: n=10, mean age 38.9 (SD 5.2) years, 91% (9/10) mothers | Purposive selection of schools (posters) |

aN/I: not informed.
<table>
<thead>
<tr>
<th>Author, country</th>
<th>Method of data collection</th>
<th>Method of analysis (software); paradigmatic approach</th>
<th>Participants' details (background, age, parents' details)</th>
<th>Place and methods of recruitment</th>
</tr>
</thead>
</table>
| Creaser et al [33], United Kingdom | Focus groups, semistructured interviews | Thematic analysis, inductive approach (NVivo, QSR International); N/I¥ | • Background: families from different ethnicities  
• Age=5-9 years  
• Parents: n=36, mean age 38 (SD 7.7) years, 67% (24/36) mothers | Purposive sampling (social media) |
| Coknaz et al [34], Germany | Focus groups, semistructured interviews | Thematic analysis, inductive approach (NVivo v.10); N/I | • Background: public primary schools  
• Age=8-13 years  
• Parents: n=N/I, mean age N/I | Purposive sampling from a clinical trial |
| De Vet et al [35], the Netherlands | Focus groups, semistructured interviews | Content analysis (ATLAS.ti v 5.2); N/I | • Background: primary schools  
• Age=8-12 years  
• Parents: n=19, mean age 42.3 (SD 4.1) years, 95% (18/19) mothers | Purposive sampling (letter) |
| Dixon et al [36], New Zealand | Focus groups | Inductive approach; N/I | • Background: different ethnicity and socioeconomic groups in urban communities  
• Age=10-14 years  
• Maori parents: n=8, mean age N/I  
• Pacific parents: n=24, mean age N/I  
• Others: n=7, mean age N/I | Purposive sampling (community and church) |
| Lindqvist et al [37], United States | Focus groups, semistructured interviews | Latent content analysis; N/I | • Background: families  
• Age=7-12 years  
• Parents: n=9, mean age 38.7 (SD N/I), 78% (79) mothers | Purposive sampling |
| Rossi et al [38], Italy | Focus groups, semistructured interview | Content analysis (NVivo), community-based participatory action research | • Background: mothers  
• Age=0-14 years b  
• Parents: n=5, mean age N/I, 100% (5/5) mothers | Purposive sampling (public health local program) |
| Sharaievska et al [39], United States | Semistructured group interviews | Open, axial, selective coding techniques, grounded theory | • Background: families in rural communities  
• Age=7-13 years  
• Parents: n=N/I, mean age N/I | Purposive sampling |
| Sobel et al [40], United States | Nonparticipant observations and semistructured interviews | Inductive-deductive approach; N/I | • Background: families playing Pokémon GO in public locations  
• Age=2-17 years b  
• Parents: n=87, mean age 42 (SD 7.2) years, 70% (61/87) mothers | Purposive sampling (parks, shopping centers, events, online platforms) |
| Barnett et al [43], Australia | In-depth semistructured telephonic interviews | Thematic analysis (NVivo), descriptive qualitative approach | • Background: N/I  
• Age=9-10 years  
• Parents: n=29, mean age N/I | Purposive sampling from a clinical trial |
| Mackintosh et al [44], Australia | Web-based and face-to-face semistructured interviews | Thematic analysis, inductive approach (NVivo v.12); N/I | • Background: families  
• Age=7-12 years  
• Parents (web interview): n=25, mean age N/I, 84% (21/25) mothers  
• Parents (face-to-face interviews): n=10, mean age N/I, 100% (10/10) mothers | Purposive sampling (email) |

¥N/I: not informed.

bSome studies mixed ages in the sample and did not provide a separate analysis by age.
Table 3. Characteristics of included studies (adolescents).

<table>
<thead>
<tr>
<th>Author, country</th>
<th>Method of data collection</th>
<th>Method of analysis (software); paradigmatic approach</th>
<th>Participants’ details (background, age, parents’ details)</th>
<th>Place and methods of recruitment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carrion et al [41], Spain</td>
<td>Focus groups</td>
<td>Content analysis, phenomenological approach</td>
<td>Background: parents from public or charter schools</td>
<td>Purposive sampling (schools)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Age=13-15 years</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Parents: n=10, mean age N/I, 50% (5/10) mothers</td>
<td></td>
</tr>
<tr>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lindqvist [45], Sweden</td>
<td>Individual semistructured interview</td>
<td>Latent content analysis (NVivo, QSR International), empowerment</td>
<td>Background: families of a municipality of North Sweden</td>
<td>Purposive sampling (from an intervention)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Age=13-15 years</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Parents: n=10, mean age N/I, 60% (6/10) mothers</td>
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<tr>
<td>McMichael et al [46], United Kingdom</td>
<td>Semistructured interview</td>
<td>Framework analysis, Medical Research Council (MRC) framework</td>
<td>Background: families</td>
<td>Purposive sampling (social media, schools, university, emails, and posters)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Age=13-17 years</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Parents: n=18, mean age 53 (SD 3) years, 72% (13/18) mothers</td>
<td></td>
</tr>
</tbody>
</table>

Study Quality

The assessment of the 18 studies included in this systematic review is presented in Multimedia Appendix 2. Only 1 (6%) study [31] met all 10 items in the JBI-QARI checklist, 8 (44%) studies [20,30,32,33,40-42,46] met 9 items, 8 (44%) [35-39,43-45] met 8 items, and 1 (6%) [34] met 5 items. No studies were rated as “excluded”; thus, none was excluded based on methodological quality. The main weaknesses were a lack of clarity and a lack of reporting on the researcher’s influence on the study and vice versa [20,30,34,35,39,40,43-45]. Other limitations were that participants and their voices were not adequately represented in 3 (17%) studies [34,36,38] and that there was no congruity between the stated philosophical perspectives and the research questions or methodology [34,35].

Synthesized Findings

We identified 4 main themes (Textbox 1) in terms of parents’ perceptions of PA electronic devices: usefulness, advantages, general perceptions, and acceptability (barriers and facilitators). The main results are shown in Table 4, and proofs are shown in Multimedia Appendix 3.
Textbox 1. Themes and subthemes describing parents’ perceptions of physical activity (PA) electronic devices.

<table>
<thead>
<tr>
<th>Usefulness of PA electronic devices</th>
</tr>
</thead>
<tbody>
<tr>
<td>• PA promotion and PA in special moments</td>
</tr>
<tr>
<td>• Learning of skills and transferability to real life</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Advantages of PA electronic devices</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Increase in motivation</td>
</tr>
<tr>
<td>• Awareness of behaviors</td>
</tr>
<tr>
<td>• Family bonding</td>
</tr>
<tr>
<td>• Socialization with peers</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>General perceptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Electronic devices for health promotion</td>
</tr>
<tr>
<td>• Preferences for real-life activities or active screen time</td>
</tr>
<tr>
<td>• Concerns: content, addiction, negative emotions, isolation, conflicts, limits</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Acceptability (barriers and facilitators)</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Lack of time and stress</td>
</tr>
<tr>
<td>• Price</td>
</tr>
<tr>
<td>• Lack of space at home</td>
</tr>
<tr>
<td>• Discomfort/discomfort</td>
</tr>
<tr>
<td>• Difficulties with electronic devices or understanding feedback given by the app</td>
</tr>
<tr>
<td>• No new activities/suggestions</td>
</tr>
<tr>
<td>• Lack of use/interest after novelty</td>
</tr>
<tr>
<td>• Attractiveness (high technology, good graphs, good quality, videos)</td>
</tr>
<tr>
<td>• Gamification (competition, challenges, goals, and rewards) and fun</td>
</tr>
<tr>
<td>• Teacher and school support</td>
</tr>
<tr>
<td>• Ease of use</td>
</tr>
<tr>
<td>• Durability</td>
</tr>
<tr>
<td>• Integrated into daily routines</td>
</tr>
</tbody>
</table>
### Table 4. Summary of findings.

<table>
<thead>
<tr>
<th>Participants included, author, country</th>
<th>Area of inquiry/aims</th>
<th>Intervention/exposure</th>
<th>Main results</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Preschoolers</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>McCloskey et al [20], United States</td>
<td>To explore parents’ beliefs about preschoolers’ use of mobile devices and the acceptability and perceptions of a PA app intervention</td>
<td>Jungle Gym: a mobile app to encourage PA, focused on movement, motor skills (running, jumping, leaping, etc), and interactions with parents/children</td>
<td>Parents supported the use of mobile apps for PA and reported that they were useful in various situations (eg, on bad-weather days). Parents also expressed concerns about the apps.</td>
</tr>
<tr>
<td>Alexandrou et al [30], Sweden</td>
<td>To explore needs and concerns among Somali, Arabic, and Swedish parents regarding a PA app</td>
<td>MINISTOP 1.0 mobile app: a 6-month program to support parents in promoting PA</td>
<td>Parents found the app useful. Insights into their needs and important features were obtained.</td>
</tr>
<tr>
<td>Costa et al [31], United Kingdom</td>
<td>To assess mothers’ opinions about the feasibility and acceptability of using an activity tracker</td>
<td>Actigraph GT3Xp, Actiheart (CamNtech Ltd), ActiPAL3 (PAL Technologies Ltd): 3 activity trackers</td>
<td>Children were most comfortable with Actigraph and least comfortable with Actiheart. Problems with the devices were the possibility of children taking them off, allergic skin reactions, or discomfort.</td>
</tr>
<tr>
<td>Phillips et al [32], United Kingdom</td>
<td>To examine parents’ acceptability and feasibility of measurement tools to assess PA</td>
<td>Actigraph GT3X+, ActiPAL4 micro, Actical (Philips Respironics Inc): 3 accelerometers</td>
<td>Parents reported that ActiPAL was the least preferred electronic device (children’s opposition to wearing it on their chest, skin irritation). Actigraph was the most accepted.</td>
</tr>
<tr>
<td>Ek et al [42], United States</td>
<td>To explore parents’ needs and perceptions of a PA app in a school setting</td>
<td>Mobile phone app to promote PA in a school setting</td>
<td>Parents reported the need for interactive features, problem-solving tasks, creativity, and music and dance activities and had a positive attitude toward the app. Children found activities more fun when adults participated.</td>
</tr>
<tr>
<td><strong>Children</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Creaser et al [33], United Kingdom</td>
<td>To examine parents’ acceptability of using wearables in a family setting</td>
<td>Fitbit Alta HR for 4 weeks, Actigraph GT3X+</td>
<td>Fitbit was considered easy and enjoyable to use, but its perceived impact on PA was mixed. Most parents were willing to purchase a wearable.</td>
</tr>
<tr>
<td>Coknaz et al [34], Germany</td>
<td>To analyze the feelings and perspectives of parents about active video games</td>
<td>Nintendo Wii® sports (boxing, tennis, golf, baseball, bowling, skiing, aerobics, running, water skiing, etc) for 50-60 minutes, 3 days/week, 12 weeks</td>
<td>Parents believed that active video games might help in physical changes, socializing, and intellectual and personal development of children.</td>
</tr>
<tr>
<td>De Vet et al [35], the Netherlands</td>
<td>To explore parents’ perceptions and opinions about active video games</td>
<td>Active video games</td>
<td>Parents had a positive attitude toward active and interactive video games. Some parents were less restrictive with them.</td>
</tr>
<tr>
<td>Dixon et al [36], New Zealand</td>
<td>To explore parents’ perceptions of active video games and the probability of sustained engagement</td>
<td>Active video games (eg, EyeToy™, Dance Mat)</td>
<td>Parents supported active video games. They preferred nonviolent and sporty video games. Benefits, such as increased PA, improved fitness, and increased socializing, were reported.</td>
</tr>
<tr>
<td>Lindqvist et al [37], United States</td>
<td>To explore parents’ perceptions of playing Pokémon GO</td>
<td>A gamification-inspired program using the Pokémon GO mobile game</td>
<td>Parents found that the game promotes PA. They were less likely to limit the time spent on this game. They suggested new features and concerns about safety.</td>
</tr>
<tr>
<td>Rossi et al [38], Italy</td>
<td>To explore parents’ perceptions of a mobile app</td>
<td>Multimodal app for parents’ mobile phones to promote children’s health, including PA</td>
<td>Mothers had a positive attitude toward the app and made suggestions (feedback, geolocation, and attractive features).</td>
</tr>
<tr>
<td>Sharaiyevsa et al [39], United States</td>
<td>To explore the perception of a PA tracker</td>
<td>PA-tracking electronic device (Fitbit Zip), which each family member was asked to wear for 2 weeks</td>
<td>Parents reported minimal changes in PA because of a lack of interest or an already active lifestyle. The electronic device provided more awareness.</td>
</tr>
</tbody>
</table>
Parents’ Perceptions of the Usefulness of PA Electronic Devices

The first theme reported was the main usefulness that eHealth technologies might have. The core concepts that support this theme included PA promotion and the learning of skills.

Parents perceived electronic devices as useful for increasing PA levels [34,35,37,39,40,44,45]; for example, parents reported that the Pokémon GO mobile game encourages children to be more active and promotes taking long walks through the neighborhood [37,40]. Alternatively, PA is not possible in specific moments when outdoors, for example, on bad-weather days [20]. Regarding activity trackers, parents reported that using activity trackers made them aware of other interesting habits of their children, such as sleep or heart rate [30,33,44]. Moreover, eHealth apps were useful for parents to become aware of their own levels of PA [39,44], and this, in turn, promoted changes in their attitude toward PA and increased their own PA levels [39]. In addition, parents said that using activity trackers made them aware of other interesting habits of their children, such as sleep or heart rate [30,33,44].

Another advantage of some electronic devices that parents highlighted is that they promote socialization [34,35,37,40,46] and cooperation and competition with peers. For example, playing video games is suitable for playing with the family and an enjoyable activity to do together, reinforcing their bonds [20,35,37,39,40,44]. Other games promoted social interactions by providing users with something in common to talk about [39,40,44-46].

Parents’ Perceptions of the Advantages of PA Electronic Devices

The advantages of PA electronic devices that parents reported included an increase in motivation for engaging in real-life sports [39,41,43], more awareness, family bonding, and socialization with peers. For example, playing video games motivates children to engage in real-life sports [33,35,37,40,43,44]. Moreover, eHealth apps were useful for parents to become aware of their own levels of PA [39,44], and this, in turn, promoted changes in their attitude toward PA and increased their own PA levels [39]. In addition, parents said that using activity trackers made them aware of other interesting habits of their children, such as sleep or heart rate [30,33,44].

Parents had a negative perception of gaming and preferred real-world PA. They reported the benefits of active games (socializing, motor skills, moving) and concerns (eg, addiction).

Parents’ perceptions of the usefulness of PA electronic devices. The core concepts that support this theme included PA promotion and the learning of skills. Parents perceived electronic devices as useful for increasing PA levels [34,35,37,39,40,44,45], for example, parents reported that the Pokémon GO mobile game encourages children to be more active and promotes taking long walks through the neighborhood [37,40]. Alternatively, PA is not possible in specific moments when outdoors, for example, on bad-weather days [20]. Regarding activity trackers, parents reported that using activity trackers made them aware of other interesting habits of their children, such as sleep or heart rate [30,33,44]. Moreover, eHealth apps were useful for parents to become aware of their own levels of PA [39,44], and this, in turn, promoted changes in their attitude toward PA and increased their own PA levels [39]. In addition, parents said that using activity trackers made them aware of other interesting habits of their children, such as sleep or heart rate [30,33,44].

Another advantage of some electronic devices that parents highlighted is that they promote socialization [34,35,37,40,46] and cooperation and competition [37,40,45] with peers and family [20,35,37,39,40,44]. Parents also reported that active video games are suitable for playing with the family and an enjoyable activity to do together, reinforcing their bonds [20,35,37,39,40,44]. Other games promoted social interactions by providing users with something in common to talk about [39,40,44-46] or by enabling them to play interactively with others [35,40,46]; these features were particularly important for video games to a real-life context, and they felt that it is unlikely that their children would benefit from learning skills from virtual apps [43].

Parents valued mobile apps for health promotion. They preferred apps that promote activity and interactions and include gamification and rewards.

Parents reported that the activity tracker was easy and useful. Barriers (lack of real-time feedback and difficulties in interpreting information) and suggestions (visual display, self-monitor activity, goal setting, and challenges) were identified.

<table>
<thead>
<tr>
<th>Participants included, author, country</th>
<th>Area of inquiry/aims</th>
<th>Intervention/exposure</th>
<th>Main results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sobel et al [40], United States</td>
<td>To explore parents’ perceptions of an app that promotes outdoor PA and to explore how they play with children</td>
<td>Pokémon GO</td>
<td>Parents reported an increased level of PA and valued how play led to family bonding. Concerns about safety and limits of game play emerged.</td>
</tr>
<tr>
<td>Barnett et al [43], Australia</td>
<td>To identify parents’ perceptions of active video games for development of movement skills</td>
<td>Active video games</td>
<td>Parents were skeptical of the capacity of video games to contribute to skill development and preferred real sports.</td>
</tr>
<tr>
<td>Mackintosh et al [44], Australia</td>
<td>To explore parents’ perceptions of the acceptability and usability of wearable activity trackers to monitor PA</td>
<td>KidFit (X-Doria International) worn by each child for 4 weeks</td>
<td>Parents reported that the activity tracker is easy and useful. Barriers (lack of real-time feedback and difficulties in interpreting information) and suggestions (visual display, self-monitor activity, goal setting, and challenges) were identified.</td>
</tr>
</tbody>
</table>

Adolescents

<table>
<thead>
<tr>
<th>Participants included, author, country</th>
<th>Area of inquiry/aims</th>
<th>Intervention/exposure</th>
<th>Main results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carrion et al [41], Spain</td>
<td>To explore parents’ perceptions, values, and preferences regarding mobile apps to promote PA</td>
<td>PEGASO Fit for Future: a mobile app to promote a healthy lifestyle, including PA, through gamification and family connections</td>
<td>Parents valued mobile apps for health promotion. They preferred apps that promote activity and interactions and include gamification and rewards.</td>
</tr>
<tr>
<td>Lindqvist [45], Sweden</td>
<td>To describe parents’ perceptions of an empowerment-inspired PA intervention via mobile phones</td>
<td>Empowerment-based intervention via Short Messaging Service (SMS)</td>
<td>Parents found that children felt involved in the process and reported that social support and encouragement had an impact on PA. Goals and rewards could be motivating for PA.</td>
</tr>
<tr>
<td>McMichael et al [46], United Kingdom</td>
<td>To understand parents’ views of PA, gaming, and virtual reality in PA interventions</td>
<td>Engage project active virtual reality</td>
<td>Parents had a negative perception of gaming and preferred real-world PA. They reported the benefits of active games (socializing, motor skills, moving) and concerns (eg, addiction).</td>
</tr>
</tbody>
</table>

aPA: physical activity.
adolescents. Thus, parents reported how cooperation and social interaction were important factors in continuing to use the apps, since they found the apps fun and motivating [37,39].

**Parents’ General Perceptions of PA Electronic Devices**

The general perceptions of parents about PA electronic devices were grouped into 3 key concepts: attitudes about electronic devices for health promotion, preference for real-life sports or active electronic devices, and concerns about the use of electronic devices.

Generally, parents were prone to using technology for health and educational purposes [20,42,46]. Furthermore, parents reported the desirability of apps being targeted not only at children but also at parents [30]. They suggested tracking their health lifestyles to be important, such as having an agenda or a reminder and the inclusion of health information [30]. Additionally, parents reported a preference for active and social video games or the active use of screens over passive screen time [35,36,46]. For example, active video games, such as Nintendo Wii, were perceived as a healthier alternative to passive screen time [35]. However, parents distinguished between real-life sports and virtual worlds, showing preferences toward playing outside rather than virtual PA [17,36,40,43,47].

In contrast, they also highlighted several concerns and dangers. Many of the parents were worried about violent content in video games, the appropriateness of content for different ages [35,46], concerns about children playing with strangers, safety [40,46], and physical accidents resulting from walking with the phone in hand [37]. In addition, psychological effects, such as anger, frustration, isolation, or addiction, were also reported [35,37,40,46]. Other common issues highlighted were conflicts when playing video games [37] and difficulties in establishing time limits, which increased with age. In that respect, although parents were more positive toward active video games and active screen use, setting limits and supervising screen use were important issues [20,35,37,40,46].

**Parents’ Perceptions of the Acceptability of PA Electronic Devices**

**Barriers**

Some barriers to using PA electronic devices were found. Commonly, parents reported a lack of time to engage in eHealth activities because of their work or children’s schedules [33,39,45]. Others found difficulties in managing extensive health information and reported feeling stressed by trying to follow all the recommendations [30]. Still, others highlighted the high prices of video games and electronic devices [35,36], and some were annoyed by the noise and space the devices occupy at home while playing [36,42,46].

Regarding the physical characteristics of activity trackers, the main issues raised included unsuitability, discomfort caused by a large size, drawbacks of wearable devices, children trying to remove electronic devices [31,32,44], and difficulties with batteries and syncing [44]. The size of the electronic device was especially important for younger children [31,32]. Other issues were difficulties in using activity trackers or understanding the information provided [33]. Several other factors impacted the use and wearability of activity trackers, including forgetting to wear them, having to remove them for certain sports, the lack of real-time feedback [44], and the lack of interest by parents [33,39]. In this sense, some parents said that activity trackers did not promote any new activity [39]. They also highlighted concerns about the lack of use of the electronic devices once they lost their novelty [33,36] and a lack of long-term wear compliance [44].

**Facilitators**

Parents reported several facilitators of the use of PA electronic devices. For example, they showed a preference for cheaper games that they could afford [35]. Other factors that facilitated engagement were the attractiveness of the game or electronic device, whether it uses high-level technology or appealing graphics [33,46], or the inclusion of videos [30,32,35].

Parents also reported that 2 important facilitators that ensure long-term engagement are gamification and fun [32,33,35,37,42,44]. Teacher support was found to be an important factor in engagement [44,45]. Parents said that goals [31,45] and rewards and new challenges [38,39,43,47] are important features—for example, different levels and new challenges to accomplish [47]. In that sense, many of the parents reported that an important feature is for an app to be fun [39,42,43]. To make apps appealing to children, parents recommended including reinforcement, such as treasure hunts or challenges, which might make the apps motivating. Regarding goal setting, the possibility of establishing goals with others, such as family members, peers, or classmates, was also recommended [31,45]. Furthermore, parents suggested that apps provide interaction with professionals, such as online forums [30,38], and be linked to the school curriculum [44], and teacher support was found to be an important factor in engagement [44,45]. Other ideas were links with sports associations and outdoor activities, such as events, active commuting, and geolocalization [38].

For activity trackers, parents reported some important characteristics that facilitate engagement. Most of them highlighted the importance of comfort [31-33,44], considering that an activity tracker should be worn all the time [32], and ease of use so that the children can understand and handle the device on their own [33,44] with an easy-to-use app [33]. Parents also reported the importance of considering the durability and damage resistance of electronic devices, since younger children might break them [32], and the integration of eHealth with their daily routines [33]. Other suggestions for activity trackers were real-time feedback and a complete dashboard showing information about scores, steps with good graphs, and demonstrations [32]. Features such as competition with others, options for new activities, and high-level technology were perceived as important.

**Age Group Differences**

Of the 18 studies, 5 (28%) [20,30-32,42] analyzed the opinions of the parents of preschoolers’ (<5 years old). Generally, parents were less worried about their children’s PA [30] because they perceived them as spontaneously active and preferred outside PA [20,42]. For preschoolers, most parents tried to limit
technology as much as they could [20,42] and used PA apps when real PA was not possible [20,30]. Regarding activity trackers, the problems of wearability due to the size of the devices were highlighted [32].

Furthermore, 10 (55%) studies [33-40,43,44] analyzed schoolchildren between 7 and 12 years old. Parents of children in this age group also showed preferences for real PA [43], although they preferred PA apps over passive screen use [35,36]. Parents were worried about content and addiction and the necessity to set limits on screen time [35-37], and they more frequently reported interactive uses of PA electronic devices with peers and family [35,37]. Regarding activity trackers, parents highlighted the requirement of usefulness for children [44] and the importance of PA electronic devices and activity trackers to be designed specifically for children’s use [33].

In addition, 3 (17%) studies [41,45,46] analyzed samples of parents of adolescents and showed that technology could be an effective strategy to connect with adolescents and help them acquire healthier habits [41]. Regarding this age group, parents were more worried about screen time, the time spent in gaming, and the time spent in sedentary pursuits and preferred technology uses that promote health, education, or socializing [45,46]. They perceived technology as unavoidable and reported difficulties in limiting screen time [46].

Discussion

Principal Findings

To the best of our knowledge, this is the first study that systematically reviews qualitative research that explores parents’ perceptions of electronic devices that promote PA in children and adolescents. Overall, parents perceived electronic devices as useful for PA promotion. Moreover, they found other advantages, such as health promotion, awareness of health behaviors, learning of motor and cognitive skills, increased motivation for PA, and promotion of family and social interactions. Parents also valued some of the features of electronic devices, such as being comfortable, easy to use, active, challenging, and fun. However, some barriers and concerns, such as the risk of addiction, safety issues, or difficulties in setting limits, emerged. Preschoolers’ parents found it less necessary to promote PA and preferred that their children spend time in outdoor activities. In contrast, in the case of older children and adolescents, when screen time increased, parents reported more advantages of using active electronic devices that promote PA.

A previous qualitative study that asked parents about their attitudes toward the use of electronic devices and media reported that parents are concerned about the total amount of time that children engage with electronic devices; specifically, they said that engaging with electronic devices prevents children from being physically active [47]. Additionally, other studies have reported positive attitudes of parents toward the use of electronic devices in children, as parents perceive them as a reality in children’s and adolescents’ lives [48], especially for educational and health purposes [49,50]. Similarly, in our study, parents had positive attitudes toward the use of technology for health purposes, such as promoting PA, and they preferred active electronic devices and dance- or sports-based video games rather than traditional sedentary screens [35] because parents perceive active electronic devices as a healthier alternative to passive screen time. Nevertheless, they preferred real PA or outdoor PA over PA on an electronic device [20,35,46]; thus, PA apps do not substitute but complement traditional forms of PA.

Other concerns that parents had, in addition to the high amount of time spent on electronic devices by children and adolescents, were the risk of addiction; the lack of skills; the emergence of negative emotions, such as anger; and violent or sexual content. These concerns are similar to those shown by previous studies, where parents reported being worried about access to inappropriate content, addiction, and negative emotions [9,47,51,52]. In this study, as in previous studies [47,52], parents perceived difficulties in setting limits on the time spent on electronic devices. Their concerns led them to implement different mediation strategies, such as couse, supervision, active mediation, restrictive mediation, and monitoring, depending on positive or negative attitudes toward media [53]. Along this line, parents reported being less restrictive in the case of active electronic devices, rather than passive ones, that promoted social interactions. Regarding social bonds, strong social and family bonds play a large role in controlling the overuse of electronic devices [52]. In this study, parents liked electronic devices that promoted family interactions to play together or that promoted peer interactions, as they believed that games that promote interactions might mitigate the lack of skills and isolation arising from the overuse of electronic devices.

Regarding age, as in a previous study [54], some differences were found, since electronic device usage and social, cultural, and cognitive experiences are vastly different between a 3-year-old child, an older child, and a teenager. In this study, parents of preschool children found no necessity for PA promotion since they perceived that their children were naturally active and used as few electronic devices as possible. In contrast, a study that analyzed general attitudes toward the use of electronic devices and media exposure in young children found that most parents have positive attitudes toward electronic devices, not only for educational purposes but also for entertainment [48]. This difference might be because our study analyzed only PA electronic devices and parents showed a general tendency to overestimate their children’s PA [55], and thus, they perceived a low necessity of electronic devices to increase PA in their children. As children grow older, parents show increasing concerns about the amount of time spent using electronic devices, due to a substantial increase in hours using electronic devices with age [56]. In older children and adolescents, parents report more conflicts and difficulties in limiting electronic device use, consistent with previous studies [18] in which parents of adolescents have reported that setting limits on electronic device use is often confrontational and frequently escalates into arguments and shouting [57]. Therefore, parents implement different mediation practices [58] to regulate the use of electronic devices according to age, as the needs of children and adolescents change with development. Regarding gender differences, only 1 study showed that girls might engage in different challenges and games than boys [46]; congruently,
a previous study found limited evidence of children’s gender differences that precluded us from drawing conclusions [54], suggesting that differences in electronic device use and preferences might be considered in further studies.

Finally, parents reported some barriers that need to be considered in further studies, such as lack of time, stress, and high prices of electronic devices. Specifically for activity trackers, comfort, ease of use, difficulties in understanding the apps, or difficulties in understanding the feedback provided were the most common barriers. Conversely, facilitating factors for engagement included the attractiveness of the app, comfort, and children’s self-efficacy in using the electronic device, similar to a previous study of eHealth programs [21]. Some suggestions provided by parents for new PA electronic devices included goal setting and rewards, usability, comfort, real-time feedback, and activities that promote interactions with friends and family, similar to a previous study [8]. In addition, parents had a favorable attitude toward the promotion of technology-based PA strategies in school contexts, and some also considered the involvement of schools and teachers in interventions and connection with the community [42,44,59].

Strengths
To the best of our knowledge, this is the first systematic review to synthesize findings from qualitative studies examining parents’ perceptions of PA electronic devices. To ensure that the search process was systematic, an exhaustive search was carried out in specialized databases and gray literature by multiple researchers. This search was reported accurately according to the ENTREQ statement [24]. The meta-aggregation approach [29] was used to extract key themes and proofs, which enhanced the reliability of the data. In addition, data were meticulously documented in a matrix, and an assessment of the methodological strength of the analyzed papers was performed.

Limitations
This review has some limitations that should be acknowledged. First, there was high heterogeneity in the studies regarding the type of electronic device (mobile phones, activity trackers, exergames, virtual reality), data collection methods, location, duration of interventions, sample recruitment strategies, and the age of users. Along this line, studies considering differences between preschoolers, children, and adolescents are needed because these 3 age groups have different lifestyles, interests, and needs. Furthermore, gender differences between boys and girls were considered only in 1 study [46], which might be a source of bias since girls and boys have different levels of PA and different uses and preferences of technology. Second, most participants in the included studies were mothers, which might be due to mothers still parenting more than fathers; however, further studies considering fathers’ opinions are recommended. Finally, some studies did not include an adequate description of the theoretical paradigm and did not provide information about how the researchers’ background was managed.

Conclusion
This review explored the perceptions of children’s and adolescents’ parents regarding the use of electronic devices for PA enhancement. Parents reported that PA electronic devices could be an effective way to promote PA in children and adolescents and to overcome barriers, such as bad weather, lack of motivation, or the high rate of sedentarism in this population. In addition, parents prefer games and apps that require PA over traditionally passive games and apps. Parents also reported negative attitudes toward the use of technology in terms of addiction, safety problems, and difficulties in establishing limits, which should be considered in future interventions. These insights might provide researchers with more knowledge of how parents manage, promote, and regulate the use their children make of PA eHealth, the acceptability of interventions, and how they use PA eHealth at home. Some important features to consider in the development of new PA apps and technology-based interventions are the developmental stage, ease of use, appropriate feedback, promotion of socialization, and motivating strategies, such as rewards, challenges, and an appealing appearance.

Authors’ Contributions
MVA contributed to writing the original draft, project administration, and visualization; VMV contributed to conceptualization and supervision; MSL and MVA performed investigation and formal analysis; ARH contributed to validation and data curation; BRM and RBG conducted supervision, methodology, and review and editing; and ISD contributed to data curation and review and editing.

Conflicts of Interest
None declared.

Multimedia Appendix 1
Search strategy.
[DOCX File, 18 KB - mhealth_v11i1e44753_app1.docx ]

Multimedia Appendix 2
Methodological quality of included studies.
[DOCX File, 21 KB - mhealth_v11i1e44753_app2.docx ]
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Abbreviations

ENTREQ: Enhancing Transparency in Reporting the Synthesis of Qualitative Research

JBI-QARI: Johanna Briggs Institute Qualitative Assessment and Review Instrument

PA: physical activity

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Original Paper

Current Status and Trends in mHealth-Based Research for Treatment and Intervention in Tinnitus: Bibliometric and Comparative Product Analysis

Yuanjia Hu¹, BSc; Yang Lu¹, BSc; Chenghua Tian¹*, MM; Yunfan He², MSc; Kaiyi Rong³, MBBS; Sijia Pan¹, BSc; Jianbo Lei⁴,⪭, MD

¹School of Medical Technology and Information Engineering, Zhejiang Chinese Medical University, Hang Zhou, China
²School of Public Health, Zhejiang University, Hangzhou, China
³The Second School of Clinical Medicine, Zhejiang Chinese Medical University, Hangzhou, China
⁴Center for Medical Informatics, Peking University, Beijing, China
⪭Institute of Medical Technology, Peking University, Beijing, China
⁶School of Medical Informatics and Engineering, Southwest Medical University, Luzhou, China
* these authors contributed equally

Corresponding Author:
Chenghua Tian, MM
School of Medical Technology and Information Engineering, Zhejiang Chinese Medical University
No. 548 Binwen Road
Hang Zhou, 310053
China
Phone: 86 (0571) 86613786
Fax: 86 (0571) 86613729
Email: 20071044@zcmu.edu.cn

Abstract

Background: As a global medical problem, tinnitus can seriously harm human health and is difficult to alleviate, ranking among the top 3 complex diseases in the otolaryngology field. Traditional cognitive behavioral therapy and sound therapy require offline face-to-face treatment with medical staff and have limited effectiveness. Mobile health (mHealth), which, in recent decades, has been greatly applied in the field of rehabilitation health care, improving access to health care resources and the quality of services, has potential research value in the adjunctive treatment of tinnitus.

Objective: This study aimed to understand the research trends, product characteristics, problems, and research transformation of tinnitus treatment software by analyzing the research progress of mHealth for tinnitus treatment based on the literature and related marketed apps.

Methods: Bibliometric methods were used to describe the characteristics of the relevant literature in terms of the number and topics of publications, authors, and institutions. We further compared the features and limitations of the currently available tinnitus treatment software.

Results: Data published until February 28, 2022, were collected. Following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) standardized screening process, 75 papers were included. The country with the highest number of publications was Germany, followed by the United Kingdom and the United States, whereas China had only a single relevant study. The most frequently found journals were the American Journal of Audiology and the Journal of the American Academy of Audiology (18/75, 24%). With regard to publication topics, cognitive behavioral therapy started to become a hot topic in 2017, and research on mHealth apps has increased. In this study, 28 tinnitus treatment apps were obtained (n=24, 86% from product data and n=4, 14% from literature data); these apps were developed mainly in the United States (10/28, 36%) or China (9/28, 32%). The main treatment methods were sound therapy (10/28, 36%) and cognitive behavioral therapy (2/28, 7%). Of the 75 publications, 7 (9%) described apps in the market stage. Of the 28 apps, 22 (79%) lacked literature studies or evidence from professional bodies.

Conclusions: We found that, as a whole, the use of mHealth for treatment and intervention in tinnitus was showing a rapid development, in which good progress had been made in studies around sound therapy and cognitive behavioral therapy, although
most of the studies (50/75, 67%) focused on treatment effects. However, the field is poorly accepted in top medical journals, and the majority are in the research design phase, with a lack of translation of the literature results and clinical validation of the marketed apps. Furthermore, in the future, novel artificial intelligence techniques should be used to address the issue of staged monitoring of tinnitus.

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KEYWORDS

tinnitus; mobile health; mHealth; internet; application; software; bibliometrics; mobile phone

**Introduction**

**Background**

The American Academy of Otolaryngology-Head and Neck Surgery defines tinnitus as “a sound perceived by the patient in the absence of an external sound source” [1]. Several studies have shown that the worldwide prevalence rate of tinnitus ranges from 5.1% to 42.7% [2]. Xu et al [3] showed that 9.6% of the global adult population has experienced tinnitus in the past 12 months. Of these, 36% had persistent tinnitus, and 27% had tinnitus for >15 years. Persistent tinnitus can lead to severe psychological disorders, such as depression, anxiety, mania, and other affective disorders. Suicide and personal injury rates are significantly increased in patients with tinnitus [4]. As a matter of concern, the decreased availability of effective treatments for tinnitus greatly increases the socioeconomic burden of this disease in medical care [5].

Tinnitus lacks effective standardized and individualized treatments. Drugs, surgery, electrical stimulation, and psychophysiological integrative therapy are traditional treatment modalities that have serious adverse effects. Moreover, their long-term safety is unknown. Mobile health (mHealth) apps are a novel tool expected to be effective in alleviating tinnitus. The popularity of smartphones and the inherent immediacy, accuracy, and low costs of the mobile internet have contributed to the unique advantages of mHealth apps in providing health interventions and other outcomes. As of 2020, there were >300,000 (this number is rapidly growing) mHealth apps available in mobile app stores [6]. These apps help users to monitor multiple physiological indicators and provide relevant health knowledge and services to address a range of health issues [7], including tinnitus. Several studies have found that mHealth apps can provide continuous and remote monitoring of tinnitus as well as diagnostic and intervention services for patients with the condition. This can, in turn, be effective in alleviating or resolving this disorder. Most Chinese researchers provide sound therapy for patients with tinnitus through software. There are also attempts to use herbal medicine, acupuncture, and electrical stimulation for the same purpose. He et al [8] used audition software for sound therapy. Cai et al [9] integrated personalized music into tinnitus software, in combination with cognitive behavioral therapy, to innovate a tinnitus treatment intervention with substantial results.

**Objectives**

Nevertheless, most studies have focused only on monotherapeutic interventions for tinnitus. As such, there is a lack of a systematic analysis of tinnitus treatment software studies and marketed apps [10]. Therefore, using bibliometric and comparative product analysis methods, this study provides a complete and detailed description of the field of tinnitus monitoring, diagnosis, and intervention with the help of mHealth apps. Our work is the first bibliometric study to comprehensively analyze trends in publication, national and institutional distribution, core journals and highly productive authors, and research topic hot spots in this area. This study aimed to understand the research trends in tinnitus treatment software, including the characteristics and limitations of the apps available in the market. The outputs of our research can help patients to choose the right tinnitus treatment software and provide suggestions to manufacturers regarding potential ways to improve the quality and use of tinnitus treatment software.

**Methods**

**Data Retrieval and Filtering**

Regarding the research literature, to ensure completeness, our study followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) principle and searched databases in 5 different fields [11,12]. In the medical field, the PubMed and Embase databases were used. In the general science field, the Web of Science core collection was chosen. In the computer field, the IEEE and ACM databases were chosen. The search queries and strategies used for the different databases are listed in Multimedia Appendix 1. The inclusion and exclusion criteria for this study are shown in Multimedia Appendix 2.

A total of 4385 papers were retrieved from 5 databases (n=1301, 29.67% from Embase; n=34, 0.78% from IEEE; n=1373, 31.31% from PubMed; n=1591, 36.28% from Web of Science; and n=86, 1.96% from ACM). After literature deduplication, of the 4385 papers, 3590 (81.87%) remained. Two trained postgraduate students screened the retrieved papers according to the established inclusion and exclusion criteria (Cohen κ=0.91), and, of the 3590 papers, 75 (2.09%) were included in the final literature pool, as illustrated in Figure 1.

After a preliminary market survey, we identified 2 sources of information in which to search for product data: the Android platform and the Apple App Store (China and the United States). For a total of 7 official mobile software marketplaces, with the Android platform accounting for 5 (71%) mobile software marketplaces (Google Play Store as well as the mobile software marketplaces operated by Huawei, Vivo, Oppo, and Xiaomi). To obtain relevant search results for mHealth apps on the Qimai app data analysis platform [13] (accessed in March 2021), we used the following search terms: “tinnitus diagnosis,” “tinnitus...
intervention,” and “tinnitus treatment” A total of 2384 mHealth apps were retrieved, with 1812 (76%) stand-alone mHealth apps remaining after data deduplication.

In this study, mHealth apps related to tinnitus treatment were screened from 75 literature reports and 1812 independent software reports, using established inclusion and exclusion criteria. A total of 28 tinnitus treatment apps were obtained (n=24, 86% from product data and n=4, 14% from literature data). The specific inclusion and exclusion criteria applied to select the target apps are listed in Textbox 1. A screening flowchart of the mHealth apps is shown in Figure 2.

Figure 1. Flowchart of literature data screening. WoS: Web of Science.

Textbox 1. Inclusion and exclusion criteria applied to select the target apps.

**Inclusion criteria**
- Inclusion criterion (IC) 1: apps identified with the search terms “tinnitus,” “hearing test,” “sound therapy,” “cognitive behavioural therapy,” “cbt,” “perceptual mask,” “perceptual masking,” “retraining therapy,” and “sleep”
- IC2: apps with either a health purpose or a medical purpose

**Exclusion criteria**
- Exclusion criterion (EC) 1: Apps consisting only of sleep aid, relaxation, or meditation software; pure mood journals; or diary functionalities (with or without cognitive behavioral therapy)
- EC2: apps consisting only of mobile hearing test, aid, or debugging software, pure mobile sound level meter software, or pure speech therapy software (not related to tinnitus)
- EC3: health management software for other diseases (not related to tinnitus)
- EC4: insufficient software information
Figure 2. The screening flowchart of the mobile health apps. EC1: exclusion criterion 1; EC2: exclusion criterion 2; EC3: exclusion criterion 3; EC4: exclusion criterion 4; IC1: inclusion criterion 1; IC2: inclusion criterion 2.

Extraction of App Information

In this study, we extracted general and specific information about 28 apps, using the Qimai app data analysis platform. General information about the apps included their names, reviews, and ratings. The specific information obtained on the apps was analyzed from 3 perspectives: time, space, and content. From a temporal perspective, the fields extracted from the specific information included the dates of product release and last update, as well as in-app, off-app, and unreleased stores. With regard to the spatial perspective, the specific information included the product’s country of origin and the name, location, and size of the product manufacturer. From the content perspective, the specific information included type, purpose, input and output information, clinical role, main treatments related to the software, their effectiveness, and software scenario.

Data Analysis Methods

To review and summarize the current status of, and research trends in, mHealth treatments and interventions for tinnitus, we used a bibliometric and comparative product analysis approach, based on a literature output-product output–literature versus product chain. We used the bibliometrix package in R for data analysis and the ggplot2 package for mapping. First, a bibliometric approach was used to analyze the literature data and obtain the current publication outputs. Second, product data were analyzed to obtain information about product outputs and applications. Finally, we compared the development of literature and product components. The purpose was to obtain the differences between the current state of research and its actual use, as well as to gain a preliminary insight into the translation of research in this field. The analysis chain and process are shown in Figure 3.
Results

Analysis of the Literature Output

Regarding the literature output, we analyzed the retrieved articles using bibliometric methods concerning 5 aspects: publication trends, journals, authors, countries and institutions, and themes.

Analysis of Publication Trends

As of February 2022, a total of 162 authors had published 75 relevant articles in 44 different journals. Among the 162 authors, 46 (28.4%) were lead authors. In addition, there were an average of 0.11 (SD 0.98) relevant articles per journal per year and an average of 0.46 (SD 1.27) articles per author. The evolution in the annual number of relevant studies published over the years is shown in Multimedia Appendix 3. With regard to the 75 articles included in this study, there was an overall increasing trend in the annual number of literature publications. There was an average annual increase rate of 24.46% (SD 0.69%), which resulted in 16 articles published in 2021. This trend demonstrates that an increasing amount of research is being carried out on this topic, indicating the increasing need for research in this field.

There was a substantially increased number of articles published in 2015 and 2021, in comparison with the previous and subsequent years. The authors of the 9 articles published in 2015 were mainly from Sweden and the United Kingdom, accounting for 3 (33%) and 2 (22%) articles, respectively. There were 4 articles by Gerhard Andersson as the lead author, from Linköping University (Linköping, Sweden), whose primary research interests were psychopathology and psychotherapy [14-17]. Of the 16 articles published in 2021, a total of 9 (56%) were from the United Kingdom, including 4 (44%) articles by Eldre Beukes, from Anglia Ruskin University, whose main research interest was audiology.

Analysis of the Major Publishing Journals

According to the Bradford law of scattering [18], all publications in a specific field, released during a given period, can be divided into core, related, or peripheral zones, according to the number of articles the zones include. The ratio of the number of publications in the 3 zones is $1:a^2$, with the approximate value of $a$ being 5. Core publications account for approximately 1 of 31 of the total number of publications. The core publications were calculated to correspond to the top 2 journals, which accounted for 36% (18/75) of the published articles: the American Journal of Audiology (12/75, 16%) and the Journal of the American Academy of Audiology (6/75, 8%). In 2021, the journal impact factors of these 2 journals were 1.636 and 1.249, respectively, and the journal citation reports divisions were Q4 and Q3, respectively. The remaining publications revealed minor differences in terms of the number of published articles.

Analysis of Article Authors

There were 162 authors in the included literature. According to the Lotka law [19], which states that authors with $>0.749$ times the square root of the number of papers published by the most prolific scientists, this study defined authors with $>4$ publications as high-producing authors, accounting for 9.9% (16/162). As can be seen in Table 1, Andersson G was the most prolific author, with 22 publications.

Next, we performed an analysis of the posting trends from highly productive authors. A graph of the annual posting trends of highly productive authors, based on their annual posting data and yearly citation frequencies, is shown in Figure 4. Here, the size of the circles indicates the annual posting volume, and the color shade indicates the annual citation frequency. Of the 16 most productive authors, 15 (94%) were found to have started focusing on mHealth-based treatments and interventions for tinnitus only after 2015. Of these 15 authors, 9 (60%) started publishing after 2018, and they have produced a steady annual output since then.
Table 1. Ranking of authors with >4 publications.

<table>
<thead>
<tr>
<th>Rank by number of articles</th>
<th>Author’s name</th>
<th>Articles (n=153), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Andersson G</td>
<td>22 (14.4)</td>
</tr>
<tr>
<td>2</td>
<td>Beukes EW</td>
<td>14 (9.2)</td>
</tr>
<tr>
<td>2</td>
<td>Manchaiah V</td>
<td>14 (9.2)</td>
</tr>
<tr>
<td>3</td>
<td>Schlee W</td>
<td>13 (8.5)</td>
</tr>
<tr>
<td>4</td>
<td>Pryss R</td>
<td>12 (7.8)</td>
</tr>
<tr>
<td>5</td>
<td>Reichert M</td>
<td>10 (6.5)</td>
</tr>
<tr>
<td>6</td>
<td>Allen PM</td>
<td>9 (5.9)</td>
</tr>
<tr>
<td>6</td>
<td>Baguley DM</td>
<td>9 (5.9)</td>
</tr>
<tr>
<td>7</td>
<td>Langguth B</td>
<td>8 (5.2)</td>
</tr>
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<td>8</td>
<td>Probst T</td>
<td>7 (4.6)</td>
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<tr>
<td>8</td>
<td>Spiliopoulou M</td>
<td>7 (4.6)</td>
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<td>9</td>
<td>Greenwell K</td>
<td>6 (3.9)</td>
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<td>9</td>
<td>Hoare DJ</td>
<td>6 (3.9)</td>
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<tr>
<td>9</td>
<td>Neff P</td>
<td>6 (3.9)</td>
</tr>
<tr>
<td>10</td>
<td>Mehdi M</td>
<td>5 (3.3)</td>
</tr>
<tr>
<td>10</td>
<td>Sereda M</td>
<td>5 (3.3)</td>
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</table>

Figure 4. Productivity of the top authors over time.

Analysis of the Publication Country of Origin

The 162 authors in our literature pool were from 15 countries. The top 10 countries (corresponding authors’ countries) are shown in Figure 5. Germany has published the largest number of articles in this field (19/75, 25%) and also has the largest number of international collaborations, followed by the United Kingdom (16/75, 21%) and the United States (12/75, 16%). The numbers of multicountry publications and single country publications for the top 10 high-output countries are shown in Figure 5.
Analysis of Posting Themes

VOSviewer Keyword Clustering Analysis

In this study, we analyzed the themes of the publications in the field from 3 aspects. First, highly frequent keywords were extracted from the abstracts. These keywords referred to literature data, common aspects of highly frequent keywords, and their co-occurrence network. The main research themes were identified from the clustering results. Second, to explore current research hot spots, the thematic map method, proposed by Cobo et al [20], was used to cluster and map themes according to their density and centrality. Finally, trends in the evolution of themes in the field were analyzed from a time-course perspective.

Next, we conducted a visual analysis of highly frequent keyword co-occurrence networks. To obtain all keywords from the relevant studies, the abstracts of the included literature articles were divided, deactivated, and lexically normalized using Python (Python Software Foundation). As shown in Figure 6, a high-frequency keyword co-occurrence network was produced using VOSviewer [21]. As shown in this figure, clustering has divided all keywords into 4 main domains, which could be further combined into 3 categories: red and yellow, green, and blue. The red and yellow categories represent the main treatments currently available for tinnitus (including cognitive behavioral therapy and music therapy), as well as clinical trials and the main feelings experienced by patients with tinnitus. Clinical trial methods include randomized controlled trials and clinical trials. The subjective feelings of patients with tinnitus include anxiety, depression, and insomnia. The green category contains computer-related keywords such as computer-assisted therapy and procedure. By contrast, the blue category includes keywords such as mobile app, smartphone, and telemedicine for mHealth and mobile devices.

It was particularly interesting to note that cognitive behavioral therapy was used as a link between the words disorder and computer. The words linking mHealth and computer were mainly basic concepts such as procedure. The words linking mHealth and disease were mainly research methods such as clinical study, which were slightly less connected than the other 2 groups.
Thematic Map Analysis

Cobo et al [20] proposed the thematic map method, which uses the division of themes into quadrants to analyze the hotness and importance of a topic. Topics located in the first quadrant (niche themes) are well developed but relatively less important. Those in the second quadrant (motor themes) are well developed and essential. Topics located in the third quadrant (emerging or declining themes) are not well developed and relatively less compelling. The topics found in the fourth quadrant (basic themes) are not well developed but necessary and generally refer to basic concepts.

By calculating the density and centrality of the already clustered coword matrix, each of the 5 categories was visualized within the 2D coordinates, as shown in Figure 7. We found that, in the first quadrant, the vocabulary of research methods (terms such as clinical and pilot study) was predominantly used, as well as concepts that have developed well and are currently being phased out. In the second quadrant, we observed that cognitive behavioral therapy and treatment outcomes were essential and well-studied topics. In the third quadrant, we observed that computer-assisted therapy was a topic that has not been well developed yet. In the fourth quadrant, as basic technologies in the field, the concepts of tinnitus, smartphones, and mobile apps were predominantly used.
Sankey Diagram Analysis

A thematic evolution analysis was carried out using coword network analysis and clustering. This analysis incorporated the time dimension to analyze the evolution of the research themes from 1993 to 2021 and to create a Sankey diagram (Figure 8).

From this observation, it was clear that there were both changing and unchanging themes. Researchers from as early as the 1993-2010 period focused on tinnitus as a disorder, without introducing further meaningful concepts. During the 2013-2016 period, the traditional research themes did not entirely dissipate, but several research methods were added to these clinical studies. During the 2017-2021 period, research moved from primary to applied, with emerging concepts such as cognitive behavioral therapy. Since 2022, cognitive behavioral therapy has remained the main research topic, whereas the concept of mHealth has not received much attention.
Analysis of the Software Development Stages Described in the Literature

In terms of the software development stages described in the literature, of the 75 papers, 49 (65%) referred to the design stage, 19 (25%) pertained to the clinical validation stage, and 7 (9%) concerned the marketing stage. This distribution reflects the negligible development of software for tinnitus treatment. Preliminary research found that the actual demand for such software was notably high.

Analysis of the Core Treatment Techniques Described in the Literature

Upon further analysis, it was found that 50 (67%) of the 75 papers primarily described treatments that used specific software. Of the remaining 25 studies, 12 (48%) mentioned only internet-based or web-based assessment tools for tinnitus, without any specific treatment associated. Of these 12 publications, 6 (50%) described mobile transient tinnitus assessment, and 4 (33%) used machine learning for predicting tinnitus, whereas 1 (8%) described a repository of tinnitus information, and 1 (8%) described a method for characterizing tinnitus heterogeneity. Of the 50 articles describing treatments, the mentioned treatments were mainly in the categories of cognitive behavioral therapy and sound therapy, with 30 (60%) and 13 (26%) papers, respectively. Of the remaining 7 studies, 1 (14%) included usual service therapy using artificial intelligence (AI) to expose the patient to the tinnitus environment, 1 (14%) used a tinnitus e-plan (an intervention coding method), 1 (14%) used visualized mobile electroencephalogram (EEG) for tinnitus detection, 1 (14%) used meditation (to help patients relieve tinnitus), 1 (14%) used machine learning for predicting tinnitus, whereas 1 (8%) described a repository of tinnitus information, and 1 (8%) described a method for characterizing tinnitus heterogeneity. Of the 50 articles describing treatments, the mentioned treatments were mainly in the categories of cognitive behavioral therapy and sound therapy, with 30 (60%) and 13 (26%) papers, respectively. Of the remaining 7 studies, 1 (14%) included usual service therapy using artificial intelligence (AI) to expose the patient to the tinnitus environment, 1 (14%) used a tinnitus e-plan (an intervention coding method), 1 (14%) used visualized mobile electroencephalogram (EEG) for tinnitus detection, 1 (14%) used meditation (to help patients relieve tinnitus), 1 (14%) used machine learning for predicting tinnitus, whereas 1 (8%) described a repository of tinnitus information, and 1 (8%) described a method for characterizing tinnitus heterogeneity.

Analysis of the Listed Apps

Analysis of the Number of Apps

Mobile tinnitus treatment software is currently in high demand. In this study, 28 apps were identified from software data sources (Figure 2), 4 of which were from software with specific names in the literature. These 28 apps consisted of 18 (64%) iOS apps and 10 (36%) Android apps (Multimedia Appendix 4). Most of these apps were developed by institutions (22/28, 79%); a few were developed by individuals (2/28, 7%). Among the 24 apps obtained from product data, 13 (54%) were medical apps, and 9 (38%) were health apps.

Regarding the software providers, of the 28 apps, 22 (79%) were available on the Apple App Store (China), and 21 (75%) were available on the Apple App Store (United States). In addition, 5 (18%) were available on the Google Play Store, and 5 (18%) were available on the Huawei, Xiaomi, Oppo, and Vivo marketplaces. Software activity can be reflected at the time of listing and at the time of the latest update. After data collection, we found that in 23 (82%) of the 28 apps, time information was complete.
Analysis of the Distribution of Source Countries

Multimedia Appendix 5 depicts the origin of the software developers. Of the 28 apps, 10 (36%) were developed in the United States, 8 (29%) in China, and 9 (32%) in other countries (n=1, 11% in the United Kingdom; n=3, 33% in Germany; n=3, 33% in Denmark; n=1, 11% in Poland; and n=1, 11% in New Zealand). Of the 28 apps, there was 1 (4%) whose country of origin could not be found. Regarding specific locations, the US software developers hailed from 7 states (3/10, 30% from Minnesota; 2/10, 20% from Texas; 1/10, 10% from Colorado; 1/10, 10% from Wisconsin; 1/10, 10% from California; 1/10, 10% from Florida; and 1/10, 10% from Oregon). Of the 8 software developers based in China, 7 (88%) were from regions within mainland China (n=3, 43% from Beijing; n=2, 29% from Jiangsu; n=1, 14% from Shanghai; and n=1, 14% from Guangdong), and 1 (13%) was from Hong Kong, China.

Analysis of the Functional Division of the Apps

When analyzing the 28 tinnitus treatment–related apps, this study divided them into three main categories: (1) screening and evaluation, (2) intervention and rehabilitation, and (3) education and information. Of the 28 software programs, 28 (100%) were related to intervention and rehabilitation, 11 (39%) were related to screening and evaluation, and 5 (18%) were related to education and information. Regarding the users of the software, of the 28 apps, 26 (93%) were intended to be used by patients or their families, and 2 (7%) were intended to be used by medical staff. In this study, we considered whether a professional was required to assist patients with the software and found that, in the case of 7 (25%) of the 28 apps, a professional was needed to assist the patient. By contrast, the remaining apps (21/28, 75%) could be used by patients without assistance from a professional.

When analyzing the specific functions of the apps, this study divided them into the following 6 areas: assessment, advice, detection, counseling, treatment, and relief. Of the 28 apps, 6 (21%) were dedicated to patient assessment, 4 (16%) could provide advice based on the actual patient situation, 5 (18%) could perform a preliminary test of the patient’s tinnitus or hearing condition, another 5 (18%) had a web-based counseling function, and 13 (46%) could provide the user with a treatment plan for the different tinnitus conditions. The primary product information is described in Multimedia Appendix 6.

Analysis of Treatments Provided by the Apps

After examining the treatments mentioned in the app descriptions, we found that, of the 28 apps, 7 (25%) used masking therapy, 2 (7%) used habituation therapy, and 2 (7%) used cognitive behavioral therapy. Moreover, of the 28 apps, 1 (4%) used sound therapy, 1 (4%) used neuromusic therapy, 1 (4%) used play therapy and frequency discrimination therapy, 1 (4%) used transcerebral vagus nerve microneural stimulation, and 1 (4%) used neuromodulation therapy. The remaining apps (12/28, 43%) did not specify the type of treatment used.

Analysis of App Validity

Regarding the validity and reliability of the apps, we found that some of the apps (6/28, 21%) were created by developers in collaboration with specific authorities. The 6 partner organizations are the American Tinnitus Association; the Eye, Ear, Nose, and Throat Hospital affiliated to Fudan University (Shanghai, China); a team of doctors from Tsinghua University (Beijing, China); a team of tinnitus specialists from well-known tertiary hospitals and first-line tinnitus experts; a Canadian team with Food and Drug Administration (FDA)–approved tinnitus rehabilitation core technology; and the University of California (Los Angeles, California, United States).

Comparative Analysis of Literature and Apps

Regarding the target audience, the software described in the literature was mostly consistent with the marketed apps. Most of the apps (26/28, 93%) focused on patients and their families, whereas a few (2/28, 7%) targeted medical staff. Most of the apps (20/28, 71%) provided different types of sounds to relieve tinnitus. A few of the apps (5/28, 18%) required the use of hearing aids, being aimed at medical staff use.

In the comparative analysis of the app scenarios, there was a strong consistency between the 2 types of apps. Most of the apps focused on the home scenario (22/28, 79%), whereas a few of the apps (6/28, 21%) are meant to be used in hospitals or other institutions dedicated to professional audiology. The tinnitus treatment apps currently available for download and use are mostly rudimentary. Most of them (22/28, 79%) can only provide initial relief to the patients or provide an assessment of their condition.

In a comparative analysis of the treatment techniques, the software described in the literature was predominantly based on sound therapy. This was a preferred approach, probably because, on the one hand, it was easier to implement in combination with mHealth software and, on the other hand, it was effective in tinnitus treatment. Half of the apps (16/28, 57%) listed in the app stores were based on acoustic and cognitive behavioral therapy, with significant user feedback available. Taking advantage of the psychoemotional characteristics of patients with tinnitus, a potential treatment method for tinnitus that involves transcranial magnetic electrical stimulation (containing 2 models: one for transcerebral vagus nerve microneural stimulation technology and one for neuromodulation therapy) needs to be developed. The other half (12/28, 43%) of the available apps did not describe the treatment method and lacked user evaluations. This was probably because of the relatively early stage of development of such apps and their limited user results.

A comparative analysis from a clinical standpoint showed that the apps mentioned in the literature were in the theoretical design stage. Relevant studies involving the application to human patients generally need ethics review committee approval, have to meet high product quality requirements, and have to sustain through long development and validation pathways, as well as overcome low translation rates. Individual apps are not marketed because they are not currently registered, despite having been rigorously designed at the theoretical level. Among the marketed apps, the proportion of those in the therapeutic intervention stage is high (5/7, 71%), with a relatively strong practicality and a modest performance.
Discussion

Current Status and Trends in Research

Literature Information

The number of studies in the field of tinnitus apps has increased yearly, with a rapid growth after 2015 and with the annual publication volume peaking in 2021. The articles were published in journals of moderate quality. Nevertheless, the acceptance rates of articles in the field by top medical journals were low. Of the 75 research articles in this field, 51 (68%) were included in the Web of Science core collection and had an average journal impact factor of 5.12 (spanning between 1.245 and 25.617 in the field of psychotherapy and psychosomatics). The studies were mainly published in the American Journal of Audiology and in the Journal of the American Academy of Audiology, with 18 (n=12, 67% and n=6, 33%, respectively) articles published as of February 2022, representing 24% (18/75) of the total number of articles. Nevertheless, the acceptance rates of articles in this field in top medical journals were poor, with no relevant studies published in the New England Journal of Medicine, The Lancet, the Journal of the American Medical Association, or The BMJ. The annual output of the most productive authors was the highest in 2021. In accordance with the Lotka law, this study identified 16 highly productive authors in the field, all of whom have published consistently in the last 3 years. This suggests that this area is steadily and rapidly growing. The authors were mainly from Germany (19/75, 25%), the United Kingdom (16/75, 21%), and the United States (12/75, 16%), with fewer authors from other countries (27/75, 36%), and only a single author from China (1/75, 1%). Of the 75 articles, 47 (63%) were published by authors from Germany, the United Kingdom, and the United States.

The current hot spot in this field is the research on sound and cognitive behavioral therapy, focusing on the outcomes for the treatment of patients with tinnitus. Thematic map analysis showed that the terms in the second quadrant of the thematic map included cognitive behavioral therapy, sound therapy, and tinnitus treatment outcomes. This indicates that research on cognitive behavioral therapy and sound therapy (with a focus on tinnitus treatment outcomes) is a current hot spot in the field of mHealth-based software interventions for tinnitus treatment. This area of research is well developed, with a focus on the assessment of tinnitus, but its importance is not sufficiently recognized yet. Our results are in agreement with those of relevant studies conducted in recent years [22].

App Information

Most of the apps (16/28, 57%) in this field have been newly developed and provide functional support for therapeutic interventions for tinnitus. Nevertheless, software development in this field lacks a research basis. Such software often has high requirements for ancillary apps [23], such as the sound quality and calibration of headphones. Cognitive behavioral therapy relies on professional tinnitus specialists for guidance. By contrast, it is difficult to achieve an accurate grasp of a user’s criteria for the use of such apps with mobile phone sensors or wearable apps alone [24]. As a result, and in comparison with other fields, the number of diagnostic apps is relatively small.

The adoption of apps under development has been poor, with the vast majority of the available apps used in very few or no real-life scenarios. The results showed that only 28 designed apps were available for download from app stores. This limitation suggests that, although many tinnitus treatment–related apps have been developed by experts and academics in recent years, most of them still lack practical use. It also suggests that these apps have a very homogeneous collection of patient information and a single-center validation of their effectiveness; in addition, they lack validity studies for clinical retesting as well as user feedback [25]. The reasons behind these aspects could be related to other attributes of the apps, such as their effectiveness and ease of use. To develop and validate apps that can be used in the clinical setting, researchers should also focus on other attributes, such as the ease of use of the apps.

Translation Status

For many years, there has been a lack of translation of the results of tinnitus treatment interventions using mHealth software and apps. This lack of translation is consistent with the results of our study on the analysis of product applications in this area. The vast majority of these apps (22/26, 85%) require both research and development, with scientific validity and effectiveness in a state of urgent need, and are far from truly achieving their goal of an effective tinnitus treatment intervention [26].

Problems and Potential

The Overall Picture of Tinnitus Treatment Apps Is Unsatisfactory

Scoring Analysis of Tinnitus Treatment Apps

Regarding the ratings of the included 28 tinnitus treatment–related apps (n=24, 86% from product data and n=4, 14% from literature data) on the Qimai app data analysis platform, 17 (61%) had ratings as high as 5.00 out of 5.00 and as low as 1.00 out of 5.00 (with an average rating of 3.84 out of 5.00). Of these 17 rated apps, China and the United States accounted for 7 (41%) and 5 (29%), respectively. The 5 apps developed in the United States had ratings of 4.40, 4.80, 4.80, 4.90, and 5.00 (average rating: 4.78), whereas the 7 apps developed in China had ratings of 1.00, 1.80, 3.80, 4.00, 4.10, 4.30, and 4.70 (average rating: 3.39).

Evaluation Analysis of Tinnitus Treatment Apps

With regard to the information on the 28 tinnitus treatment–related apps provided on the Qimai app data analysis platform, 10 good reviews were collected over 1 year. All these reviews referred to 6 (21%) of the 28 apps and were about their usefulness and usability. After analyzing the geographical regions of origin, our study found that the developers of 5 (83%) of these 6 apps were from China, with 5 positive reviews and 3 negative reviews.

https://mhealth.jmir.org/2023/1/e47553
Traditional Treatment Methods Are Far From Satisfactory

There is currently no international uniform treatment protocol for tinnitus. Moreover, evidence-based medical research has not found a single method with definitive efficacy for all types of tinnitus. The available methods include medications, repetitive transcranial magnetic stimulation, electrical stimulation of the tympanic capsule, cochlear implants, electrical stimulation of the vagus nerve, and acupuncture [27]. The treatment of tinnitus relies on obtaining an accurate hearing profile of the patient as well as indicators of the central frequency and intensity of the sound produced by tinnitus. After excluding the etiologies associated with tinnitus, counseling, cognitive behavioral therapy, and sound therapy have become the main treatment approaches [28]. Other approaches include relaxation and sequential therapy [29]. The lack of adjunctive therapies to improve outcomes in complex conditions is a common problem in tinnitus treatment, recognized both domestically and internationally.

Clear Differences in Tinnitus Treatment Apps at the Research Level Versus the App Level

Current research has uncovered the lack of connection between mHealth apps and their applications. In recent years, national and international research scholars have recognized the roles of neural synchronization and remodeling the mechanisms of action in tinnitus [30]. On the basis of these findings, adjunctive sound therapy involves the administration of appropriate acoustic stimulation (of a specific frequency and duration) to break abnormal nerve synchronization and remodeling. This procedure seeks to form a new auditory center, thereby reducing or eliminating tinnitus [31]. The use of mHealth apps to provide appropriate auditory training for patients with tinnitus has proven effective at the research level. Nevertheless, important aspects are lacking and need to be addressed. These include a scientific basis for software function, the standardization and calibration of the sounds emitted, real-time guidance from experts during the use of the apps by patients, clinical validation and feedback from patients on product effectiveness, and the connection between research and apps in this field.

Significant Differences in the Status of Relevant Research and Apps Between China and Other Countries

Our study showed that, although most research and apps in this area were developed outside China, there are still important limitations. The sample size of research and apps in this field, both domestically and abroad, was small. The final number of apps found to meet all inclusion criteria was only 28, of which only 4 (14%) were documented in the literature. This limitation has a particular impact on the results of our study. Moreover, it also reflects the decreased volume of research in this field, which strengthens the innovation and value of our work.

Tinnitus Is Difficult to Treat and Requires Urgent Assistance From Emerging Technologies

With the increased stress levels in modern work and life, tinnitus does not appear in isolation. Nevertheless, it is a combination of symptoms closely related to the etiological mechanisms and aggravating factors of several systemic diseases. More than 50% of patients with tinnitus experience sleep disturbances [32]. In the United Kingdom, the prevalence rate of tinnitus in the adult population is 10.1%, with the disorder severely affecting the quality of daily life [33]. In the United States, the prevalence rate of tinnitus in adolescents is from 7% to 9%, and in older people, it is approximately 25% [34]. In Japan, the prevalence rate of tinnitus in the adult population is 11.9% [35]. Although there are no large-scale epidemiological data on the prevalence rates of tinnitus in China, available studies have reported its prevalence rate in the adult population to be approximately 10%. Approximately 5% of the patients with tinnitus seek medical treatment, and approximately 2% of the patients have tinnitus that severely affects their life, sleep, the ability to concentrate and work, and social activities [36]. The complex and heterogeneous etiology of tinnitus as well as its unclear pathogenesis have contributed to the poor treatment outcomes for this disorder. Nevertheless, as industry and technology continue to develop and society ages, the prevalence of tinnitus is gradually increasing, making its early detection, diagnosis, and effective treatment urgent.

The evidence-based guidelines for clinicians managing patients with tinnitus [1] recommend an acoustic therapy approach, in which any sound can be used to alter the perception of, and response to, tinnitus, for the patient’s benefit. This therapy can be performed with environmental optimization devices such as hearing aids, sound generators, and tinnitus hybrid acoustic therapy devices, as well as commonly used devices such as mp3 players, smartphones, and radios. Tinnitus rehabilitation approaches must not disregard the integration of traditional methods with innovative technologies [37]. With the expansion and increased application of the mobile internet in various industries, health care–focused mobile internet technology has been receiving increased interest owing to its rapid development. Therefore, the combination of sound therapy and cognitive behavioral therapy for tinnitus has led to the development of an mHealth app model with this purpose.

Future Developments and Outlook

The Theory of mHealth for Adjunctive Treatment and Intervention in Tinnitus Is Logically Clear and Scientifically Solid

To address the ineffectiveness of traditional treatments for tinnitus, one of the 3 most difficult conditions plaguing human health in the otolaryngology field (the other 2 being deafness and vertigo), researchers have been exploring interdisciplinary avenues [38]. The evidence-based guidelines for clinicians managing patients with tinnitus recommend cognitive behavioral therapy for patients with chronic compensatory tinnitus, as well as effective and feasible acoustic treatment options provided by physicians or hearing aids for patients with tinnitus with hearing loss [39]. mHealth is unique in providing behavioral health interventions. One of its scientific theories is cognitive behavioral therapy. The future integration of mHealth for tinnitus treatment and intervention is in line with the recommendations of professional guidelines and has a sound scientific and theoretical basis.
The Pathway for mHealth to Be Used as an Adjunctive Treatment and Intervention in Tinnitus Is Clear and Highly Feasible

One of the theoretical foundations of mHealth is cognitive behavioral therapy. As of 2016, approximately 500 mHealth apps based on cognitive behavioral theory were available in the Apple App Store and Google Play Store. Current mobile apps are relatively well established in the use of cognitive behavioral therapy interventions in psychosocial health services to relieve anxiety, depression, and stress as well as treat other physical ailments and improve maladaptive behavioral problems (such as eating disorders and substance abuse). As a result, the product experience in mHealth is relatively mature. More than half of all patients with tinnitus have comorbid psychological problems such as anxiety, depression, and sleep disorders [40]. On the basis of the existing experience with mHealth, there is a clear and feasible pathway for adjunctive treatment and intervention in tinnitus.

The Use of mHealth for Adjunctive Treatment and Intervention in Tinnitus Is Effective and Has Good Generalizability

Our findings regarding mHealth use in mental health, disease management, and health behavior promotion indicate that mHealth apps, combined with cognitive behavioral therapy, were highly effective in reducing tinnitus pain, anxiety, and depression as well as in improving the patients' quality of life. In 2019, Aazh et al [41] found that the use of cognitive behavioral therapy for tinnitus was more effective when used 8 to 24 times per week for 60 to 120 minutes each time. The treatment could be remotely guided through an mHealth App to accommodate more patients and promote research progress on effective tools for treating tinnitus [42].

Limitations

Our study has some limitations. First, the data used were mainly from published literature (which included only scientific literature). Second, this study performed a simplified analysis of the product translation. We only analyzed the overall conversion rate and did not analyze specific apps and specific application scenarios. Finally, owing to the difficulty of obtaining complete data on apps and scientific research funds, we have only preliminarily explored the input-output relationship of some of the apps.

Conclusions

The field of monitoring, diagnosing, and treating tinnitus disorders using mHealth apps has shown rapid overall growth during recent years. Accordingly, there has been an increase in the number of relevant publications per year. Progress has been made in research on cognitive behavioral therapy, with a focus on the improvement of tinnitus symptoms and on the development of apps to support tinnitus monitoring and interventions. Nevertheless, the number of studies in this area is still low, international collaborations are lacking, the acceptance rates of articles in this field in refereed medical journals are poor, and most of the developed apps are not used in real-world settings. Future research should address the need for increasing tinnitus awareness and strengthening international collaborations to achieve an improved monitoring of tinnitus, using novel AI tools. In addition to the validation of tinnitus treatment apps, future research should also focus on the app properties that can promote the application of such apps in the real world.

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Data Availability

This study was conducted using public databases. Users can download relevant data free of charge.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Query strategy and results.
[DOCX File, 13 KB - mhealth_v11i1e47553_app1.docx ]

Multimedia Appendix 2
Inclusion and exclusion criteria applied to select the target literature.
[DOCX File, 13 KB - mhealth_v11i1e47553_app2.docx ]

Multimedia Appendix 3
The evolution in the annual number of relevant studies published over the years.
Multimedia Appendix 4
Description of basic app information.

Multimedia Appendix 5
Distribution of software sources.

Multimedia Appendix 6
Distribution of source countries.

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Abbreviations

AI: artificial intelligence
EEG: electroencephalogram
FDA: Food and Drug Administration
mHealth: mobile health
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
Collecting Food and Drink Intake Data With Voice Input: Development, Usability, and Acceptability Study

Louise A C Millard1,2, BSc, MSc, PhD; Laura Johnson1,2,3,4, BSc, MSc, PhD; Samuel R Neaves1,2, BSc, MSc, PhD; Peter A Flach5, MSc, PhD; Kate Tilling1,2, BSc, MSc, PhD; Deborah A Lawlor1,2, MBChB, MSc, PhD

1Medical Research Council (MRC) Integrative Epidemiology Unit, University of Bristol, Bristol, United Kingdom
2Department of Population Health Sciences, Bristol Medical School, University of Bristol, Bristol, United Kingdom
3Centre for Exercise, Nutrition and Health Sciences, School for Policy Studies, University of Bristol, Bristol, United Kingdom
4Centre for Health, National Centre for Social Research (NatCen), London, United Kingdom
5Faculty of Engineering, University of Bristol, Bristol, United Kingdom

Corresponding Author:
Louise A C Millard, BSc, MSc, PhD
Medical Research Council (MRC) Integrative Epidemiology Unit
University of Bristol
Oakfield House
Oakfield Grove
Bristol, BS8 2BN
United Kingdom
Phone: 44 0117 455 7676
Email: louise.millard@bristol.ac.uk

Abstract

Background: Voice-based systems such as Amazon Alexa may be useful for collecting self-reported information in real time from participants of epidemiology studies using verbal input. In epidemiological research studies, self-reported data tend to be collected using short, infrequent questionnaires, in which the items require participants to select from predefined options, which may lead to errors in the information collected and lack of coverage. Voice-based systems give the potential to collect self-reported information “continuously” over several days or weeks. At present, to the best of our knowledge, voice-based systems have not been used or evaluated for collecting epidemiological data.

Objective: We aimed to demonstrate the technical feasibility of using Alexa to collect information from participants, investigate participant acceptability, and provide an initial evaluation of the validity of the collected data. We used food and drink information as an exemplar.

Methods: We recruited 45 staff members and students at the University of Bristol (United Kingdom). Participants were asked to tell Alexa what they ate or drank for 7 days and to also submit this information using a web-based form. Questionnaires asked for basic demographic information, about their experience during the study, and the acceptability of using Alexa.

Results: Of the 37 participants with valid data, most (n=30, 81%) were aged 20 to 39 years and 23 (62%) were female. Across 29 participants with Alexa and web entries corresponding to the same intake event, 60.1% (357/588) of Alexa entries contained the same food and drink information as the corresponding web entry. Most participants reported that Alexa interjected, and this was worse when entering the food and drink information (17/35, 49% of participants said this happened often; 1/35, 3% said this happened always) than when entering the event date and time (6/35, 17% of participants said this happened often; 1/35, 3% said this happened always). Most (28/35, 80%) said they would be happy to use a voice-controlled system for future research.

Conclusions: Although there were some issues interacting with the Alexa skill, largely because of its conversational nature and because Alexa interjected if there was a pause in speech, participants were mostly willing to participate in future research studies using Alexa. More studies are needed, especially to trial less conversational interfaces.

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KEYWORDS
digital health; data collection; voice-based approaches; Amazon Alexa; self-reported data; food and drink
Introduction

Epidemiological cohorts typically collect data at widely spaced time points (eg, every 1-5 years) [1,2]. Although some types of traits (eg, weight or height) are fairly stable or change gradually over time, others such as activity levels, blood glucose levels, mental well-being, and dietary intake can vary more acutely, for example, within days, hours, or even minutes. For these traits, prospectively capturing how they vary across time allows us to assess how this variability relates to other traits and disease. Some acutely varying traits can be collected continuously and objectively using wearable digital devices; for example, physical activity can be tracked using accelerometers or blood glucose can be measured using continuous glucose monitors [3]. For others, such as mental health traits and dietary intake, no objective approach to measuring within-day variation in these traits exists, and they need to be collected by self-report.

One possible approach to providing real-time self-reported information is verbal input, which could enable participants to conveniently enter free text. Over the last few years, several technology companies have released voice-controlled “smart” systems. These systems, such as Amazon Alexa, Google Assistant, and Samsung’s Bixby, allow users to talk to a device rather than typing or pressing a button. They each have core functionality available by default (eg, saying the time when asked) and have developer platforms that allow anyone to produce and publish a custom voice-based app. This means that it is now technically possible to collect self-reported data continuously over a day or several days using verbal input.

Voice-based data collection may be most useful for collecting self-reported data that are both complex and variable across a day. One possible example is the food and drink consumed by a person and the time when they consume it. Traditionally, cohorts have collected dietary intake information using paper or web-based food frequency questionnaires or (less commonly) diaries. The limitations of these include retrospective recording, requiring conversion to an electronic form, potential for missing data because participants are not prompted for missing information, and the inconvenience of having to carry a diary. More recently, other approaches have been developed such as web-based dietary recall tools [4] and approaches using photographs [5-7]. Although these methods can collect detailed dietary information, they are burdensome, so they can only be used for short periods by highly motivated participants [3]. Approaches have been developed to detect eating events using wearable devices [8,9], for example, using wrist-worn accelerometers and gyroscopes [8]—these detect when an event occurs and not what was consumed. Wearable camera devices that capture images throughout the day have been trialed, but identifying and classifying food in images is challenging [10].

In this pilot study, we explored the potential of voice-based data collection in epidemiological research using food and drink diaries as an exemplar. Epidemiology studies are a challenging potential application of voice-based data collection because they are used to inform health policy and medical interventions; therefore, it is important to understand the biases in the collected data (eg, which food and drinks can be recorded correctly vs with error) to avoid incorrect conclusions being made. In addition, participation in epidemiological studies is predominantly altruistic, with participants usually receiving little direct benefit from participation, such that these studies aim to minimize participant burden to maximize participation. Our study has three key aims: (1) to demonstrate the technical feasibility of collecting data using Alexa, (2) to gain initial insight into participant acceptability, and (3) to provide an initial evaluation of the validity of the collected data. In general, we view the capture and processing of information as separate steps and, in this study, focused on demonstrating and evaluating the former.

Methods

Ethics Approval

Ethics approval was obtained from the University of Bristol Faculty of Health Sciences Research Ethics Committee (approval number 63861).

Study Participants

Power calculations based on 2 measures suggested that a sample size of at least 35 is needed (see details in Section S1 in Multimedia Appendix 1). We recruited volunteers from the University of Bristol staff and student email lists. Participants were compensated with a £30 (US $36) voucher after they submitted the postparticipation questionnaire (receiving the voucher was not dependent on them submitting any food diary entries).

Description of the System Architecture: a Voice-Based System Using Amazon Alexa

In this study, we used the Amazon Alexa voice system (a comparison with other voice-based systems such as Google Assistant and Samsung’s Bixby is left for future work). The Alexa system enables the development of custom functionality, referred to as a custom skill. Alexa skills comprise intents that each define an interaction that a user can have with the skill. We developed a custom skill to collect food and drink intake events, with intents that allow participants to (1) add the date and time of an intake event, (2) add ≥1 items they ate or drank at this time, (3) cancel the event, (4) cancel the last item added to the event, and (5) submit the event. See example utterances in Table S1 in Multimedia Appendix 1 and an example conversation in Figure 1. Section S2 in Multimedia Appendix 1 provides further details on the system architecture.
Data Collection Protocol

An overview of the data collection protocol is shown in Figure 2. Owing to the COVID-19 pandemic, participants took part at home. We sent an initial email with an accompanying participation information sheet (Multimedia Appendix 2) inviting staff and students to participate in this study. Upon replying, participants were sent a preparticipation questionnaire asking for basic demographic information such as their age and sex (questionnaire 1 in Multimedia Appendix 3). On completion, participants were booked for a 7-day data collection period using Alexa.

The equipment was stored in the principal investigator’s (LACM) home. On day 1 of the participants’ data collection period using Alexa, the equipment was delivered to their home by courier, along with a participant guide (Multimedia Appendix 4). The participant was asked to set up the equipment and start using it as soon as possible. Participants were instructed with the following statement: “After you have had something to eat or drink, we would like you to submit your food and drink information to Alexa first, and then submit it on the web form.” Entering the food and drink information using both Alexa and a web form (questionnaire 4 in Multimedia Appendix 3) allowed us to compare the data entered using these approaches (ie, relative validity [11]). As participants entered the date and time of the intake event, they were able to enter events consumed earlier on the same day or on a previous day (including those consumed outside the home). On day 7, the equipment was returned to the principal investigator’s home via courier. Participants were then asked to complete a postparticipation
questionnaire on their experiences during the study and the acceptability of using Alexa (questionnaire 2 in Multimedia Appendix 3).

To understand views on the acceptability of using voice-based interfaces more widely (beyond our participant group), we also sent a further invitation (to the same email lists) asking those who did not participate to complete a short questionnaire about their feelings on using voice-based devices and their reasons for not participating (questionnaire 3 in Multimedia Appendix 3).

The questionnaires were deployed via the University of Bristol REDCap (Research Electronic Data Capture; Vanderbilt University) secure web platform [12]. The content of the study emails is provided in Multimedia Appendix 5.

Analytical Sample
A participant flow diagram is shown in Figure S1 in Multimedia Appendix 1. Of the 45 participants who registered to participate, 1 (2%) withdrew and 7 (16%) were excluded owing to equipment issues (Section S3 in Multimedia Appendix 1). The remaining 82% (37/45) of participants comprised our analytical sample. Among these, 3% (1/37) of participants did not attempt to use Alexa. In addition, 19% (7/37) of participants had Alexa entries but no web diary entries completed within the 30 minutes directly following the Alexa submission. As Alexa and web entries must be submitted within 30 minutes to be identified as corresponding to the same intake event in our data processing approach (see below), the Alexa and web entries from these participants could not be compared. The entries from the remaining 78% (29/37) of participants were used to compare the information entered via the web form versus Alexa (“comparison” sample).

Data Preprocessing

Mapping Web Food Form Entries to Alexa Intake Events
The web and Alexa entries both included the following information: (1) intake timestamp—the date and time the participant (said they) ate or drank; (2) submission timestamp—the date and time the participant submitted the entry; and (3) intake items—1 food and drink intake items. To compare the content of the web and Alexa entries, we first undertook an automated process to identify Alexa and web entry pairs that correspond to the same intake event, referred to as counterpart entries. This was nontrivial because a participant might not have entered each entry with the web form immediately after entering it via Alexa or the intake timestamp—the date and time the participant submitted the entry might not have entered each entry with the web form.

We identified counterpart entries using intake and submission timestamps. The process we used was as follows (illustrated in Figure S5 in Multimedia Appendix 1):

1. Identify counterparts as the set of entries in which the web and Alexa intake timestamps were within 5 minutes of each other, and the Alexa submission timestamp was up to 30 minutes before the web submission timestamp. The nonexact match of the intake time was because participants can tell Alexa this using a phrase such as “just now” or “ten minutes ago,” which may not correspond exactly to the intake time entered using the web form.
2. Identify web counterpart entries of the Alexa submissions not matched in step 1 as the nearest subsequent web entry where one occurs within 30 minutes of the Alexa entry.

Comparing Food and Drink Descriptions in counterpart Web and Alexa Entries
We compared counterpart entries using 2 approaches, an automated approach and a systematic manual approach.

Automated Approach
We compared the text content of the counterpart entries by comparing the set of words contained in each. Entries were preprocessed to remove plurality of words (eg, “crisps” becomes “crisp”) [13] and convert numbers to numeric values (eg, “one” and “a” both become 1). For each counterpart pair, we calculated the number of words in (1) the web word set but not the Alexa word set, (2) the Alexa word set but not the web word set, and (3) both word sets.

Systematic Manual Approach
Our systematic manual approach was conducted by LACM. As this approach has some degree of judgment, we also asked 5 researchers independent to the project (within the same unit but not involved in this study) to review 10 random entries (none repeated across researchers) so that we can evaluate the interresearcher variability of these manual evaluations.

We used a 2-step process to conduct this manual review. First, the intake items of each counterpart pair were compared to determine whether there was any similarity. If the set of items was completely different, then they were marked as most likely corresponding to different intake events (ie, the counterpart pairing did not work in this case, eg, “a cup of coffee with milk” vs “spaghetti bolognaise”). All other entries were performed in step 2.

Step 2 involved reviewing each counterpart entry and, for each, recording the number of food or drink items in a counterpart pair in the following categories:

1. Same item semantically (the 2 entries are equivalent with no additional or different information in each)
2. Same item but with different details (eg, “cup of tea” vs “mug of tea”)
3. Same item, Alexa information has less detail (eg, “cheese and salad sandwich” vs “a sandwich”)
4. Same item, Alexa item has more detail
5. Same item, misspelling in Alexa input, but still understandable, that is, there is no loss of information (eg, “to bagels” vs “two bagels”)
6. Same item, misspelling in web form input, but still understandable
7. Same item, with Alexa entry issue, in which the consumed item is still identifiable (eg, “ball of yoghurt” rather than “bowl of yoghurt”)
8. Item with major entry issue, such that it contains no food or drink information, or the main essence of the food or
9. Extra Alexa item with major entry issue (which can happen if a participant makes a mistake or stops talking, then tries again so there is an extra item, eg, “two”)  
10. Extra Alexa item that is recognizable as a food or drink (ie, should not be assigned to category 9)  
11. Extra web item  

Table S2 in Multimedia Appendix 1 shows some example assignments using this approach.  

The independent researchers who completed 10 entries were provided with an information sheet describing the task (Multimedia Appendix 6). We visually evaluated the agreement between the assignments of LACM and independent researchers using a stacked bar chart.  

The automated and systematic manual approaches are complementary because the former is objective but is likely to be a more pessimistic assessment of agreement. This is because participants may not write an entry in the same way that they would speak it. For example, a participant might write “1 x apple. 1 bar of chocolate” but say “one apple and a chocolate bar,” which has differences in the words used even though they are semantically the same.  

Statistical Analyses  

Use Summary  

We summarized the participants’ use of the web and Alexa approaches using the median and IQR of the number of submitted web and Alexa entries, respectively.  

Comparison of Counterpart Diary Entries  

We compared the intake timestamps in the counterpart pairs using a plot similar to a Bland-Altman plot but in which the x-axis is the intake time entered using the web form rather than the average. Assuming that the intake timestamp entered on the web form will be largely correct, this is to help show whether the intake time submitted via Alexa may be less accurate for particular times of the day. We summarized automated and systematic manual comparisons using stacked bar charts.  

Summarizing the Number of Incomplete Attempts  

The Alexa skill saves partial entries (ie, those that have not been submitted, perhaps because the internet connection was interrupted) in addition to completed entries. We estimated the median (IQR) number of unsuccessful attempts across participants.  

Evaluating Participant Questionnaire Responses on Usability and Acceptability  

We summarized the responses to the postparticipation questionnaire (questionnaire 2 in Multimedia Appendix 3) and the nonparticipation questionnaire (questionnaire 3 in Multimedia Appendix 3) by calculating the number of participants (and percentage) that responded to each questionnaire item option. Responses to free-text items were read and reread to identify the key themes.  

The Alexa skill and web service code, and analysis code, are publicly available [14,15]. Git tag version 0.1 of the analysis code corresponds to the version of the analyses presented here.  

Results  

Participant Characteristics  

The participant characteristics are summarized in Table 1. Most participants (30/37, 81%) were in their early adulthood (aged 20-39 years). Our sample included more female participants than male participants (23/37, 62% female). The majority (31/37, 84%) reported that they did not believe they had a strong regional UK accent, with 68% (25/37) reporting that they did not have an accent because English was a second language. In total, 43% (16/37) of participants have an Alexa device at home that they use.
Table 1. Participant demographics (n=37).

<table>
<thead>
<tr>
<th>Participant characteristics</th>
<th>Values, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age range (years)</td>
<td></td>
</tr>
<tr>
<td>&lt;20</td>
<td>4 (11)</td>
</tr>
<tr>
<td>20-29</td>
<td>16 (43)</td>
</tr>
<tr>
<td>30-39</td>
<td>14 (38)</td>
</tr>
<tr>
<td>40-49</td>
<td>2 (5)</td>
</tr>
<tr>
<td>50-59</td>
<td>1 (3)</td>
</tr>
<tr>
<td>Sex</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>23 (62)</td>
</tr>
<tr>
<td>Male</td>
<td>14 (38)</td>
</tr>
<tr>
<td>Other</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Has a regional UK accent</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>31 (84)</td>
</tr>
<tr>
<td>A little</td>
<td>4 (11)</td>
</tr>
<tr>
<td>Yes</td>
<td>2 (5)</td>
</tr>
<tr>
<td>Has a non-English accent</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>25 (68)</td>
</tr>
<tr>
<td>A little</td>
<td>9 (24)</td>
</tr>
<tr>
<td>Yes</td>
<td>3 (8)</td>
</tr>
<tr>
<td>Has a voice-controlled device</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>16 (43)</td>
</tr>
<tr>
<td>Yes, but it is used by others, not me</td>
<td>5 (14)</td>
</tr>
<tr>
<td>Yes, and I use it</td>
<td>16 (43)</td>
</tr>
</tbody>
</table>

*The characteristics shown are those collected in this study.

**Use Summary**

On average, participants completed more web diary entries than Alexa entries (median number of entries was 17, IQR 13-27 compared with 11, IQR 7-21; paired 2-tailed *t* test *P* value <.001; comparison shown in Figure S6 in Multimedia Appendix 1). The median number of partial Alexa attempts across all participants was 6 (IQR 1-9).

**Comparison of Counterpart Diary Entries**

**Intake Timestamp Comparison of Web Form Versus Alexa Entries**

Across the 29 participants in the comparison subsample, there were 310 counterpart entries. Of these, 71.6% (222/310) had a matching timestamp (Figure S7 in Multimedia Appendix 1). The median proportion of completed counterpart entries with a matching timestamp across the participants was 0.67 (IQR 0.5-1).

**Food and Drink Description Comparison of Web Form Versus Alexa Entries**

The results comparing the submitted food and drink information using automated and manual comparison approaches are shown in Figures 3 and 4, respectively. Of the 310 counterpart entries manually reviewed, 21 (6.8%) were classified as corresponding to different intake events. The remaining 93.2% (289/310) of counterpart entries included 612 web form items and 588 Alexa items, with 33 extra web items (not identified in the counterpart Alexa entry) compared with 9 extra Alexa items (not found in the counterpart web entry). The majority (357/612, 58.3% and 357/588, 60.7% for the web and Alexa items, respectively) of the items entered via the web form and Alexa were the same, containing the same information. Of the 194 items that were identified as corresponding to the same intake item but containing different information, 64 (33%) had less detail from Alexa, 12 (6.2%) had more detail from Alexa, 15 (7.7%) had different detail, 3 (1.5%) had a web entry issue, 36 (18.6%) had an Alexa entry issue, 4 (2.1%) had spelling mistakes in the web version not the Alexa version, 59 (30.4%) had a misspelling in Alexa only, and 1 (0.5%) had a misspelling in both the Alexa and web input. Of the 59 items with an Alexa misspelling, 40 (68%) were owing to Alexa recording the word “to” rather than “two.” Of the 588 items entered via Alexa, 28 (5%) were classified as having a major entry issue.

We did not identify systematic differences in the assignments by LACM for the systematic manual approach compared with those of independent researchers (Figure S8 in Multimedia Appendix 1).
Evaluating Participant Questionnaire Responses on Usability and Acceptability

The summaries of the postparticipation questionnaire responses are provided in Table 2. Of the 35 participants who completed the postparticipation questionnaire, 26 (74%) said they would be happy to use a voice-controlled system at home for future research and 28 (80%) said they would be happy to use one on a wearable device (eg, a smart watch). Alexa sometimes interjected when participants were telling her when they ate or drank, with 20% (7/35) of participants saying that this happened often or always and 31% (11/35) saying that this happened occasionally. Alexa often interjected when participants were telling her what they ate or drank, with 51% (18/35) of participants saying that this happened often or always and 34% (12/35) saying that this happened occasionally. In terms of
convenience, enjoyment, and efficiency, 51% (18/35), 60% (21/35), and 43% (15/35) of participants, respectively, said that they found using Alexa “OK” or better.

Of the 35 participants who completed the postparticipation questionnaire, 25 (71%) had previously used another approach to record their food and drink intake (Table S3 in Multimedia Appendix 1). Of the 13 participants who have previously used a traditional diary (on paper or a computer), 7 (54%) found using Alexa at least as convenient, 5 (56%) found using Alexa at least as enjoyable, and 2 (22%) found using Alexa at least as efficient. Of the 34% (12/35) of participants who have previously used MyFitnessPal, 75% (9/12) found Alexa at least as convenient, 64% (7/12) found Alexa at least as enjoyable, and 36% (4/12) found Alexa at least as efficient.
<table>
<thead>
<tr>
<th>Questionnaire items</th>
<th>Values, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Participant was able to accurately tell Alexa what they ate and drank (n=35)</strong></td>
<td></td>
</tr>
<tr>
<td>Completely agree</td>
<td>3 (9)</td>
</tr>
<tr>
<td>Somewhat agree</td>
<td>16 (46)</td>
</tr>
<tr>
<td>Neither agree not disagree</td>
<td>2 (6)</td>
</tr>
<tr>
<td>Somewhat disagree</td>
<td>12 (34)</td>
</tr>
<tr>
<td>Completely disagree</td>
<td>2 (6)</td>
</tr>
<tr>
<td><strong>Participant was able to estimate accurate quantities describing how much they ate (n=34)</strong></td>
<td></td>
</tr>
<tr>
<td>Completely agree</td>
<td>3 (9)</td>
</tr>
<tr>
<td>Somewhat agree</td>
<td>11 (32)</td>
</tr>
<tr>
<td>Neither agree not disagree</td>
<td>10 (29)</td>
</tr>
<tr>
<td>Somewhat disagree</td>
<td>9 (26)</td>
</tr>
<tr>
<td>Completely disagree</td>
<td>1 (3)</td>
</tr>
<tr>
<td><strong>Participant chose not to record particular snacks or meals (eg, because it was unhealthy; n=35)</strong></td>
<td></td>
</tr>
<tr>
<td>Completely agree</td>
<td>1 (3)</td>
</tr>
<tr>
<td>Somewhat agree</td>
<td>5 (14)</td>
</tr>
<tr>
<td>Neither agree not disagree</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Somewhat disagree</td>
<td>7 (20)</td>
</tr>
<tr>
<td>Completely disagree</td>
<td>22 (63)</td>
</tr>
<tr>
<td><strong>Participant sometimes chose to be selective with the truth (n=35)</strong></td>
<td></td>
</tr>
<tr>
<td>Completely agree</td>
<td>3 (9)</td>
</tr>
<tr>
<td>Somewhat agree</td>
<td>5 (14)</td>
</tr>
<tr>
<td>Neither agree not disagree</td>
<td>3 (9)</td>
</tr>
<tr>
<td>Somewhat disagree</td>
<td>6 (17)</td>
</tr>
<tr>
<td>Completely disagree</td>
<td>18 (51)</td>
</tr>
<tr>
<td><strong>Participant felt they remembered to submit food and drink information (n=35)</strong></td>
<td></td>
</tr>
<tr>
<td>Completely agree</td>
<td>9 (26)</td>
</tr>
<tr>
<td>Somewhat agree</td>
<td>19 (54)</td>
</tr>
<tr>
<td>Neither agree not disagree</td>
<td>1 (3)</td>
</tr>
<tr>
<td>Somewhat disagree</td>
<td>6 (17)</td>
</tr>
<tr>
<td>Completely disagree</td>
<td>0 (0)</td>
</tr>
<tr>
<td><strong>Alexa interjected when I had not finished telling her when I ate or drank (n=35)</strong></td>
<td></td>
</tr>
<tr>
<td>Never</td>
<td>4 (11)</td>
</tr>
<tr>
<td>Rarely</td>
<td>13 (37)</td>
</tr>
<tr>
<td>Occasionally</td>
<td>11 (31)</td>
</tr>
<tr>
<td>Often</td>
<td>6 (17)</td>
</tr>
<tr>
<td>Always</td>
<td>1 (3)</td>
</tr>
<tr>
<td><strong>Alexa interjected when I had not finished telling her what I ate or drank (n=35)</strong></td>
<td></td>
</tr>
<tr>
<td>Never</td>
<td>2 (6)</td>
</tr>
<tr>
<td>Rarely</td>
<td>3 (9)</td>
</tr>
<tr>
<td>Occasionally</td>
<td>12 (34)</td>
</tr>
<tr>
<td>Often</td>
<td>17 (49)</td>
</tr>
<tr>
<td>Always</td>
<td>1 (3)</td>
</tr>
<tr>
<td>Questionnaire items</td>
<td>Values, n (%)</td>
</tr>
<tr>
<td>-------------------------------------------------------------</td>
<td>----------------</td>
</tr>
<tr>
<td><strong>How convenient or inconvenient did you find providing information using Alexa? (n=35)</strong></td>
<td></td>
</tr>
<tr>
<td>Very inconvenient</td>
<td>4 (11)</td>
</tr>
<tr>
<td>Somewhat inconvenient</td>
<td>13 (37)</td>
</tr>
<tr>
<td>OK</td>
<td>10 (29)</td>
</tr>
<tr>
<td>Somewhat convenient</td>
<td>7 (20)</td>
</tr>
<tr>
<td>Very convenient</td>
<td>1 (3)</td>
</tr>
<tr>
<td><strong>How enjoyable or unenjoyable did you find providing information using Alexa? (n=35)</strong></td>
<td></td>
</tr>
<tr>
<td>Very unenjoyable</td>
<td>3 (9)</td>
</tr>
<tr>
<td>Somewhat unenjoyable</td>
<td>11 (31)</td>
</tr>
<tr>
<td>OK</td>
<td>15 (43)</td>
</tr>
<tr>
<td>Somewhat enjoyable</td>
<td>6 (17)</td>
</tr>
<tr>
<td>Very enjoyable</td>
<td>0 (0)</td>
</tr>
<tr>
<td><strong>How efficient or inefficient did you find providing information using Alexa? (n=35)</strong></td>
<td></td>
</tr>
<tr>
<td>Very inefficient</td>
<td>5 (14)</td>
</tr>
<tr>
<td>Somewhat inefficient</td>
<td>15 (43)</td>
</tr>
<tr>
<td>OK</td>
<td>6 (17)</td>
</tr>
<tr>
<td>Somewhat efficient</td>
<td>8 (23)</td>
</tr>
<tr>
<td>Very efficient</td>
<td>1 (3)</td>
</tr>
<tr>
<td><strong>How easy or hard did you find providing information using Alexa? (n=35)</strong></td>
<td></td>
</tr>
<tr>
<td>Could not use at all</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Very hard</td>
<td>3 (9)</td>
</tr>
<tr>
<td>Somewhat hard</td>
<td>18 (51)</td>
</tr>
<tr>
<td>OK</td>
<td>7 (10)</td>
</tr>
<tr>
<td>Somewhat easy</td>
<td>7 (20)</td>
</tr>
<tr>
<td>Very easy</td>
<td>0 (0)</td>
</tr>
<tr>
<td><strong>Happy to use a voice-controlled system (eg, Alexa) at home for research in the future (n=35)</strong></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>26 (74)</td>
</tr>
<tr>
<td>No</td>
<td>2 (6)</td>
</tr>
<tr>
<td>Not sure</td>
<td>7 (20)</td>
</tr>
<tr>
<td><strong>Happy to use a voice-controlled system (eg, Alexa) on a wearable device such as a smart watch, for research (n=35)</strong></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>28 (80)</td>
</tr>
<tr>
<td>No</td>
<td>1 (3)</td>
</tr>
<tr>
<td>Not sure</td>
<td>6 (17)</td>
</tr>
</tbody>
</table>

*A summary of all items in the postparticipation questionnaire is provided in Table S3 in Multimedia Appendix 1.

**Evaluating Nonparticipation Questionnaire Responses**

Of the 69 participants who responded, 11 (16%) did not take part because of privacy concerns (with respect to Amazon, researchers collecting their diet information, or Alexa inadvertently listening to other conversations; Table 3). In total, 61% (42/69) stated that they would be happy to use Alexa at home for future research, whereas 57% (39/69) said that they would be happy to use Alexa on a wearable device for research purposes.
Table 3. Nonparticipation questionnaire summary (n=69).

<table>
<thead>
<tr>
<th>Questionnaire items</th>
<th>Value, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age range (years)</td>
<td></td>
</tr>
<tr>
<td>&lt;20</td>
<td>13 (19)</td>
</tr>
<tr>
<td>20-29</td>
<td>36 (52)</td>
</tr>
<tr>
<td>30-39</td>
<td>11 (16)</td>
</tr>
<tr>
<td>40-49</td>
<td>5 (7)</td>
</tr>
<tr>
<td>50-59</td>
<td>2 (3)</td>
</tr>
<tr>
<td>Prefer not to answer</td>
<td>2 (3)</td>
</tr>
<tr>
<td>Sex</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>51 (74)</td>
</tr>
<tr>
<td>Male</td>
<td>18 (26)</td>
</tr>
<tr>
<td>Other</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Reasons did not take part</td>
<td></td>
</tr>
<tr>
<td>Not available during the study session times</td>
<td>30 (43)</td>
</tr>
<tr>
<td>Data privacy concerns around Amazon collecting information on my diet</td>
<td>9 (13)</td>
</tr>
<tr>
<td>Data privacy concerns around researchers collecting information on my diet</td>
<td>3 (4)</td>
</tr>
<tr>
<td>Concerns that Alexa will inadvertently listen to other conversations</td>
<td>9 (13)</td>
</tr>
<tr>
<td>I do not eat or drink during my working hours</td>
<td>3 (4)</td>
</tr>
<tr>
<td>Picking up and returning the device was inconvenient</td>
<td>5 (7)</td>
</tr>
<tr>
<td>Other reason*</td>
<td>21 (30)</td>
</tr>
</tbody>
</table>

Has a voice-controlled device

- No                                                      | 35 (51)      |
- Yes, but it is used by others, not me                   | 10 (14)      |
- Yes, and I use it                                      | 24 (35)      |

Happy to use a voice-controlled system (eg, Alexa) at home for research in the future

- Yes                                                    | 42 (61)      |
- No                                                     | 13 (19)      |
- Not sure                                               | 14 (20)      |

Happy to use a voice-controlled system (eg, Alexa) on a wearable device such as a smart watch for research

- Yes                                                    | 39 (57)      |
- No                                                     | 18 (26)      |
- Not sure                                               | 12 (17)      |

*Participants who stated “other” were able to complete a free-text response; these are summarized in Section S4 in Multimedia Appendix 1. A summary of all items in the nonparticipation questionnaire is provided in Table S4 in Multimedia Appendix 1.

Discussion

In this study, we have demonstrated the technical feasibility of collecting data using Alexa for epidemiological research by successfully developing an Alexa skill to collect food and drink information and using it to collect data from 37 participants across a period of 7 days (5 full days). Our results provide useful initial insight into the participant acceptability of using this approach and validity of the collected data. On average, more entries were submitted via the web form than via Alexa. Our results suggest that intake date and time was largely entered accurately via Alexa. The majority of the Alexa entries (357/588, 60.7%) contained the same food and drink information as the corresponding web entry, according to our systematic manual approach. The most common differences were Alexa information having less detail or a homophone error (most often “to” rather than “two”).

Overall, the usability of our Alexa skill was fairly poor. Most participants reported that Alexa interjected while they were trying to enter food and drink information (12/35, 34% of participants sometimes and 18/35, 51% often or always), with better results for the date or time of the intake event (11/35,
31% of participants sometimes and 7/35, 20% often or always). Several participants reported finding it difficult to avoid pausing while articulating what they ate or drank, which might cause Alexa to interject or cut out. Some reported reducing the information they provided, so that Alexa would be more likely to accept it. The participants also reported that Alexa sometimes did not understand or would exit the skill during use.

The voice interface we trialed comprises our Alexa skill implementation and the Amazon back-end logic, and only the former is under our control. The implementation and deployment of the Alexa skill has several components, with many choices regarding the design of the voice interface, the technical infrastructure, and the study protocol (e.g., location of data collection, which was home based in our study). Each of these factors may have affected the usability of the skill to collect food and drink information. Most notably, we conclude that the conversational interface of our skill (in which participants first tell Alexa the time, then each of the items consumed) was not successful, because when the skill inadvertently cut out (e.g., because of multiple failed attempts to converse with Alexa or a poor internet connection), the participant would have to start that entry from the beginning. A less conversational interface in which the participant states the information without separate prompts would likely be more usable. Although our results suggest that Alexa may be more appropriate for entering short summaries of information, in the longer term, the integration of this approach with other approaches (such as a phone app) can be used to supplement voice-collected data. For example, using Alexa to log events directly after eating or drinking (e.g., on a wearable device) and then entering more detail via a phone app when convenient. Therefore, while in this study, participants entered more events and provided more detail using the web form, there are some opportunities to improve the skill for future studies.

The strengths of our study include the collection of pilot data “in the wild” rather than in a controlled laboratory-based setting. We collected food and drink information via a web form, in addition to Alexa, to allow the comparison of the data collected using these approaches. Our study had several limitations. While asking participants to provide information via both Alexa and a web form was valuable, interactions with one of these approaches may have affected their interaction and perceived feelings toward the other. The Alexa and web entries in our data had no explicit link and identifying entries that corresponded to the same intake event was difficult. We could only assess the relative validity of the Alexa entries (relative to the web form entries), that is, we have no absolute ground truth. Although the intake date and time could be easily compared between the Alexa and web form entries in an automated manner, comparing the free-text food and drink information was nontrivial as differences in the way the participant conveyed this information would not necessarily amount to meaningful differences in the submitted information. Most of these limitations could be rectified by integrating this voice-based approach with a phone app in which the participant can review each entry and either correct it or mark it as correct, instead of requiring a web diary, so that validity can be assessed in an automated manner by evaluating the corrections made by the participant. This would likely increase the number of Alexa entries that could be evaluated and could also reduce the participant burden because entries would either need to be marked as correct or corrected, rather than inputting all the information on a web form. Additional strengths and limitations and details are provided in Section S5 in Multimedia Appendix 1.

Although other studies have used voice-based approaches in other health settings [16-19], to the best of our knowledge, this is the first study to assess collecting self-reported epidemiology data with a voice-based system (to the best of our knowledge, a previous grant that sought to create a voice-based interface did not achieve this objective [20]). Furthermore, although our focus was on using this technology for collecting epidemiological data, the results of our study are likely to be useful more broadly, for example, to inform the development of technologies for personalized health care or commercial systems (collecting self-reported data to track behavior).

Table 4 summarizes the main findings of this study. More studies are needed to understand the strengths and limitations of different approaches to collect epidemiological data using voice, for example, with different voice-based systems (e.g., comparing Amazon Alexa vs Google Assistant), different types of devices (e.g., wearables vs smartphones), different voice interface designs, particularly those that are less conversational, and to further evaluate biases in the collected data [21]. Although this study used an Amazon Echo Dot device situated in the participants’ home, it is also possible to deploy an Alexa skill on other devices, for example, on smartphones and wearables. The acceptability of collecting epidemiological data with voice (including the length of time a participant may be willing to use such an approach), and the accuracy of the collected data, may differ depending on the device used (e.g., because of differing levels of background noise when “on the go” vs in the home environment). Further studies are needed to investigate this. Voice-based approaches may be particularly useful in populations that might not be able to write (or write with ease), for example, those with learning difficulties, such as dyslexia, or certain diseases, such as motor neuron disease.
Table 4. Summary of the main results and implications for future research.

<table>
<thead>
<tr>
<th>Results</th>
<th>Implications for future research</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voice-based data collection is technically feasible.</td>
<td>Future studies are needed to understand the strengths and limitations of different voice interfaces.</td>
</tr>
<tr>
<td>Conversational interface was a frustration for users because it could cut out (eg, owing to a poor internet connection) and the conversation would have to start from the beginning.</td>
<td>Design a less conversational voice interface.</td>
</tr>
<tr>
<td>Alexa more suited to entering short bits of information.</td>
<td>Integration with a phone app would allow supplementing information to be entered with voice entries.</td>
</tr>
<tr>
<td>The majority of the Alexa entries (357/588, 60.7%) contained the same food or drink information as the corresponding web entry, but a substantial proportion contained differences.</td>
<td>Trial and compare different voice-based systems such as the Google Assistant.</td>
</tr>
<tr>
<td>Matching voice entry with corresponding web form entry was difficult and many could not be matched (and therefore compared).</td>
<td>Use a phone app to evaluate the collected data by asking participant to validate the entry, either marking the entry as correct or providing a correction.</td>
</tr>
</tbody>
</table>

Acknowledgments

This work was supported by the University of Bristol and the UK Medical Research Council (grants MC_UU_00011/3 and MC_UU_00011/6). LACM received funding from a University of Bristol Vice-Chancellor’s Fellowship. This study was also supported by the National Institute for Health and Care Research Biomedical Research Centre at the University Hospitals Bristol National Health Service Foundation Trust and the University of Bristol (specifically via a Biomedical Research Centre Directors Fund grant). DAL's contribution is supported by the British Heart Foundation (grants CH/F/20/90003 and AA/18/7/34219). The authors are extremely grateful to the study participants. They are grateful to Mrs Shirley Jenkins for providing the administrative support for this study. The authors thank Professor Katrina Turner for helpful feedback on the qualitative review of the questionnaire responses. The authors also thank Mr Tom Clark, Dr Emily Kawabata, Dr Michael Lawton, Dr Nancy McBride, and Dr Tom Palmer, who conducted independent manual assessments of subsamples of food and drink entries.

Authors' Contributions

LACM and SRN conceptualized the use of Alexa for epidemiological data collection. LACM conceptualized the study, led the designing of the study, and wrote the first version of the manuscript. All authors contributed to the study design. All authors critically reviewed and revised the manuscript. LACM acts as the guarantor for this study.

Conflicts of Interest

DAL has received support from numerous national and international governments and charitable funders as well as Roche Diagnostics and Medtronic Ltd for work unrelated to this paper. KT received grant support including from the UK Government and US Government for research unrelated to this work.

Multimedia Appendix 1
Supplementary text, figures, and tables.
[PDF File (Adobe PDF File), 501 KB - mhealth_v11i1e41117_app1.pdf ]

Multimedia Appendix 2
Study participant information sheet.
[PDF File (Adobe PDF File), 138 KB - mhealth_v11i1e41117_app2.pdf ]

Multimedia Appendix 3
Study questionnaires.
[PDF File (Adobe PDF File), 198 KB - mhealth_v11i1e41117_app3.pdf ]

Multimedia Appendix 4
Study participant guide.
[PDF File (Adobe PDF File), 412 KB - mhealth_v11i1e41117_app4.pdf ]
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**Abbreviations**

REDCap: Research Electronic Data Capture

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G Tolerance Prediction Model Using Mobile Device–Measured Cardiac Force Index for Military Aircrew: Observational Study

Ming-Hao Kuo¹, MSc; You-Jin Lin², MSc; Wun-Wei Huang³, BSc; Kwo-Tsao Chiang⁴,⁵,⁶, MSc, MD; Min-Yu Tu⁷,⁸,⁹, MD, PhD; Chi-Ming Chu¹⁵,¹⁰,¹¹,¹²,¹³, PhD; Chung-Yu Lai⁶, PhD

¹Graduate Institute of Medical Sciences, National Defense Medical Center, Taipei City, Taiwan
²Thoracic Department, China Medical University Beigang Hospital, Yunlin County, Taiwan
³Aviation Physiology Research Laboratory, Kaohsiung Armed Forces General Hospital Gangshan Branch, Kaohsiung City, Taiwan
⁴Superintendent Office, Taipei Veterans General Hospital Fonglin Branch, Hualien County, Taiwan
⁵School of Public Health, National Defense Medical Center, Taipei City, Taiwan
⁶Graduate Institute of Aerospace and Undersea Medicine, National Defense Medical Center, Taipei City, Taiwan
⁷Orthopedics Division, Taichung Armed Forces General Hospital, Taichung City, Taiwan
⁸Department of Health Business Administration, Meiho University, Pingtung County, Taiwan
⁹Department of Life Sciences, National Chung Hsing University, Taichung City, Taiwan
¹⁰Graduate Institute of Life Sciences, National Defense Medical Center, Taipei City, Taiwan
¹¹Big Data Research Center, College of Medicine, Fu-Jen Catholic University, New Taipei City, Taiwan
¹²Department of Public Health, Kaohsiung Medical University, Kaohsiung City, Taiwan
¹³Department of Public Health, China Medical University, Taichung City, Taiwan

Corresponding Author:
Chung-Yu Lai, PhD
Graduate Institute of Aerospace and Undersea Medicine
National Defense Medical Center
Rm 8118, No 161, Sec 6, Minquan E Rd
Neihu Dist
Taipei City, 11490
Taiwan
Phone: 886 287923100 ext 19066
Email: multi0912@gmail.com

Abstract

Background: During flight, G force compels blood to stay in leg muscles and reduces blood flow to the heart. Cardiovascular responses activated by the autonomic nerve system and strengthened by anti-G straining maneuvers can alleviate the challenges faced during G loading. To our knowledge, no definite cardiac information measured using a mobile health device exists for analyzing G tolerance. However, our previous study developed the cardiac force index (CFI) for analyzing the G tolerance of military aircrew.

Objective: This study used the CFI to verify participants’ cardiac performance when walking and obtained a formula for predicting an individual’s G tolerance during centrifuge training.

Methods: Participants from an air force aircrew undertook high-G training from January 2020 to December 2022. Their heart rate (HR) in beats per minute and activity level per second were recorded using the wearable BioHarness 3.0 device. The CFI was computed using the following formula: weight × activity / HR during resting or walking. Relaxed G tolerance (RGT) and straining G tolerance (SGT) were assessed at a slowly increasing rate of G loading (0.1 G/s) during training. Other demographic factors were included in the multivariate regression to generate a model for predicting G tolerance from the CFI.

Results: A total of 213 eligible trainees from a military aircrew were recruited. The average age was 25.61 (SD 3.66) years, and 13.1% (28/213) of the participants were women. The mean resting CFI and walking CFI (WCFI) were 0.016 (SD 0.001) and 0.141 (SD 0.037) kg × G/beats per minute, respectively. The models for predicting RGT and SGT were as follows:

- RGT = 0.066 × age + 0.043 × (WCFI × 100) − 0.037 × height + 0.015 × systolic blood pressure − 0.010 × HR + 7.724 and SGT = 0.103 × (WCFI × 100) − 0.069 × height + 0.018 × systolic blood pressure + 15.899.

Thus, the WCFI is a positive factor for predicting the RGT and SGT before centrifuge training.
Conclusions: The WCFI is a vital component of the formula for estimating G tolerance prior to training. The WCFI can be used to monitor physiological conditions against G stress.

**KEYWORDS**
G force; baroreflex; anti-G straining maneuver; G tolerance; cardiac force index; anti-G suit; relaxed G tolerance; straining G tolerance; cardiac force ratio

**Introduction**

**Background**

On the Earth’s surface, humans are exposed to gravitational forces. The applied acceleration of gravity, 9.8 m/s², is defined as 1 Gz (1 G) in the direction from the head to the feet when a person is standing vertically. During flight, changes in speed or direction result in acceleration. The same magnitude of inertial force is generated in the opposite direction of the acceleration. Because fighter aircrafts are highly agile, military pilots experience high levels of G force, which decrease blood pressure and cause massive shifts in and redistributions of bodily fluid, especially during acrobatic combat maneuvers. The cardiovascular system is highly sensitive to G force, and its ability to maintain sufficient cerebral perfusion can be impaired under high-G force. Military pilots commonly experience visual degradation (eg, grayouts and blackouts) due to a decrease in the blood volume entering the retina [1-3]. If the supply of blood to the brain ceases, a military pilot experiences G-induced loss of consciousness (GLOC). In such cases, the pilot loses their ability to manipulate the aircraft, and a catastrophic event may occur.

Baroreflex is a well-known compensatory regulation activated by decreases in the arterial baroreceptor input under G load. The physiological reactions that are usually observed are an elevated heart rate (HR), increased peripheral vessel resistance, and greater cardiac contractility moderated by the autonomic nerve system [4,5]. The anti-G straining maneuver (AGSM) is considered the most crucial technique for increasing the cardiovascular system’s ability to withstand G stress [6-8]. Additionally, several studies have found that anthropometric parameters are associated with G tolerance [9-11].

Because no appropriate integrated cardiac parameter exists for monitoring G tolerance, we successfully introduced the cardiac force index (CFI) into the high-G training undergone by military aircrew [12]. Initially, the CFI was monitored using a wearable device and used to predict the running performance of military academy students [13-16]. The CFI consists of 3 factors that are relevant to G tolerance, namely body weight, dynamic changes in acceleration, and HR. The findings of the aforementioned studies revealed that the walking CFI (WCFI)—that is, the CFI while an individual is walking on the ground—was significantly positively correlated with G tolerance, as determined through centrifuge training.

**Objective**

High-G training is commonly used to assess the G tolerance of military pilots and determine whether they are fit to fly a modern jet. To our best knowledge, almost no studies have designed a model for predicting the G tolerance of aircrew before the training. Our previous study demonstrated that the WCFI calculated using mobile health technology can be used to identify potential factors affecting the ability to withstand G levels.

Followed the former finding, we attempted to develop a mathematical formula for predicting G tolerance on the basis of the CFI, which can be calculated before the beginning of training. Therefore, we can measure cardiac health and detect the low G tolerance of military pilots via mobile wearable devices during daily activity. In the future, we will try to establish the strategy of rapid G-resistance ability assessment by monitoring mobile cardiac data before the flight and to ensure pilots’ safety during flight missions.

**Methods**

**Study Design and Participants**

This longitudinal, observational study was conducted to evaluate the relationship between the CFI and G tolerance. The acceleration rate was set to 0.1 G/s during training. We also developed a formula for using CFI data to determine the level of G tolerance.

The participants were air force aircrew trainees attending high-G training at the Aviation Physiology Research Laboratory (APRL), Kaohsiung City, Taiwan. The participants were required to undergo medical examinations and meet the standards to be deemed fit for centrifuge training, which was conducted from January 2020 to December 2022.

**Ethics Approval and Informed Consent**

The documents and permission to perform this study were issued by the ethics committee of the Institutional Review Board of Kaohsiung Armed Forces General Hospital in Taiwan (approvals KAFGH 109-001 and 110-009). Before the study, written informed consent was provided by each participant to ensure that they understood the purpose and content of the study.

**Protocol of Cardiac Data Collection**

Air force aircrew attended a 1-day high-G training at the APRL. Their cardiovascular performance at rest and while walking was monitored using mobile technology and sensors. Centrifuge training was performed to simulate the hypergravitational environment and examine their G tolerance. A flowchart of the study protocol is presented in Figure 1.
**Mobile Monitoring Device**

This study used a mobile health (mHealth) BioHarness 3.0 module (Zephyr Technology Corporation), which is noninvasive and equipped with a gyroscope and accelerometers. Activity and HR were the 2 key indicators in this study. The BioHarness 3.0 sensor detected the distance that the participants moved by using its internal 3-axis accelerometers and calculated the activity per second. Activity levels were recorded using piezoelectric technology and are presented as the square roots of the acceleration values in the x, y, and z directions.

HR is presented as the number of beats per minute (bpm) and was measured using a conductive electrode sensor, with the thoracic loop strap fitted elastically to the skin over the thorax. To reduce noise during body movement, a shoulder strap was used to minimize the displacement of the BioHarness 3.0 sensor [17].

**Ground Phase**

The instructor, who was an aviation physiology officer at the APRL, held a lecture on acceleration physiology and G awareness. After the lesson, we explained the study protocol to aircrew willing to participate and used a questionnaire to collect their personal data, namely their birth year, gender, height, and weight; whether they smoked; whether they drank alcohol; and their exercise habits. Thereafter, all aircrew mastered the AGSM, and the instructor examined the participants’ execution of the AGSM before G-tolerance tests were performed. The 2 main components of the AGSM are the holding of a preparatory breath against the closed glottis every 3 seconds followed by rapid air exchange and isometric muscle tensing with an emphasis on the legs, buttocks, and abdomen. The trainees wore a standard anti-G suit (AGS) and were outfitted with a BioHarness 3.0 sensor, which was placed under the left central armpit and strapped to the chest and shoulder (Figure 2). After the fit of the AGS was checked, we pressed the central button to power on the BioHarness 3.0 sensor and started collecting cardiac data. After the participants had rested for 5 minutes in a chair, their systolic blood pressure (SBP), diastolic blood pressure (DBP), and HR were evaluated using an Omron 1100U sphygmomanometer (Omron Healthcare Company; Figure 3). After the resting data had been obtained, the participants performed relaxed and normal walking for 3 minutes. The participants performed squats before and after walking. Walking data could be obtained from the changes in activity identified by the 3-axis accelerometers.

**Figure 1.** Study protocol. AGS: anti-G suit; AGSM: anti-G straining maneuver; HR: heart rate; RGT: relaxed G tolerance; SGT: straining G tolerance.

**Figure 2.** BioHarness 3.0 module with chest and shoulder straps.
Centrifuge Phase

After they had completed the ground phase, the trainees entered the human centrifuge gondola (Latécoère) at the APRL. The human centrifuge trained 1 person at a time, and the maximum training capacity was 8 trainees per day. The length of the centrifuge’s arm was 20 feet (6.1 meters). The hydraulic power system could achieve a training onset rate and G level of up to 6 G/s and 9 G, respectively.

The participant wore a safety belt and sat on the simulated cockpit seat, which leaned back by 13°. After the foot pedals had been adjusted, the participant practiced the AGSM again and then rested for 2 minutes in a seated position. The APRL instructor started the centrifuge at an idle run of 1.4 G. Before the trainee’s G tolerance was assessed, the instructor accelerated the centrifuge at an onset rate of 0.1 G/s. The participant’s relaxed G tolerance (RGT) and straining G tolerance (SGT) were determined without inflating the AGS [11]. The RGT value was defined as the G value at which the participant experienced complete loss of peripheral vision or 50% loss of their central vision in the relaxed state. Thereafter, the participant commenced the AGSM to resist the physiological effect of G force as the level of centrifugation was increased. The SGT value was the G value at which the participant experienced the same visual degradation or a G force equal to the upper limit of 9 G. The level of visual loss for each participant was analyzed using the light bar in front of them inside the gondola [11].

Data Handling and Conversion Procedure

The mHealth BioHarness 3.0 device obtained data every second on the participants while they were on the ground. We used the charging and configuration cradle to download and save the digital data to a folder named “Summary.” If the signal values of the HR confidence or system confidence were below 20%, the data were considered unstable and unreliable [18]. There were 219 military aircrew members enrolled in this study. However, 6 participants were excluded from the analysis due to poor data quality, resulting in a final sample size of 213 participants. Resting and walking data were extracted and analyzed using previously proposed research methods [12,13].

Regarding the digital data, the activity and HR variables combined with the individual’s body weight were used to calculate the CFI and cardiac force ratio (CFR). For every second for which data were collected, the weight and activity values were multiplied and divided by the HR. The mathematical formula was as follows: \( \text{CFI} = \frac{\text{weight} \times \text{activity}}{\text{HR}} \) [13,14]. The average resting CFI (RCFI) and WCFI on the ground over a 2-minute period were calculated, and the CFR was obtained by dividing the WCFI by the RCFI.

Statistical Analysis

Descriptive statistics were calculated, and continuous variables are presented as means, SDs, and ranges. We used values and proportions to describe discrete data.

In the statistical analysis, the relationship between cardiac function on the ground and G tolerance in the centrifuge was assessed using Pearson correlation. A model for predicting G tolerance that is connected to the CFI was developed using stepwise multiple linear regression and by adjusting other covariates.

Statistical analyses were conducted using SPSS software (version 27.0; IBM Corp). Two-tailed \( P \) values <.05 were considered significant.

Results

Analysis of Demographic Data

The demographic data are displayed in Table 1. This study recruited 213 aircrew who finished the study. The average age of the participants was 25.61 (SD 3.66) years, and 13.1% (28/213) of the participants were women. The average height of the participants was 173.18 (SD 6.75) cm, their average weight was 70.39 (SD 11.44) kg, and their average BMI was 23.38 (SD 2.91) kg/m\(^2\). A total of 50 (23.5%) aircrew members smoked, 38 (17.8%) drank alcohol, and over half (n=114, 53.5%) habitually exercised.
Table 1. Characteristics of the enrolled aircrew (n=213).

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years), mean (SD; range)</td>
<td>25.61 (3.66; 22-27)</td>
</tr>
<tr>
<td>Gender, women, n (%)</td>
<td>28 (13.1)</td>
</tr>
<tr>
<td>Height (cm), mean (SD; range)</td>
<td>173.18 (6.75; 156-188)</td>
</tr>
<tr>
<td>Weight (kg), mean (SD; range)</td>
<td>70.39 (11.44; 48-99)</td>
</tr>
<tr>
<td>BMI (kg/m^2), mean (SD; range)</td>
<td>23.38 (2.91; 17.31-32.70)</td>
</tr>
</tbody>
</table>

Smoking status, n (%) 
No: 163 (76.5)
Yes: 50 (23.5)

Drinking status, n (%) 
No: 175 (82.2)
Yes: 38 (17.8)

Habitually exercised, n (%) 
No: 99 (46.5)
Yes: 114 (53.5)

Physiological Recordings on the Ground or Before Centrifuge Training

The changes in cardiovascular responses are listed in Table 2. The mean SBP, DBP, and HR while sitting and before centrifuge training were 140.40 (SD 14.47) mm Hg, 81.42 (SD 8.33) mm Hg, and 88.56 (SD 15.33) bpm, respectively. The mean WCFI was much higher than the mean RCFI (WCFI: 0.141, SD 0.037 vs RCFI: 0.016, SD 0.001 kg × G/bpm). The average CFR, computed by dividing the WCFI by the RCFI, was 10.76 (SD 4.38). During the G tolerance test, the RGT and SGT were 4.9 (SD 0.9) and 7.9 (SD 1.1) G, respectively, under a slow onset rate. Out of 213 aircrew members, 23 (10.9%) had a RGT greater than 6 G, and 60 (28.2%) had an SGT greater than 8 G (Tables 3 and 4). Pearson correlation coefficients were used to determine the relationship of RGT with SBP (r=.149; P=.03), HR (r=-.187; P=.006), and WCFI (r=.234; P=.001). Additionally, SGT was positively associated with SBP (r=.167; P=.02), DBP (r=.199; P=.01), and WCFI (r=.256; P<.001), as shown in Table 5.

Table 2. Descriptive analysis of cardiovascular and physiological information.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Value, mean (SD; range)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBP^a (mm Hg)</td>
<td>140.40 (14.47; 102-177)</td>
</tr>
<tr>
<td>DBP^b (mm Hg)</td>
<td>81.42 (8.33; 50-107)</td>
</tr>
<tr>
<td>HR^c (bpm^d)</td>
<td>88.56 (15.33; 56-145)</td>
</tr>
<tr>
<td>RCFI^e (kg × G/bpm)</td>
<td>0.016 (0.001; 0.006-0.088)</td>
</tr>
<tr>
<td>WCFI^f (kg × G/bpm)</td>
<td>0.141 (0.037; 0.020-0.266)</td>
</tr>
<tr>
<td>CFR^g</td>
<td>10.76 (4.38; 1.52-23.02)</td>
</tr>
</tbody>
</table>

^aSBP: systolic blood pressure.
^bDBP: diastolic blood pressure.
^cHR: heart rate.
^d.bpm: beats per minute.
^eRCFI: resting cardiac force index.
^fWCFI: walking cardiac force index.
^gCFR: cardiac force ratio.
### Table 3. Relaxed G tolerance distribution.

<table>
<thead>
<tr>
<th>Relaxed G tolerance (G)</th>
<th>Participant (n=213), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.0-3.4</td>
<td>8 (3.8)</td>
</tr>
<tr>
<td>3.5-3.9</td>
<td>17 (8)</td>
</tr>
<tr>
<td>4.0-4.4</td>
<td>40 (18.8)</td>
</tr>
<tr>
<td>4.5-4.9</td>
<td>53 (24.9)</td>
</tr>
<tr>
<td>5.0-5.4</td>
<td>45 (21.1)</td>
</tr>
<tr>
<td>5.5-5.9</td>
<td>27 (12.7)</td>
</tr>
<tr>
<td>6.0-6.4</td>
<td>10 (4.7)</td>
</tr>
<tr>
<td>6.5-6.9</td>
<td>8 (3.8)</td>
</tr>
<tr>
<td>7.0-7.4</td>
<td>3 (1.4)</td>
</tr>
<tr>
<td>7.5-7.9</td>
<td>1 (0.5)</td>
</tr>
<tr>
<td>8.0-8.4</td>
<td>1 (0.5)</td>
</tr>
</tbody>
</table>

### Table 4. Straining G tolerance distribution.

<table>
<thead>
<tr>
<th>Straining G tolerance (G)</th>
<th>Participant (n=213), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.5-4.9</td>
<td>1 (0.5)</td>
</tr>
<tr>
<td>5.0-5.4</td>
<td>4 (1.9)</td>
</tr>
<tr>
<td>5.5-5.9</td>
<td>9 (4.2)</td>
</tr>
<tr>
<td>6.0-6.4</td>
<td>13 (6.1)</td>
</tr>
<tr>
<td>6.5-6.9</td>
<td>18 (8.5)</td>
</tr>
<tr>
<td>7.0-7.4</td>
<td>19 (8.9)</td>
</tr>
<tr>
<td>7.5-7.9</td>
<td>36 (16.9)</td>
</tr>
<tr>
<td>8.0-8.4</td>
<td>35 (16.4)</td>
</tr>
<tr>
<td>8.5-8.9</td>
<td>18 (8.5)</td>
</tr>
<tr>
<td>9.0</td>
<td>60 (28.2)</td>
</tr>
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Table 5. Pearson correlation coefficients between G tolerance and cardiac function.

<table>
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<tr>
<th>Variables</th>
<th>RGT&lt;sup&gt;a&lt;/sup&gt;</th>
<th>SGT&lt;sup&gt;b&lt;/sup&gt;</th>
<th>SBP&lt;sup&gt;c&lt;/sup&gt;</th>
<th>DBP&lt;sup&gt;d&lt;/sup&gt;</th>
<th>HR&lt;sup&gt;e&lt;/sup&gt;</th>
<th>RCFI&lt;sup&gt;f&lt;/sup&gt;</th>
<th>WCFI&lt;sup&gt;g&lt;/sup&gt;</th>
<th>CFR&lt;sup&gt;h&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>RGT</strong></td>
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<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>r</td>
<td>1</td>
<td>.535</td>
<td>.149</td>
<td>.127</td>
<td>-.187</td>
<td>.087</td>
<td>.234</td>
<td>-.025</td>
</tr>
<tr>
<td>P value</td>
<td>—</td>
<td>&lt;.001</td>
<td>.03</td>
<td>.07</td>
<td>.006</td>
<td>.20</td>
<td>.001</td>
<td>.72</td>
</tr>
<tr>
<td><strong>SGT</strong></td>
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<td></td>
</tr>
<tr>
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<td>.199</td>
<td>-.111</td>
<td>.124</td>
<td>.256</td>
<td>-.048</td>
</tr>
<tr>
<td>P value</td>
<td>&lt;.001</td>
<td>—</td>
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<td>.01</td>
<td>.11</td>
<td>.07</td>
<td>&lt;.001</td>
<td>.49</td>
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<tr>
<td><strong>SBP</strong></td>
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<td></td>
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<tr>
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<td>.149</td>
<td>.167</td>
<td>1</td>
<td>.519</td>
<td>.181</td>
<td>-.034</td>
<td>.245</td>
<td>.068</td>
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<tr>
<td>P value</td>
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<td>.02</td>
<td>—</td>
<td>&lt;.001</td>
<td>.008</td>
<td>.62</td>
<td>&lt;.001</td>
<td>.07</td>
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<td><strong>DBP</strong></td>
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</tr>
<tr>
<td>r</td>
<td>.127</td>
<td>.199</td>
<td>.519</td>
<td>1</td>
<td>.372</td>
<td>-.020</td>
<td>.091</td>
<td>.060</td>
</tr>
<tr>
<td>P value</td>
<td>.07</td>
<td>.01</td>
<td>&lt;.001</td>
<td>—</td>
<td>&lt;.001</td>
<td>.78</td>
<td>.19</td>
<td>.38</td>
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<tr>
<td><strong>HR</strong></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>r</td>
<td>-.187</td>
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<td>.372</td>
<td>1</td>
<td>-.310</td>
<td>-.337</td>
<td>.203</td>
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<tr>
<td>P value</td>
<td>.006</td>
<td>.11</td>
<td>.008</td>
<td>&lt;.001</td>
<td>—</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>.003</td>
</tr>
<tr>
<td><strong>RCFI</strong></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>r</td>
<td>.087</td>
<td>.124</td>
<td>-.034</td>
<td>-.020</td>
<td>-.310</td>
<td>1</td>
<td>.329</td>
<td>-.724</td>
</tr>
<tr>
<td>P value</td>
<td>.20</td>
<td>.07</td>
<td>.62</td>
<td>.78</td>
<td>&lt;.001</td>
<td>—</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
</tr>
<tr>
<td><strong>WCFI</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>r</td>
<td>.234</td>
<td>.256</td>
<td>.245</td>
<td>.091</td>
<td>-.337</td>
<td>.329</td>
<td>1</td>
<td>.177</td>
</tr>
<tr>
<td>P value</td>
<td>.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>.19</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>—</td>
<td>.009</td>
</tr>
<tr>
<td><strong>CFR</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>r</td>
<td>-.025</td>
<td>-.048</td>
<td>.068</td>
<td>.060</td>
<td>.203</td>
<td>-.724</td>
<td>.177</td>
<td>1</td>
</tr>
<tr>
<td>P value</td>
<td>.72</td>
<td>.49</td>
<td>.07</td>
<td>.38</td>
<td>.003</td>
<td>&lt;.001</td>
<td>.009</td>
<td>—</td>
</tr>
</tbody>
</table>

<sup>a</sup>RGT: relaxed G tolerance.
<sup>b</sup>SGT: straining G tolerance.
<sup>c</sup>SBP: systolic blood pressure.
<sup>d</sup>DBP: diastolic blood pressure.
<sup>e</sup>HR: heart rate.
<sup>f</sup>RCFI: resting cardiac force index.
<sup>g</sup>WCFI: walking cardiac force index.
<sup>h</sup>CFR: cardiac force ratio.

**Model for Predicting G Tolerance From the CFI Through Multivariate Linear Regression**

As shown in Table 6, the model for predicting G tolerance was established using multivariate linear regression with stepwise selection. The WCFI was found to be the significant parameter for predicting RGT (<i>P</i>=.01) and SGT (<i>P</i><.001). The formula for predicting RGT was as follows: 
\[
\text{RGT} = 0.066 \times \text{age} + 0.043 \times (\text{WCFI} \times 100) - 0.037 \times \text{height} + 0.015 \times \text{SBP} - 0.010 \times \text{HR} + 7.724
\]

In the RGT model, each 100-unit increase in the WCFI increased the RGT by 0.043 G (SE 0.015; 95% CI 0.009-0.078). The equation for estimating the SGT was as follows: 
\[
\text{SGT} = 0.103 \times (\text{WCFI} \times 100) - 0.069 \times \text{height} + 0.018 \times \text{SBP} + 15.899
\]

Thus, the SGT increased by 0.103 G for each 100-unit increase in the WCFI (SE 0.019; 95% CI 0.065-0.141). The findings indicated no significant differences between the observed and estimated value of the RGT (<i>P</i>=.49) or SGT (<i>P</i>=.80) when the predictive model was used (Table 7).
Table 6. Predictors of relaxed G tolerance (RGT) and straining G tolerance (SGT) in the multivariate linear regression.

<table>
<thead>
<tr>
<th>Model and variables</th>
<th>β</th>
<th>SE</th>
<th>95% CI</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>RGT model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.066</td>
<td>0.015</td>
<td>0.037 to 0.095</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>WCFI (\times 100 \text{ (kg} \times \text{G/bpm)})</td>
<td>0.043</td>
<td>0.017</td>
<td>0.009 to 0.078</td>
<td>.01</td>
</tr>
<tr>
<td>Height (cm)</td>
<td>-0.037</td>
<td>0.009</td>
<td>-0.055 to -0.020</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>SBP (mm Hg)</td>
<td>0.015</td>
<td>0.004</td>
<td>0.007 to 0.023</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>HR (bpm)</td>
<td>-0.010</td>
<td>0.004</td>
<td>-0.017 to -0.001</td>
<td>.02</td>
</tr>
<tr>
<td>Constant</td>
<td>7.724</td>
<td>1.516</td>
<td>4.736 to 10.712</td>
<td>&lt;.001</td>
</tr>
<tr>
<td><strong>SGT model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WCFI (\times 100 \text{ (kg} \times \text{G/bpm)})</td>
<td>0.103</td>
<td>0.019</td>
<td>0.065 to 0.141</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Height (cm)</td>
<td>-0.069</td>
<td>0.011</td>
<td>-0.091 to -0.048</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>SBP (mm Hg)</td>
<td>0.018</td>
<td>0.005</td>
<td>0.008 to 0.028</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Constant</td>
<td>15.899</td>
<td>1.700</td>
<td>12.549 to 19.250</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

\(^a\text{WCFI: walking cardiac force index.}\)
\(^b\text{bpm: beats per minute.}\)
\(^c\text{SBP: systolic blood pressure.}\)
\(^d\text{HR: heart rate.}\)

Table 7. Comparison of the observed and estimated relaxed G tolerance (RGT) and straining G tolerance (SGT) values.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimated value, mean (SD)</th>
<th>Observed value, mean (SD)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>RGT</td>
<td>4.9 (0.4)</td>
<td>4.9 (0.9)</td>
<td>.49</td>
</tr>
<tr>
<td>SGT</td>
<td>7.9 (0.5)</td>
<td>7.9 (1.06)</td>
<td>.80</td>
</tr>
</tbody>
</table>

**Discussion**

**Principal Findings**

Several studies have measured HR responses to determine G tolerance [19-21]. We used the mHealth BioHarness device to collect HR data during physical activity performed before centrifuge training. Regarding the CFI values, the results revealed that the WCFI was positively related to G tolerance when the G level was increased at a gradual rate, which was consistent with other studies [12]. Additionally, this study successfully developed a new model for predicting G tolerance on the basis of changes in cardiac function. Age, height, resting blood pressure, and resting HR variables also influenced G tolerance.

**Age and Height**

We observed that for every 1 extra year of age of the individuals undergoing centrifuge training, their RGT increased by 0.066 G. Older participants had higher G tolerance than younger participants, which was similar to the results of another study [22]. According to Webb et al [11], the RGT and SGT of fighter pilots in the US Air Force were both positively associated with age. In the Korean Air Force, older trainees were more likely to be able to tolerate 6 G exposure profile [8]. Several researchers have also observed that younger aircrew members, those with less flying experience, and those with fewer hours more frequently experience GLOC during flight [23-25]. Park et al [26] suggested that for well-experienced young aviators, age may not affect the frequency of GLOC episodes in centrifuge trials. In one study in the US Navy, Johanson et al [27] revealed that the mean age of those experiencing GLOC was not different from those not experiencing GLOC, which may be linked to past experience, aircraft type, flight maneuver, and situational awareness.

Older jet and fighter pilots often have more years of flying experience. Such pilots are also more frequently exposed to high-G forces during flight. Some evidence indicates that the cardiac performance of fighter pilots is higher after they have been repeatedly exposed to G force [28,29]. This adaptation to G force increases baroreflex activity and G tolerance by altering the G-time tolerance curve [30]. Therefore, our study participants may have had experience in adapting to G force in flight.

Because of greater hydrostatic pressure in taller people, height has been identified as a factor negatively affecting both G tolerance and sustained duration of G force exposure [10,11,31]. In a neutral standing posture, brain-level blood pressure is theoretically approximately 22 mm Hg lower than heart-level blood pressure in a 1 G environment. Thus, a longer distance between the brain and heart might mean lower blood pressure in taller aircrew. In agreement with previous findings, the height of our participants was negatively correlated with their G tolerance in our predictive model.
SBP and HR
The heart ejects blood into cerebral tissue, and BP gradually decreases as blood travels further from the heart. Theoretically, elevated BP is conducive to modulating the effect of G stress. The cardiovascular system can sustain effective cerebral perfusion at up to approximately 4.5 to 5.5 G when the rate of increase is slow. However, the average resting SBP of our participants on the ground was approximately 140 mm Hg, which was slightly higher than usual. This may have been caused by the participants wearing the fitted AGS on their lower body and feeling stressed about their training. In our study, we also discovered that resting SBP was positively associated with RGT and SGT, similar to the US Air Force study that concluded that BP influences G tolerance [11].

In contrast to blood pressure, increased resting HR was disadvantageous for tolerating hypergravity. Our previous report similarly concluded that air force academy student pilots with elevated HR are less likely to tolerate a peak of 7.5 G when sustained for 15 seconds [9]. When arterial pressure and stroke volume drop due to exposure to high-G force, the sympathetic nerves trigger an increase in HR and strengthen cardiovascular function. Exertion levels during exercise can be determined using the maximum HR. The HR response is closely related to sport performance. By subtracting the participant’s age from 220, the target HR zones for different activities could be estimated. High-G training is a type of vigorous physical activity, and HR can rise to 160 bpm during G loading [7,9]. Nonetheless, if resting HR was elevated during the pretraining stage, the HR reserve (HRR) would be limited to a narrow range. HRR is one parameter of cardiovascular fitness. Consistent with some reports, we found that trainees with a lower HR or higher HRR were better able to resist the effects of G force [32,33].

This study verified the need to use mobile technology applications for obtaining cardiac data and understanding changes in the G tolerance levels of aviators.

RGT and SGT
At slow acceleration, RGT is mainly determined by BP and baroreflexes. RGT typically ranges from 4.5 to 6 G and varies depending on the individual and the time [34]. When the G force surpasses the RGT, trainees initiate the AGSM to assist their cardiovascular system against the G stress. Inside the centrifuge, visual loss was subjectively assessed using a light bar. To avoid variation between participants, we used a large sample size. Our previous study indicated that the mean RGT and SGT were 5.1 and 7.8 G, respectively [12]. We identified nearly the same RGT and SGT values (RGT: 4.9 G and SGT: 7.9 G) in our sample of 213 participants.

We used the wearable mHealth BioHarness 3.0 device to record cardiovascular function and found that G tolerance was associated with the cardiac data. The CFI is composed of 3 factors, namely body weight, activity, and HR. Our findings indicated that cardiovascular responses on the ground can be used to predict the resistance of z-axis forces during exercise involving mild exertion. Research on the prevention of GLOC may focus on the development of a precaution system based on the CFI. Further monitoring of the CFI during G loading is recommended to track any instantaneous changes in the CFI prior to GLOC.

Until now, there is still no convenient and proper method to monitor the cardiac performance and G tolerance on the ground. Our study showed that the ability for G tolerance could be predicted by the WCFI. Because G tolerance changes every day, therefore, mobile technology combined with a wearable device is highly applicable to calculate the real-time WCFI and predict G tolerance. Military aircrew can directly understand their G tolerance anytime and anywhere by monitoring their cardiac health and performance via a mobile device during their daily activity. Before the flight, they can know their “low-G day” and maintain the good G awareness. Warning mechanisms based on the cardiac health recorded by a mobile device could be considered to develop and prevent in-flight GLOC and catastrophic mishap.

Limitations
This study has some limitations. We included data obtained from women in our analysis, and our results suggest that gender did not have a significant effect on the outcome. However, this result may have been due to the small proportion of women. Second, for the calculation of the WCFI, the participants were asked to walk at their normal speed, but “normal” was subjective and their speed varied. Their HR values during walking were lower than 120 bpm, and the walking activity data covered a narrow range and exhibited a central tendency. Therefore, walking speed variation was unlikely to have significantly affected the outcomes. Although we have collected more data to develop and verify the predictive model, more participants are required to conduct an analysis and perform an external validation. Finally, depending on the airframes they were training on, aircrew had to have reached different levels and profiles relating to high-G training before they could participate in flight training. In this study, all participants met the standards of all the test profiles during training. Therefore, the authors could not clarify the relationship between the pass rate of high-G training and the CFI on the ground.

Conclusions
Using mobile devices, we monitored the cardiac function of aircrew while they walked in a relaxed manner. We verified that the WCFI is positively associated with the level of G tolerance. Moreover, this study developed a model for estimating the G tolerance of military aircrew before they begin high-G training. The development and application of a WCFI-monitoring system for daily life could be considered to evaluate their G tolerance prior to flights.

Acknowledgments
The authors thank the Medical Affairs Bureau, Ministry of National Defense (MND-MAB-C05-111018) and Kaohsiung Armed Forces General Hospital Gangshan Branch, Taiwan (MND-MAB-110-150 and MND-MAB-D-111158), for their support.
Conflicts of Interest

None declared.

References


Abbreviations

AGS: anti-G suit
AGSM: anti-G straining maneuver
APRL: Aviation Physiology Research Laboratory
bpm: beats per minute
CFI: cardiac force index
CFR: cardiac force ratio
DBP: diastolic blood pressure
GLOC: G-induced loss of consciousness
HR: heart rate
HRR: heart rate reserve
mHealth: mobile health
RCFI: resting cardiac force index
RGT: relaxed G tolerance
SBP: systolic blood pressure
SGT: straining G tolerance
WCFI: walking cardiac force index

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The Use of a Decision Support System (MyFood) to Assess Dietary Intake Among Free-Living Older Adults in Norway: Evaluation Study

Frida Severinsen\textsuperscript{1}, MSc; Lene Frost Andersen\textsuperscript{1}, PhD; Mari Mohn Paulsen\textsuperscript{1}, PhD

Department of Nutrition, Institute of Basic Medical Sciences, University of Oslo, Oslo, Norway

Corresponding Author:
Mari Mohn Paulsen, PhD
Department of Nutrition
Institute of Basic Medical Sciences
University of Oslo
Postboks 1046
Blindern
Oslo, 0317
Norway
Phone: 47 95772048
Email: m.m.paulsen@medisin.uio.no

Abstract

**Background:** The proportion of older adults in the world is constantly increasing, and malnutrition is a common challenge among the older adults aged \( \geq 65 \) years. This poses a need for better tools to prevent, assess, and treat malnutrition among older adults. MyFood is a decision support system developed with the intention to prevent and treat malnutrition.

**Objective:** This study aimed to evaluate the ability of the MyFood app to estimate the intake of energy, protein, fluids, and food and beverage items among free-living older adults aged \( \geq 65 \) years, primarily at an individual level and secondarily at a group level. In addition, the aim was to measure the experiences of free-living older adults using the app.

**Methods:** Participants were instructed to record their dietary intake in the MyFood app for 4 consecutive days. In addition, each participant completed two 24-hour recalls, which were used as a reference method to evaluate the dietary assessment function in the MyFood app. Differences in the estimations of energy, protein, fluid, and food groups were analyzed at both the individual and group levels, by comparing the recorded intake in MyFood with the 2 corresponding recalls and by comparing the mean of all 4 recording days with the mean of the 2 recalls, respectively. A short, study-specific questionnaire was used to measure the participants’ experiences with the app.

**Results:** This study included 35 free-living older adults residing in Norway. Approximately half of the participants had \( \geq 80\% \) agreement between MyFood and the 24-hour recalls for energy intake on both days. For protein and fluids, approximately 60\% of the participants had \( \geq 80\% \) agreement on the first day of comparison. Dinner was the meal with the lowest agreement between the methods, at both the individual and group levels. MyFood tended to underestimate the intake of energy, protein, fluid, and food items at both the individual and group levels. The food groups that achieved the greatest agreement between the 2 methods were eggs, yogurt, self-composed dinner, and hot beverages. All participants found the app easy to use, and 74\% (26/35) of the participants reported that the app was easy to navigate.

**Conclusions:** The results showed that the MyFood app tended to underestimate the participants’ dietary intake compared with the 24-hour recalls at both the individual and group levels. The app’s ability to estimate intake within food groups was greater for eggs, yogurt, and self-composed dinner than for spreads, mixed meals, vegetables, and snacks. The app was well accepted among the study participants and may be a useful tool among free-living older adults, given that the users are provided follow-up and support in how to record their dietary intake.

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**KEYWORDS**
dietary assessment; malnutrition; eHealth; validation study; older adults; mobile phone
Introduction

Background

Globally, the number of people aged ≥65 years is expected to increase considerably in the coming decades [1,2]. Most of the older adults prefer to stay in their own homes, although they experience various illnesses [3], and home care services may contribute to encouraging or enabling individuals to live in their own homes as long as possible [4]. Malnutrition in terms of undernutrition is a condition associated with increased morbidity and mortality risk, reduced quality of life, longer length of hospital stay, and greater economic costs for the health care sector [5-9]. Among home care recipients, malnutrition, or the risk of malnutrition, is common [10-12].

Guidelines for Nutritional Screening

Guidelines by the European Society for Clinical Nutrition and Metabolism recommend that all older adults should be screened for malnutrition routinely to ensure early identification of risk [13]. According to the European Society for Clinical Nutrition and Metabolism guidelines, individuals found to be malnourished or at risk of malnutrition should receive a comprehensive nutritional assessment and an individualized plan including monitoring and goals for the treatment [13]. With the aim of facilitating dietary assessment, the use of electronic tools in primary health care is emerging, including the use of apps and websites [14].

The MyFood Decision Support System

MyFood is a digital decision support system consisting of an app for dietary recording and automatic evaluation of the recorded dietary intake as well as a web report for health care professionals including tailored recommendations for nutritional treatment and a nutrition care plan for each patient [15,16]. MyFood was initially developed because of the need for a standardized system to prevent and treat disease-related malnutrition among hospitalized patients in Norway. The dietary assessment functionality in the MyFood system has previously been evaluated in a hospital setting [16], but it has not been validated in other health care settings.

Objectives

The primary aim of this study was to evaluate the ability of the dietary assessment function in the MyFood app to estimate individual intake of energy, protein, fluid, and food and beverage items among free-living older adults aged ≥65 years at both the individual and group levels using two 24-hour recalls as a reference method. We also aimed to measure the participants’ experiences using the app.

Methods

Study Participants and Recruitment

Free-living older adults (aged ≥65 years) were recruited from June 2021 to December 2021 through home care services in a Norwegian municipality, pensioner’s associations, and senior centers. In addition, a web page at the University of Oslo was created with an associated registration form for individuals to express their interest in participation. Finally, participants were recruited by combining convenience sampling and snowball sampling. Eligible participants had to be free-living older adults aged ≥65 years and have a Mini-Mental State Examination–Norwegian Revised (MMSE-NR) score >27. Patients who were terminally ill or psychiatric were excluded from the study.

The User Interface of the MyFood System

MyFood is a decision support system developed by researchers at the University of Oslo and Oslo University Hospital in Norway [16]. The MyFood system includes the following four functions: (1) user registration including anthropometric measures, (2) a dietary recording function, (3) automatic evaluation of recorded nutritional intake, and (4) a report to health care professionals including tailored recommendations for measures to improve nutritional status and a template for a nutrition care plan. The user interface of the MyFood system consists of an app including functions 1 to 3 and a website including function 4. Figure 1 illustrates functions 2 and 3.
Dietary Recording
Participants were instructed to record their intake in the dietary recording function by selecting 1 of the 5 meal categories (breakfast, lunch, dinner, supper, and snacks). Then, they had to select the correct food or beverage item before recording the amount consumed. Food and beverage items could either be found on the menu or through a free-text search and were illustrated with photographs. When recording dinner intake, the user could choose to select a category of precomposed mixed meals of standardized portions or assemble their own meal using the function assemble your own dinner (Figure 1) by selecting all components of the dinner meal manually. During the recording of each meal, the user was presented with prompting questions regarding what proportion of the dish was eaten, whether anything else was eaten with the meal, and whether any beverages or desserts were consumed with the meal.

Data Collection
The free-living older adults who were recruited as described in the Methods section above were contacted by telephone by a project worker, and a suitable time for a visit was agreed upon. At the visit, the participants received written and oral information about the study and signed a consent form. Information on the participants’ age and self-reported height and body weight was retrieved. Participants also completed a Mini Nutritional Assessment (MNA) [17] to assess whether they were at risk of malnutrition and an MMSE-NR [18] to assess whether they had any cognitive impairments that could affect their ability to participate.

All participants were provided guidance on how to download the MyFood app on their personal device, either a tablet or smartphone, except for 2 participants who borrowed tablets available for the project. Then, they were provided with a demonstration of how to use the app. During the demonstration, participants were shown how to navigate the app and how to record their intake of food and beverages.

Study Design
The participants completed a 4-day recording period, during which they were instructed to record their entire intake of foods and beverages in the MyFood app. As a reference method, all participants completed two 24-hour recalls by phone on 2 days overlapping with the recording period. The overlapping days were on the first and the third day of recording for all participants except for 2, as presented in Figure 2, and are further referred to as “comparison day 1” and “comparison day 2.”
The 24-hour recall procedure used a 3-step sequence within an in-house dietary assessment program (KostBeregningsSystem [KBS]) at the University of Oslo, resembling the US Department of Agriculture’s Automated Multiple-Pass Method [19]. Each recall lasted for approximately 20 to 30 minutes. All participants received a picture booklet to assist in the estimation of portion sizes during the 24-hour recalls, before the registration period. The booklets contained 41 photo series of 4 pictures, in ascending order, of various household measures, food items, and dishes. All food and beverage items recorded in the MyFood app were categorized into 13 food groups: bread and cereals, spreads, eggs, yogurt, cold beverages, hot beverages, self-composed dinner meals, mixed meals, dessert, fruit, vegetables, snacks, and condiments. Mixed meals included all predefined dinner dishes and dinner components recorded without using the function “assemble your own dinner,” and the condiment category included all types of sauces, spices, dressings, etc. The food and beverage items reported in the 24-hour recalls were subsequently allocated to the same categories as the items recorded in the MyFood app for comparison.

**Experience Form**

At the end of the 4-day registration period, all participants completed an experience form including 5 claims regarding their perceived usability and applicability of the app, using a 5-point Likert scale ranging from “Strongly disagree” to “Strongly agree.” The content of the experience form was adapted from the System Usability Scale, which is a 10-question scale based on the 5-point Likert scale that provides information about the perceived usability of a digital system [20]. The experience form used in this study has also been used in a previous evaluation study of the MyFood system in a hospital setting [16].

**Sample Size**

The sample size estimation was calculated based on the same prerequisites that were used in the previous evaluation study in a hospital setting [21] using a clinically relevant difference between dietary intake recorded in the MyFood app and estimated intake with 24-hour recalls of 50 kcal per day. With a test power of 80%, a significance level of 5%, and a calculated standardized difference of 1, a total of 35 participants were required.

**Data Handling and Statistics**

The 24-hour recalls were directly coded into KBS (version 7.4), in which estimations of energy, protein, and fluids were performed using the KBS food composition database AE18. Database AE18 is an extended version of the official Norwegian Food Composition Table (version 2018). Dietary information in the MyFood app for energy (kcal), protein (g), and fluid (mL) was based on the Norwegian Food Composition Table from 2019 and the product information from the manufacturer.

The dietary intake recorded in the MyFood app was compared with the intake reported in the 24-hour recalls. Data were analyzed at both the individual and group levels. Evaluation studies are usually performed at the group level to evaluate tools used in different population groups or settings. As the MyFood system was intended to capture dietary intake at an individual level, the main aim of this study was to evaluate its ability to assess individual intake among the free-living older adults. To be able to use MyFood in groups of older adults, analyses were also included to evaluate the accuracy of the dietary recording function at the group level.

At the individual level, dietary intake data from 2 of the 4 days of dietary recording in the MyFood app were compared with the dietary intake data obtained from the two 24-hour recalls on the corresponding days. The differences in the estimated intake of energy, protein, fluid, and selected food groups between the MyFood app and the 24-hour recalls were presented from the 2 overlapping recording days with both methods. The differences were presented in a series of drop plots for comparison days 1 and 2. In addition, the individual-level data of the differences between the 2 methods were analyzed for the breakfast, lunch, dinner, supper, and snack meals separately, for both comparison days 1 and 2 (Multimedia Appendices 1 and 2). Omitted items were counted as an item mentioned in the recalls but not recorded in the MyFood app.

At the group level, the mean intake from the 4 days of dietary recording in the MyFood app was compared with the mean intake obtained from the two 24-hour recalls. The data were presented with mean and SD. The comparison of the mean intake of energy, protein, and fluid between the 2 methods was analyzed using 2-tailed paired samples t tests.

Statistical analyses were performed using SPSS Statistics Software (version 28.0; IBM Corp). The level of statistical significance was set at *P*<.05, and all tests were 2 sided.

**Ethics Approval and Informed Consent**

The study was performed in accordance with the Declaration of Helsinki, and the research protocol was reported to The Norwegian Centre for Research Data (reference number:...
Results

Participants

In total, 35 (13 men and 22 women) free-living older adults aged 65-89 years were included in the analyses. The participants had a median age of 71 years and a mean BMI of 25.4 (SD 4.03) kg/m\(^2\). Most of the participants (20/35, 57%) had a normal nutritional status according to the MNA screening. The median MMSE-NR score was 29, ranging from 27 to 30, indicating a good cognitive function among the participants. The characteristics of the study participants are presented in Table 1.

Table 1. Participant characteristics (N=35).

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Participants, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age (years)</strong></td>
<td></td>
</tr>
<tr>
<td>65-69</td>
<td>12 (34)</td>
</tr>
<tr>
<td>70-74</td>
<td>11 (31)</td>
</tr>
<tr>
<td>75-79</td>
<td>11 (31)</td>
</tr>
<tr>
<td>80-84</td>
<td>0 (0)</td>
</tr>
<tr>
<td>≥85</td>
<td>1 (2)</td>
</tr>
<tr>
<td><strong>Sex</strong></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>13 (37)</td>
</tr>
<tr>
<td>Female</td>
<td>22 (63)</td>
</tr>
<tr>
<td><strong>BMI (kg/m(^2))</strong>(^a)</td>
<td></td>
</tr>
<tr>
<td>Underweight: &lt;18.5</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Normal weight: 18.5-24.9</td>
<td>20 (57)</td>
</tr>
<tr>
<td>Overweight: 25-29.9</td>
<td>9 (26)</td>
</tr>
<tr>
<td>Obese: ≥30</td>
<td>6 (17)</td>
</tr>
<tr>
<td><strong>MNA(^b) score</strong></td>
<td></td>
</tr>
<tr>
<td>Malnourished: 0-7</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Risk of malnutrition: 8-11</td>
<td>5 (14)</td>
</tr>
<tr>
<td>Normal nutritional status: 12-14</td>
<td>30 (86)</td>
</tr>
<tr>
<td><strong>MMSE(^c) score</strong></td>
<td></td>
</tr>
<tr>
<td>0-26</td>
<td>0 (0)</td>
</tr>
<tr>
<td>27-30</td>
<td>35 (100)</td>
</tr>
</tbody>
</table>

\(^a\)Weight (kg)/height (m)^2.

\(^b\)MNA: Mini Nutritional Assessment.

\(^c\)MMSE-NR: Mini-Mental State Examination–Norwegian Revised.

Intake of Energy, Protein, and Fluid at the Individual Level

Energy Intake

Individual drop plots for the total intake of energy on the 2 comparison days are presented in Figure 3, showing the estimated intake in the MyFood app compared with the 24-hour recalls. The MyFood app tended to underestimate the total intake of energy on both comparison days compared with the 24-hour recalls, and the discrepancies tended to increase with increasing intake of energy.
**Figure 3.** Drop plots illustrating the individual intake of energy on comparison days 1 (section A) and 2 (section B). The y-axis represents the energy intake (kcal). The x-axis represents the participants’ ID numbers. In cases where only a white dot is present, the recorded intake in MyFood was identical to that in the 24-hour recall.

**Protein Intake**

Individual drop plots for the total intake of protein on the 2 comparison days are presented in Figure 4, showing the estimated intake in the MyFood app and the 24-hour recalls. As for energy, the MyFood app tended to underestimate the intake of protein compared with the 24-hour recalls on both comparison days. The level of discrepancies between the 2 methods seemed to increase with increasing intake of protein.
**Figure 4.** Drop plots illustrating the individual intake of protein on comparison days 1 (section A) and 2 (section B). The y-axis represents the protein intake (g). The x-axis represents the participants’ ID numbers. In cases where only a white dot is present, the recorded intake in MyFood was identical to that in the 24-hour recall.

**Fluid Intake**
Individual drop plots for the total intake of fluids on the 2 comparison days are presented in **Figure 5**, showing the total intake of fluid estimated in MyFood and the 24-hour recalls. For most participants, there was a relatively good agreement between the 2 methods. In cases of discrepancies, the MyFood app mainly underestimated the intake of fluids compared with the 24-hour recalls.
Figure 5. Drop plots illustrating the individual intake of fluids on comparison days 1 (section A) and 2 (section B). The y-axis represents the fluid intake (mL). The x-axis represents the participants’ ID numbers. In cases where only a white dot is present, the recorded intake in MyFood was identical to that in the 24-hour recall.

An overview of the proportion of the participants having ≥80% agreement between their recordings in the MyFood app and the intake reported in the 24-hour recalls, in total and for each meal separately, on both comparison days, is presented in Multimedia Appendix 3.

On the first and second comparison day, 49% (17/35) and 51% (18/35) of the participants, respectively, had ≥80% agreement for the total intake of energy. For the total intake of fluids, 63% (22/35) and 60% (21/35) of the participants had ≥80% agreement on comparison days 1 and 2, respectively. For protein, 63% (22/35) of the participants had ≥80% agreement on the first comparison day compared with 46% (16/35) of the participants on the second comparison day.
On the first and second comparison day, 53% (18/34) and 54% (19/34) of the participants had ≥80% agreement for the intake of protein for breakfast, respectively. For lunch, the number of participants having ≥80% agreement on protein intake was somewhat lower, with 48% (14/29) on the first comparison day and 45% (14/30) on the second comparison day.

The dinner was the meal with the lowest proportion of participants having ≥80% agreement between the 2 methods for energy intake, with 41% (14/34) of the participants on the first comparison day and 17% (6/35) of the participants on the second comparison day. The dinner was also the meal that most participants did not record in the MyFood app, with 9% (3/33) of the participants on the first day and 17% (5/30) of the participants on the second day.

The meal with the lowest proportion of participants with ≥80% agreement for fluid intake was snacks, with 27% (9/33) participants on the first comparison day and 25% (8/32) participants on the second comparison day.

### Intake of Energy, Protein, and Fluid at the Group Level

Table 2 presents the mean (SD) intake of energy, protein, and fluid estimated for the 4 days of dietary recording in the MyFood app and the two 24-hour recalls. At the group level, the participants recorded approximately 17% less energy, protein, and fluids in the MyFood app compared with what was reported in the 24-hour recalls, representing approximately 350 kcal, 15 g, and 400 mL, respectively.

<table>
<thead>
<tr>
<th></th>
<th>MyFood (N=35), mean (SD)</th>
<th>24-hour recalls (N=35), mean (SD)</th>
<th>P value&lt;sup&gt;a&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy (kcal)</td>
<td>1733 (527)</td>
<td>2114 (630)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Protein (g)</td>
<td>72 (25)</td>
<td>86 (25)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Fluid (mL)</td>
<td>2017 (719)</td>
<td>2450 (611)</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

<sup>a</sup>Differences between the estimated intake recorded in MyFood and the 24-hour recalls were tested using the paired sample t test.

### Intake of Food and Beverage Items at the Individual Level

The proportion of participants having ≥80% agreement between their recordings in the MyFood app and the 24-hour recalls within the different food groups on comparison days 1 and 2 varied between the different food groups (Multimedia Appendix 4). Eggs and yogurt were the food groups with the greatest proportion of participants having ≥80% agreement between the 2 methods, with 69% (9/13) and 94% (15/16) of the participants for eggs and 67% (10/15) and 89% (8/9) of the participants for yogurt on days 1 and 2, respectively. The food group with the lowest proportion of participants with ≥80% agreement was condiments. For dinner, the food group “self-composed dinner” achieved better agreement than the food group “mixed meals.” On the first comparison day, a total of 14 participants used the “assemble your own dinner” function, compared with 9 participants on the second comparison day.

An overview of the omitted food and beverage items is presented in Multimedia Appendix 5. Omitted items were counted as an item mentioned in the recalls but not recorded in the MyFood app. The food groups with the most omissions were cold beverages, condiments, and spreads. Approximately 40 cold beverage items and >20 spreads were reported in the 24-hour recalls but not recorded in the MyFood app.

### Participants’ Experiences Using the MyFood App

All participants reported that the MyFood app was easy to use (Table 3). In total, 74% (26/35) of participants agreed that the app was easy to navigate, and 83% (29/35) of the participants reported that they managed to record the amount of foods and beverages correctly. Moreover, 9% (3/35) of the participants reported that they had to acquire new knowledge to use the app, and 77% (27/35) of the participants reported that they became more aware of their own nutritional requirements.

<table>
<thead>
<tr>
<th></th>
<th>Easy to use, n (%)</th>
<th>Easy to navigate, n (%)</th>
<th>Correct amount of foods and beverages recorded, n (%)</th>
<th>New knowledge was acquired to use the app, n (%)</th>
<th>Increased awareness of their own requirements, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Totally disagree</td>
<td>0 (0)</td>
<td>0 (0)</td>
<td>0 (0)</td>
<td>24 (69)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Slightly disagree</td>
<td>0 (0)</td>
<td>3 (9)</td>
<td>2 (6)</td>
<td>8 (23)</td>
<td>3 (9)</td>
</tr>
<tr>
<td>Neutral</td>
<td>0 (0)</td>
<td>6 (17)</td>
<td>4 (11)</td>
<td>0 (0)</td>
<td>5 (14)</td>
</tr>
<tr>
<td>Slightly agree</td>
<td>19 (54)</td>
<td>20 (57)</td>
<td>15 (43)</td>
<td>2 (6)</td>
<td>5 (14)</td>
</tr>
<tr>
<td>Totally agree</td>
<td>16 (46)</td>
<td>6 (17)</td>
<td>14 (40)</td>
<td>1 (3)</td>
<td>22 (63)</td>
</tr>
</tbody>
</table>

Table 3. Participants’ user experiences (responses from the experience form; N=35).
Discussion

Principal Findings

This study evaluated the dietary assessment function of the MyFood app among free-living older adults aged ≥65 years residing in Norway. MyFood is intended to be used to assess and monitor the nutritional intake of individuals at risk of malnutrition, and the evaluation of individual intake data was therefore of primary interest. This study found that the MyFood app underestimated the dietary intake of food and beverages at both the individual and group levels. At the individual level, there was a variation in the precision of the recordings between the participants, and the level of underestimation tended to increase with increasing intake. The agreement between the MyFood app and the 24-hour recalls for energy, protein, and fluids was higher for breakfast, lunch, and supper than for dinner and snacks. The food groups with the highest agreement between the 2 methods on both comparison days were eggs, yogurt, and self-composed dinner meals, whereas the food groups with the lowest agreement were condiments, vegetables, mixed meals, and cold beverages. All participants found the app easy to use, and most participants (27/35, 77%) experienced that they became more aware of their own nutritional requirements after 4 days of use.

The MyFood App’s Ability to Estimate the Intake of Energy, Protein, and Fluid at the Individual Level

To the best of our knowledge, only a few applications for dietary assessment have been developed for use or evaluated among free-living older adults aged ≥65 years [22-25]. Furthermore, most evaluation studies have been performed at the group level, whereas this study mainly intended to evaluate the use of the MyFood app at the individual level, as the purpose of the app is to monitor the nutritional intake of individuals to provide customized nutritional follow-up. Thus, this study provides novel knowledge to the field of using digital tools for nutritional assessment among the free-living older adults.

The MyFood app underestimated the total intake of energy compared with the 24-hour recalls for most participants. An explanation may be that several participants only recorded part of their intake in the app, compared with what they reported in the recalls, possibly because of inaccurate recordings. They may also have forgotten to record their intake in the MyFood app. It has previously been demonstrated that incorrect estimates of portion sizes account for approximately half of the errors in energy intake estimations from dietary records administered using technological devices [26]. During the 24-hour recalls, the participants used a picture booklet to describe their portion sizes, whereas the MyFood app included standardized portion sizes using household measures and illustration photos. In an evaluation study of an app-based food record in Switzerland, Bucher Della Torre et al [27] found that participants tended to choose the app-proposed portions even if their real portions were different. Another possible explanation is the omission of food and beverage items in the MyFood app compared with the 24-hour recalls, such as spreads and cold beverages. This was also seen in the previous evaluation study of the MyFood app among hospitalized patients [16], in which spreads and cold beverages were the food groups with the most omissions. Underreporting of energy intake was also observed in a recent study by Hopstock et al [28], in which a web-based dietary assessment tool was evaluated among Norwegian men and women aged ≥60 years.

The largest discrepancies between the methods in estimated energy intake were found for dinner on both the recording days. This finding is in accordance with observations from the previous evaluation study of the MyFood app [16]. A possible explanation for this may be that some participants forgot to record their dinner in the app or that the predefined meals available in the app did not represent the meals that the participants would eat for dinner, as these meals were adapted to an institutional setting and not tailored for a home setting. We observed that the participants who used the function “assemble your own dinner” (Figure 1) achieved better agreement between the 2 methods in energy intake for dinner than those selecting predefined meals in the app. This was possibly a result of them being forced to manually record all meal items. Thus, they could not lean on prerecorded items, which may explain why the “assemble your own dinner” function achieved greater accuracy than the predefined dinner meals. Although less than half of the participants used this function on each comparison day, with only 14 participants on the first day and 9 on the second day, this knowledge will be used in the future development of the dinner recording function in the MyFood app.

The agreement between the 2 methods for the estimated intake of energy, protein, and fluids was greater for participants with low intakes, with increased deviations observed with higher intakes on both comparison days. This corresponds to previous findings of underestimation of protein and fluids in MyFood in a hospital setting [16]. Other studies have shown that adults tend to underestimate large portion sizes compared with smaller ones [29]. The underestimation of protein in the MyFood app may have been caused by the omission of spreads (Multimedia Appendix 5). As sliced bread with spreads such as cheese and ham is often consumed for breakfast and lunch in Norway, spreads are an important source of protein in the Norwegian diet. Spreads were also found to be one of the food groups most often omitted in a Canadian validation study of an automated web-based 24-hour dietary recall using fully controlled feeding studies as the reference method [29]. Fluid intake was also underestimated in the MyFood app. This may have been because of the high omission rate for beverages, causing the reported intake of beverages in the recalls to be greater than those recorded in the app. Another possible explanation is the overestimation of fluid intake, as shown by the very high reported intake for some of the participants in the 24-hour recalls. For each of the meals separately, the agreement between the 2 methods for fluids was poor, with snacks being the meal category with the lowest agreement. This may have been because of the drinks not being recorded together with the meal with which they were consumed but rather being recorded as part of the snack category.

For energy, protein, and fluids, there was a tendency for better agreement between the methods on comparison day 1 than on comparison day 2. This contradicts previous studies, including...
the former evaluation study on MyFood [16], which demonstrated a “learning effect,” with an improved agreement on the second recording day compared with the first recording day [30].

**MyFood’s Ability to Estimate the Intake of Energy, Protein, and Fluid at the Group Level**

The estimated mean total intake of energy, protein, and fluid was underestimated in the MyFood app. A recent systematic review and meta-analysis by Zhang et al [31] on dietary assessment apps found that all apps underestimated energy intake compared with their reference methods. Zhang et al [31] argued that conducting 24-hour recalls the day after using the app might cause a memory effect and reduce the extent of underreporting in the recalls compared with recording in the app. Moreover, the availability of feedback and advice in the app may positively affect the 24-hour recalls performed afterward [32]. In this study, the two 24-hour recalls were conducted after recording in the MyFood app asking the participants to report on the exact same days. This may have led to improved memory and precision in the recalls compared with the recordings in the app.

**MyFood’s Ability to Estimate Intake in Food Groups**

The food groups that showed the best agreement between the methods were eggs, yogurt, and self-composed dinners. This may be because eggs and yogurt are presented in standardized units in the app, such as 1 egg or 1 cup of yogurt, which are similar to the units available in the grocery store. We also observed that the meals in which the participants assembled the dishes themselves, that is, breakfast, lunch, and self-composed dinners, achieved greater agreement than the predefined meals, such as mixed meals. For spreads, the agreement between the methods was quite low, which may be a result of spreads being among the food groups with the most omissions, as described in the Results section. However, the low agreement between the 2 methods for the spreads in this study may also be because of participants only recording part of the spreads they put on their bread slices or because they had difficulties estimating the correct amount of spreads eaten.

**User Experiences**

All participants reported that the MyFood app was easy to use and 74% (26/35) reported that it was easy to navigate. In addition, most participants (27/35, 77%) reported that they became more aware of their own nutritional requirements after using the MyFood app. This corresponds with the findings of the previous evaluation study of the MyFood app in a hospital setting [16]. Most participants (32/35, 91%) responded that they did not have to acquire a lot of new knowledge to use the app. This contradicts the findings of a study by Hopstock et al [28], in which they found that about one-third of the participating Norwegian men and women aged 60-74 years experienced that they needed to learn a lot of things before using a digital tool for dietary assessment. However, in the study by Hopstock et al [28], the participants did not receive any guidance on using the tool, in contrast with this study.

**Strengths and Limitations**

This study evaluated the dietary assessment functionality of the MyFood app among free-living older adults, which is considered an important strength, as most studies investigate the use of apps as dietary assessment tools among younger individuals. In addition to evaluating the dietary assessment functionality of the MyFood app, the participants’ experiences with using the app were investigated. Data on the usability of dietary assessment apps among the free-living older adults are scarce.

A limitation of using 24-hour recalls as the reference method is that the 24-hour recalls are prone to error, such as underestimation of intake, which may have affected the basis of comparison, as both the reference method and the test method inhabit the same measurement error [33,34]. The dietary recording functionality of the MyFood app was evaluated in free-living older adults, most of whom did not receive home care services and were not at risk of malnutrition according to the MNA. Thus, the study sample was probably healthier than what may be expected from the general population of free-living older adults aged ≥65 years. Furthermore, many of the participants were still working, and thus, they had a busier everyday life than what many free-living older adults are expected to have. Therefore, we do not know whether the results are representative of the free-living older adult population in Norway. The results indicate that free-living older adults need follow-up to be able to record accurate portion sizes and to avoid omissions in the MyFood app, and future studies should investigate how health care professionals or next-of-kin may be involved in this task.

**Conclusions**

The MyFood app was evaluated for its ability to estimate the intake of energy, protein, fluid, and food and beverage items among free-living older adults aged ≥65 years residing in Norway. The results showed that the MyFood app underestimated the participants’ dietary intake compared with 24-hour recalls as a reference method, both at the individual and group levels. The breakfast and the lunch meals showed better agreement between the methods than the dinner and snack meals. The MyFood app may be a useful tool among free-living older adults; however, the results indicate that the free-living older adults need follow-up and support to accurately report portion sizes and avoid omissions. All participants found the MyFood app easy to use, 74% (26/35) found it easy to navigate, and most participants (27/35, 77%) reported becoming more aware of their nutritional requirements.

**Acknowledgments**

The MyFood app was developed on Tjenester for Sensitive Data (TSD) facilities; owned by the University of Oslo; and operated and developed by the TSD service group at the University of Oslo, IT Department. The authors thank the participants of this study. This study was funded by UNIFOR (Forvaltningsstiftelse for fond og legater), Freia Chocolade Fabriks Medisinske fond.
Data Availability
The data sets used and analyzed during this study are available from the corresponding author upon reasonable request.

Authors' Contributions
FS, LFA, and MMP designed the research; FS conducted the data collection and performed statistical analysis; FS wrote the paper; and MMP had the primary responsibility for the final content. All authors critically revised the manuscript for important intellectual content and approved the final manuscript.

Conflicts of Interest
LFA and MMP are shareholders in FoodCapture AS, which commercializes the MyFood system. All other authors declare no other conflicts of interest.

Multimedia Appendix 1
Drop plots for the intake of energy, protein, and fluids for each meal on comparison day 1.
[DOCX File, 1458 KB - mhealth_v111e45079_app1.docx]

Multimedia Appendix 2
Drop plots for the intake of energy, protein, and fluids for each meal on comparison day 2.
[DOCX File, 1470 KB - mhealth_v111e45079_app2.docx]

Multimedia Appendix 3
An overview of the proportion of participants having ≥80% agreement between MyFood and the 24-hour recalls for the estimated intake of energy, protein, and fluid in total and for each meal on comparison days 1 and 2. n1: number of consumers on the first comparison day. n2: number of consumers on the second comparison day.
[ PNG File, 114 KB - mhealth_v111e45079_app3.png ]

Multimedia Appendix 4
An overview of participants having ≥80% agreement between MyFood and the 24-hour recalls in the estimated intake of selected food groups on comparison day 1 and day 2. n1: number of consumers comparison day 1. n2: number of consumers comparison day 2.
[ PNG File, 116 KB - mhealth_v111e45079_app4.png ]

Multimedia Appendix 5
Number of omitted food items in each food group for comparison days 1 and 2. The light gray bar represents the number of omissions on the first comparison day, and the dark gray bar represents the number of omissions on the second comparison day. In cases where no bars were present, there were no omissions on that day.
[ PNG File, 107 KB - mhealth_v111e45079_app5.png ]

References


21. Paulsen MM. Development and evaluation of a decision support system to prevent and treat disease-related malnutrition. University of Oslo. 2019. URL: https://www.duo.uio.no/bitstream/handle/10852/77479/PhD-Paulsen-2020.pdf?sequence=1&isAllowed=y [accessed 2021-12-03]


Abbreviations

KBS: KostBeregningsSystem
MMSE-NR: Mini-Mental State Examination–Norwegian Revised
MNA: Mini Nutritional Assessment

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An Overview of Chatbot-Based Mobile Mental Health Apps: Insights From App Description and User Reviews

M D Romael Haque¹, BSc, MSc; Sabirat Rubya¹, BSc, PhD
Department of Computer Science, Marquette University, Milwaukee, WI, United States

Corresponding Author:
M D Romael Haque, BSc, MSc
Department of Computer Science, Marquette University
1313 W Wisconsin Ave
Milwaukee, WI, 53233
United States
Phone: 1 4144397646
Email: mdromael.haque@marquette.edu

Abstract

Background: Chatbots are an emerging technology that show potential for mental health care apps to enable effective and practical evidence-based therapies. As this technology is still relatively new, little is known about recently developed apps and their characteristics and effectiveness.

Objective: In this study, we aimed to provide an overview of the commercially available popular mental health chatbots and how they are perceived by users.

Methods: We conducted an exploratory observation of 10 apps that offer support and treatment for a variety of mental health concerns with a built-in chatbot feature and qualitatively analyzed 3621 consumer reviews from the Google Play Store and 2624 consumer reviews from the Apple App Store.

Results: We found that although chatbots’ personalized, humanlike interactions were positively received by users, improper responses and assumptions about the personalities of users led to a loss of interest. As chatbots are always accessible and convenient, users can become overly attached to them and prefer them over interacting with friends and family. Furthermore, a chatbot may offer crisis care whenever the user needs it because of its 24/7 availability, but even recently developed chatbots lack the understanding of properly identifying a crisis. Chatbots considered in this study fostered a judgment-free environment and helped users feel more comfortable sharing sensitive information.

Conclusions: Our findings suggest that chatbots have great potential to offer social and psychological support in situations where real-world human interaction, such as connecting to friends or family members or seeking professional support, is not preferred or possible to achieve. However, there are several restrictions and limitations that these chatbots must establish according to the level of service they offer. Too much reliance on technology can pose risks, such as isolation and insufficient assistance during times of crisis. Recommendations for customization and balanced persuasion to inform the design of effective chatbots for mental health support have been outlined based on the insights of our findings.

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KEYWORDS
chatbot; mobile mental health apps; consumer reviews; health care app; mental health app; app development; user experience; mHealth intervention; mobile health

Introduction

Mental Health Chatbots as an Emerging Technology
A chatbot is a system that can converse and interact with human users using spoken, written, and visual languages [1]. In recent years, chatbots have been used more frequently in various industries, including retail [2], customer service [3], education [4], and so on because of the advances in artificial intelligence (AI) and machine learning (ML) domains. Facebook Messenger currently offers more than 300,000 text-based chatbots [5]. Chatbots have primarily been used for commercial purposes and profitable businesses. However, more recent research has demonstrated that chatbots have considerable promise in the health care industry in treating patients and offering them support in a cost-effective and convenient manner [6].
In the context of mental health (MH), chatbots may encourage interaction with those who have traditionally been reluctant to seek health-related advice because of stigmatization [7]. Chatbots are an emerging technology that shows potential for mobile MH apps to boost user engagement and adherence [8]. The effectiveness of chatbots has been explored for self-disclosure and expressive writing [7,9,10]. Young people with MH issues have experienced various types of social support such as appraisal, informational, emotional, and instrumental support from chatbots [11]. In addition, chatbots have been designed to educate underprivileged communities on MH and stigmatized topics [12,13]. Emerging evidence has shown user acceptance of chatbots for supporting various MH issues and early promises in boosting health outcomes in the physical and MH domains.

The adoption of new technology, especially those heavily related to AI and ML, relies first on ascertaining the levels of safety, effectiveness, and user comfort. Despite the increasing adoption and benefits of emerging technologies such as chatbots to support MH and well-being, little research has been conducted to gain an understanding of consumers' real-life user experiences of interacting with MH chatbot apps. Recent research on MH apps in general points out that patient safety is rarely examined, health outcomes are evaluated on a small scale, and no standard evaluation methods are present [14], and these findings also apply to MH chatbot apps. Similar to many other emerging technologies, recent developments in chatbots are because of a massive technology push, with little attention paid to human needs and experiences [15]. This can lead to unintended negative consequences, such as biases, inadequate and failed responses, and privacy issues, all of which can negatively affect the quality of the experience of chatbots as a source of support [16,17]. Thus, it is critical to gain an understanding of the nuances in users' perceptions and experiences of using MH chatbots.

Commercially available MH chatbot apps for popular platforms (eg, iOS [Apple Inc] and Android [Google Inc]) are used by a large user base with varying demographic backgrounds. These users can provide feedback through ratings and text reviews [18]. These platforms can be leveraged to gain a holistic understanding of the features that recently developed MH chatbots offer and how users assess them. Knowledge of user perceptions from real-life experiences can inform future research and the design of more effective chatbots. Previous studies have identified user reviews as a great source for understanding the benefits and drawbacks of technology [19,20]. This allows researchers to incorporate community values and needs into product design and improves user-friendliness [21]. Consumers often make decisions about using new tools based on user rating scores and reviews in web-based marketplaces. According to previous studies, users trust reviews and feel at ease based on their decisions them [21]. Moreover, previous literature emphasizes analyzing user reviews of mobile MH apps that have chatbot features [22,23] to obtain in-depth knowledge about this new technology intervention in mobile MH apps. For this study, we decided to analyze commercially available well-known chatbot-based mobile MH apps and their corresponding user reviews from the Apple App Store and Google Play Store. To obtain a comprehensive overview of these apps and understand the nuances of user opinions, we aimed to answer the following 2 research questions (RQs):

- RQ1: What are the state-of-the-art features and properties of chatbot-based mobile MH apps?
- RQ2: What concerns and opinions are expressed in user reviews published on web-based app store platforms regarding the usability and efficiency of chatbot-based mobile MH apps?

We conducted an exploratory observation of 10 apps that offer support and treatment for a variety of MH concerns with a built-in chatbot feature and qualitatively analyzed their user reviews available on the Google Play Store and Apple App Store. Publicly available data (user reviews) provide in-depth analyses of consumers' personal app user experiences. We found that although chatbots' personalized, humanlike interactions were positively received by users, improper responses and assumptions about the personalities of users led to a loss of interest. As chatbots are always accessible and convenient, users can become overly attached to them and prefer them over interacting with their friends and family members. Furthermore, a chatbot may offer support for a crisis whenever the user needs it because of its 24/7 availability, but even the recently developed chatbots lack the understanding of properly identifying a crisis. Chatbots in this study fostered a judgment-free environment and helped users feel more comfortable sharing sensitive information.

Before implementing a technological solution for MH, researchers in digital health communities are constantly interested in the support needs and preferences of groups or communities [24-26]. Researchers have analyzed the effectiveness of technologies used for MH assistance [24,27], proposing ethical concerns [28], policy recommendations [29,30], and designing automated or human-in-the-loop interactive systems [7,10]. These studies stressed the significance of designing and evaluating systems for susceptible populations, such as people with MH issues, from the perspective of users. To contribute to this body of work, we discussed our study’s findings with respect to the research and design implications for future MH chatbots. We outlined specific recommendations for customizing certain features, careful consideration of incorporating persuasive strategies, and trust building. Finally, we discussed the impact of excessive reliance on chatbots for MH support. We believe that considering these insights while developing a chatbot-based MH support system will make the design user-centric and, thus, more effective.

**Background and Related Work**

Chatbots are software programs that can imitate human behavior and undertake specific tasks by intelligently conversing with users [1]. They are conversational agents that use text and speech recognition to engage with users [31]. Chatbots are commonly used in various web-based and mobile-based apps. In recent years, it has taken on the role of an internet-based entity that can act as a travel agent [32], customer service representative [3], financial adviser [2], and personal assistant [33] and is becoming increasingly sophisticated. Some of the available chatbots can have a personality of their own, store information becoming increasingly sophisticated. Some of the available chatbots can have a personality of their own, store information
time by learning about their users to provide better services [34].

In this section, we provide a brief overview of research on chatbots in health care, including mobile MH chatbots, and provide a rationale for using app reviews to capture perceptions and opinions of users.

Chatbots in Health Care
Chatbots have recently received much attention in the health care and wellness industries [6] and have been tested using a variety of elements and characteristics depending on the behavior they were attempting to achieve. Chatbots function as digital personal assistants [35], allowing patients to learn more [13], obtain support [36], and take prompt action in response to new symptoms [37]. Some chatbots can assist users in collecting medical data via text discussions and then delivering it to the (selected) physicians in a format that is easier to use for diagnostic purposes [36]. Chatbot interventions are effective in increasing physical activity, achieving relevant weight loss, and improving diet [38-40] by sending daily check-in reminders [41] and offering relevant resources [40]. They are also sufficiently sophisticated to interact with users through daily adaptive little chats and show progress toward goals using analytics and graphs to encourage self-reflection [42].

Mobile MH Chatbots
Among the numerous chatbots being used in different aspects of health and well-being, chatbots in mobile MH care have demonstrated effectiveness in broadening traditional therapy in a cost-effective and convenient manner [43]. MH chatbots are AI-powered chatbots that provide MH support, guidance, and resources through a conversational interface [44]. These chatbots replicate human interactions, respond to user inputs, and deliver tailored MH care [34]. MH chatbots can target a range of MH concerns, including anxiety, depression, and stress [14,22]. These can provide coping strategies, mindfulness exercises, and information about MH conditions and treatments and, in some cases, connect users to MH professionals [14,22].

A 2021 national survey found that 22% of adults had used an MH chatbot, and 47% said they would be interested in using it if needed. Among the respondents who had tried an MH chatbot, nearly 60% said they began this use during the COVID-19 pandemic, and 44% said they used chatbots exclusively and did not see a human therapist [45]. Currently, there are at least 9 chatbot apps on app markets with more than 500,000 downloads. Chatbots have been shown to effectively reduce the severity of MH concerns for people from different demographics and backgrounds, including people in rural communities [12], shift workers with accessibility issues [46], students with anxiety and stress [47], employees of health care systems who require emotional support [48], veterans and adolescents who feel stigmatized in sharing their concerns [12], etc.

Rather than providing generic suggestions, chatbots can deliver individualized suggestions and resources based on the needs and requirements of users [34,44]. They were designed to identify MH concerns [34], track moods [49], deliver cognitive behavioral therapy (CBT) [47], and promote positive psychology [50]. Several well-known chatbots such as Wysa [34], Woebot [47], Replika [51], Youper [52], and Tess [53] were discussed in prior literature. Inkster et al [34] examined the potency of Wysa and found a positive influence on reducing depressive symptoms in a randomized controlled experiment. Fitzpatrick et al [47] evaluated the effectiveness of the AI chatbot Woebot in giving CBT to college students with anxiety and depression and found that the Woebot notably decreased depressive symptoms. Ta et al [51] investigated social support received from artificial agents in everyday contexts when interacting with the social chatbot Replika. Mehta et al [52] examined the acceptability and effectiveness of Youper. In addition to commercial apps, in recent years, research communities have also been increasingly involved in designing chatbots for specific purposes, such as teaching self-compassion (“Vincent”) [9], enabling self-disclosure [7,10], facilitating positive messages within social groups [54], improving the quality of life of older people and making them more active to fight their sense of loneliness [55], supporting interpersonal skills (“Sunny”) [56], and reducing stress (“Mylo”) [57]. Kim et al [11] explored teenagers’ expectations when interacting with a chatbot intended to support their emotional needs. Although most prior studies focused on developing and evaluating new chatbot systems or assessing the effectiveness of the evidence-based techniques used by existing chatbots, there is inadequate research on how end users perceive the usefulness of these app-based chatbots.

User Reviews as a Versatile Source for Capturing User Experience and Preferences
In general, the internet is considered a rich source of information about personal experiences of a wide variety of illnesses, with websites and discussion forums [58]. An increasing number of studies exploit web-based sources as repositories of primary data on health and illness experiences [58]. People who are otherwise socially isolated or geographically dispersed and are therefore hard to include in conventionally drawn samples (especially for qualitative studies relying on snowball sampling) might be more likely to be included because of the ease with which such people can access the internet [59]. Large amounts of material can be collected within a short period. Individuals can use the relative anonymity of the internet to reveal things that they would not discuss in a face-to-face research setting [60]. As of 2022, there are more than 10 million user reviews on the Google Play Store and Apple App Store [61]. Therefore, user reviews collected from these popular app stores can provide rich insights into personal user experiences from people spanning a wide range of backgrounds and demographic characteristics when compared with traditional methods of qualitative data collection (ie, interviews) [62].

User reviews can be defined as feedback published by individuals about their opinions and satisfaction or dissatisfaction with a product [18]. The star ratings and elaborated feedback in the textual reviews provide developers with a chance to explore user complaints and improve apps [21]. For new or potential users of mobile MH apps, the reviews work as a deciding factor to determine if an app would be helpful based on how it worked out for other users with similar expectations [63]. Approximately 80% of potential users check ratings and reviews before downloading an app [64]. In research settings, user ratings and reviews have been leveraged for a
variety of reasons, including determining why adherence to mobile MH apps is poor [65], informing developers of design priorities rather than just guiding purchasing decisions [66], and gaining a better understanding of ethical issues faced by users [28]. Vasa et al [20] investigated the hypothesis that despite the abundance of positive reviews for mobile apps, it is worthwhile to examine negative reviews to gather useful data from users. In the mobile MH domain, Haque et al [23] leveraged user reviews to thoroughly capture user experiences and provided implications for designing future MH apps.

Our study is inspired by the body of work that considers user-generated reviews as a vital source for understanding varied perspectives and derives meaningful implications from them [62,63]. This enables us to gain perspectives from people with diverse demographic characteristics that would otherwise be challenging to collect using conventional data collection methods [62,67].

Research Gap and Contribution

As an emerging technology, the development and application of chatbots in mobile MH apps are in their early phases, and there are still considerable challenges to overcome in the development of this technology. According to recent studies, patient safety has rarely been evaluated, health outcomes have been inadequately quantified, and no standardized evaluation procedures have been used [14]. Some chatbots are reported to be unable to understand the complex use of language associated with an MH crisis and fail to recognize symptoms and respond appropriately [17]. Privacy is a major concern for users of these apps; because users are still less familiar with this emerging technology, there is a higher risk of exposing users to privacy risks through data sharing [16]. Furthermore, although poor adherence is a common problem with digital MH interventions, by contrast, some susceptible people may begin to rely on them too much, which may lead to anxiety when these apps are unavailable [16].

Overall, there is a need for a better understanding of how all mobile MH services can and should encourage the safe and ethical use of chatbots [14]. Although a handful of studies have shown the potential benefits of MH chatbot apps, users’ real-life experiences and challenges are not yet well understood [22]. Haque et al [23] recently provided a high-level discussion on some common user concerns frequently raised in user reviews and implied that researchers and developers in this space could benefit from a comprehensive analysis of the existing commercial MH chatbot apps. As an extension to these prior works [22,23], people’s perceptions and mental models of chatbots can be studied to address critical concerns such as how users gain trust in chatbots, user values, and requirements in this space and ultimately to provide concrete research and design recommendations for future chatbot apps. A user-centric analysis will also assist researchers in mapping an evidence-based framework for the proposed intervention and minimizing the psychological effects of such treatments.

Methods

In this section, we outline the techniques for selecting and filtering the mobile apps for this study, the data analysis methods we used, the ethical standards we followed, our positionality statement, and methodological limitations.

Selection of Sample Apps and Reviews

Selection of Apps

To obtain a comprehensive list of commercially available MH apps that include chatbot features, we conducted our search using different sources. First, we considered open-access articles in recent literature on MH chatbots [14,22]. Next, we conducted search queries on 2 different expert MH app review platforms: Mindtools [68] and Psyberguide [69]. Finally, we searched 2 dominant web-based mobile app stores (Google Play for Android and Apple App Store for iOS). We used the search terms Mental health and chatbot on expert review platforms and app stores. In addition, we explored the recommended applications or similar apps section of the corresponding website after discovering an MH app with a chatbot feature to determine if the other apps meet our criteria. Without logging into a specific account, the search was performed on the app stores’ home pages. This action was performed to ensure that the system could not use a ranking algorithm to prioritize any user choice. As these apps represent the sample in (nearly) the same order that consumers are likely to be exposed to and hence most likely to use, although the search results may not be entirely comprehensive (as observed by convenience sampling), they still represent the sample.

After the initial search from these 3 sources, we obtained 19 apps. The authors carefully read the app descriptions, observed screenshots of the app features, and in some cases analyzed these apps’ promotional websites to ensure whether these apps include a chatbot feature that provides support for different MH concerns. We observed that some of these apps included intelligent questions and answers (Q/A) based on AI and ML. Intelligent Q/A is based on a collection of questions, and by responding to them, it can offer individualized summaries, diagnoses, recommendations, and other information. In this study, we described MH chatbots as intelligent machines that can simulate and process conversations with users regarding their MH needs. An intelligent Q/A system is designed to provide accurate and precise answers to specific questions based on a given input, usually in the form of a natural language. In contrast, a chatbot is a more general-purpose conversational agent that can handle a wide range of inputs and provide a range of responses, from simple greetings to more complex interactions. Intelligent Q/A systems are usually triggered by a question or request for information, whereas chatbots can initiate the conversation or respond to user inputs in an open-ended manner and are capable of producing a wider range of outputs compared with intelligent Q/A systems. The most crucial aspect of a chatbot is the “conversational design,” which is defined between the user and the bot. Although the guidance chatbots offer is usually correct and scientifically supported, it will be a computer program speaking back to the users, usually in the shape of a nice character, to facilitate their ability to...
communicate. User expectations can vary while interacting with chatbots as opposed to intelligent Q/A systems with predefined patterns of questions. Therefore, we only considered chatbots with the capability to start and continue conversations with users. To ensure that our list includes apps that fall under this definition, one of the authors opted to download each app separately (for the iOS platform) and use it for at least 3 days.

**Figure 1.** Flowchart of the app selection process. Q/A: questions and answers.

**Selection of User Reviews**

We created scraping scripts using the Python Selenium library to collect the public user reviews of the 10 apps that were accessible from the Google Play Store and Apple App Store. User reviews can illustrate examples of user satisfaction and dissatisfaction with app features. Reviews are therefore recognized as an important source of information to gain insights into the real-life use of mobile apps [20]. Following the work of Haque et al [23] on analyzing user reviews of mobile MH apps, we used the 2 following inclusion criteria for filtering to extract recent and crucial user feedback for the apps.

- **Timeline:** We considered reviews posted between January 1, 2019, and May 1, 2022. Most recent reviews are likely to be more useful because app stores change quickly with the addition of new apps and upgrade to existing apps.
- **Length:** As shorter reviews might not provide deeper insights in general and are frequently false or promotional in nature [70], the minimum character length was considered 200 for the scope of our study.

A total of 3621 reviews from the Google Play Store and 2624 reviews from the Apple App Store met all the inclusion criteria. These reviews are based on 9 apps from the Google Play Store (only Elomia is not available in the Google Play Store) and 10 from the Apple App Store. All reviews have a unique coding system that can be easily traced back to the apps and platforms from which they emerged. During the analysis, the lead author was responsible for carefully reading each review and ensuring that all personally identifying information was replaced or removed.

**Data Analysis**

First, to gain an understanding of the descriptive overview of the commercially available chatbot-based MH apps, we analyzed app descriptions from marketplace websites and incorporated the key information in our observation notes. The observation note was then divided into 6 main themes with the aim of providing a comprehensive overview of these apps in collaboration with another author. The authors did not include their judgments regarding the effectiveness of these apps. Among the chatbot-based MH apps we considered, 4 apps mentioned the evidence-based techniques used in their description. For the remaining apps, we determined the technique through a combination of an analysis of the description and observation notes from interacting with the apps. The findings of this categorization are described in the **Overview of the Aspects Commonly Used in Chatbot MH Apps**.
To understand user perspectives, the selected user reviews from the 10 apps were examined using inductive analysis [71]. Thematic analysis was chosen because it enables systematic analysis of large data sets and facilitates the comprehension of textual patterns while considering the context [21,72]. A total of 2 passes were performed during the analysis. Open codes were created during the first pass to collect various perspectives from reviews. We recorded the subtleties in the insights provided in each review, which resulted in a high number of open codes that were substantially decreased through memoing and clustering [71]. In the second phase of the analysis, we memoed and clustered the codes using a constant comparison method, operationalized as affinity mapping. Each open code was compared with the others and positioned to reflect its affinity for emerging themes and clusters. The reported themes consisted of those that appeared consistently across multiple reviews and those that came from reviews that represented divergent responses and opinions. The findings from the reviews are described in the Results section, and each quote is identified by the review’s particular ID generated from the platform, app name, and a random number.

Data Integrity

App stores, similar to many other web-based marketplaces, can have reviews posted by fake and paid users. However, prior research [70] showed that in the “Health & Fitness” category, the percentage of potentially fake reviews was very low (approximately 6%). Fake reviews also tend to be shorter [70], and by considering reviews of ≥200-character length, we assume that almost all the included reviews are original.

We understand that if data or information is only accessible to a particular group of individuals or groups, it is unethical for researchers to use it [73]. As a result, we made sure the websites from which we obtained the data were accessible to everyone and not just for some groups or populations [73]. Although these pages were public, we purposefully avoided publishing or disclosing any personally identifying information that was shared. The language of the user reviews reported here has been carefully modified, keeping the meaning intact.

Ethical Considerations

This study was assessed as not human subjects research by the Institutional Review Board of Marquette University (Protocol # 3935) as it does not meet the regulatory definition of human subject-public reviews and the information provided is not about themselves.

Limitations

Our selection criteria have certain limitations. First, we primarily used ratings from the 2 most widely used mobile platforms (Google and Apple). Other mobile platforms were not considered in this study. Second, it is likely that users who do not feel comfortable (or do not care) discussing their experiences on web-based platforms are not contributing. However, we can confidently conclude that the perceptions we identified are typical of user perceptions, given the larger number of evaluations obtained from the 2 most well-known web-based marketplaces.

Results

Overview

For this research purpose, we chose 10 commercially available mobile MH apps that have built-in chatbot features. All these apps, except Elomia, are available on the 2 most popular platforms (Apple App Store and Google Play Store). Elomia is exclusively available for iOS. A descriptive overview of these apps is provided in Table 1. All these apps are extremely popular in terms of both the number of downloads and the number of ratings. Thus, we can assume that a comprehensive overview of these apps can assist in understanding the perspectives of a wide and diverse user base.

Table 1. A descriptive overview of the selected 10 mobile mental health apps with a built-in chatbot technology.

<table>
<thead>
<tr>
<th>App</th>
<th>Number of ratings in Apple App Store</th>
<th>Number of ratings in Google Play Store</th>
<th>Number of downloads in Google Play Store</th>
<th>Age rating (years)</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADA</td>
<td>125</td>
<td>323,000</td>
<td>≥5 million</td>
<td>≥17</td>
<td>Free</td>
</tr>
<tr>
<td>Chai</td>
<td>27,900</td>
<td>34,000</td>
<td>≥1 million</td>
<td>≥17</td>
<td>Free with in-app purchases</td>
</tr>
<tr>
<td>Elomia</td>
<td>193</td>
<td>N/Aa</td>
<td>N/A</td>
<td>≥12</td>
<td>Free with in-app purchases</td>
</tr>
<tr>
<td>Mindspa</td>
<td>107</td>
<td>2970</td>
<td>≥500,000</td>
<td>≥17</td>
<td>Free with in-app purchases</td>
</tr>
<tr>
<td>Nuna</td>
<td>68</td>
<td>93</td>
<td>≥10,000</td>
<td>≥4</td>
<td>Free with in-app purchases</td>
</tr>
<tr>
<td>Serenity: Guided Mental Health</td>
<td>20</td>
<td>146</td>
<td>≥10,000</td>
<td>≥12</td>
<td>Free</td>
</tr>
<tr>
<td>Stresscoach</td>
<td>None</td>
<td>495</td>
<td>≥10,000</td>
<td>≥12</td>
<td>Free</td>
</tr>
<tr>
<td>Woebot</td>
<td>5500</td>
<td>11,800</td>
<td>≥500,000</td>
<td>≥12</td>
<td>Free</td>
</tr>
<tr>
<td>Wysa</td>
<td>13,500</td>
<td>126,000</td>
<td>≥1 million</td>
<td>≥12</td>
<td>Free with in-app purchases</td>
</tr>
<tr>
<td>Youper–Self Care Friend</td>
<td>14,400</td>
<td>49,100</td>
<td>≥1 million</td>
<td>≥12</td>
<td>Free with in-app purchases</td>
</tr>
</tbody>
</table>

*a/N/A: not applicable.*
Overview of the Aspects Commonly Used in Chatbot MH Apps

Overall, we consider 6 core characteristics that can be used to understand the current status of MH chatbot technology. A few of these aspects were adopted from 2 previous review articles on MH chatbots [14,22]. These studies compiled a list of recent research articles on MH chatbots and provided typologies based on their purpose, targeted concerns, and supported evidence-based techniques. We included these 3 categories in our analysis to gain a broad overview of the current state of the art of commercially available MH chatbot apps. These studies also emphasized the capability of these chatbots to conduct and continue conversations. We considered this crucial aspect of chatbot apps and added 2 new categories to explore: conversation style and media types used by chatbots. A total of 3 different conversational styles were used: chatbot guided, semiguided, and open-ended (Table 2). Finally, Haque et al [23] provided useful insights into the necessity of providing crisis support through MH apps, as potential users of the apps are more susceptible to the crisis than the general population. We have added this specific criterion to be analyzed in our observational study. An outline of these criteria and types is presented in Table 2.

Table 2. Criteria of features related to chatbot-based mental health apps used in our study.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Types</th>
</tr>
</thead>
<tbody>
<tr>
<td>Purpose</td>
<td>• Digital coach—assist users to reach their small goals</td>
</tr>
<tr>
<td></td>
<td>• Digital screener—alert users to potential mental health concerns based on reported symptoms</td>
</tr>
<tr>
<td></td>
<td>• Conversational companion—simulate being someone the user can speak to</td>
</tr>
<tr>
<td></td>
<td>• Virtual therapist—ability to engage in therapeutic conversations</td>
</tr>
<tr>
<td>Targeted concerns</td>
<td>• Stress, anxiety, depression, self-care, sleep disorder, panic disorder, relationship issues, low self-esteem, and loneliness</td>
</tr>
<tr>
<td>Conversation Flow</td>
<td>• Guided conversation—only allows the users to communicate with the chatbot with predefined responses from the chatbot. It does not allow any form of open input from the users.</td>
</tr>
<tr>
<td></td>
<td>• Semiguided conversation—mostly allows the users to communicate with the chatbot with predefined responses and sometimes allows open inputs from the users. However, the bot cannot recognize the open user inputs and extract any information from them.</td>
</tr>
<tr>
<td></td>
<td>• Open-ended conversation—allows the users to communicate with the chatbot with predefined responses and open inputs from the users. The bot can recognize the open user inputs and extract information from them.</td>
</tr>
<tr>
<td>Media types used</td>
<td>• GIFs, text, audio, video, emoji, images, and acronyms</td>
</tr>
<tr>
<td>Crisis support</td>
<td>• Availability of crisis information—provides information regarded crisis-related helplines and emergency services</td>
</tr>
<tr>
<td></td>
<td>• Ability to detect potential crises from the chat—detects potential crises through conversation with the users</td>
</tr>
<tr>
<td></td>
<td>• Access to a professional therapist—provides access to a professional therapist is an alternative to avoid possible ramifications of the potential crisis</td>
</tr>
<tr>
<td></td>
<td>• Ability to notify designated personnel—notifies designated personnel if crisis is being detected</td>
</tr>
<tr>
<td></td>
<td>• Access to self-care tools—recommend self-care activities</td>
</tr>
<tr>
<td>Evidence-based techniques</td>
<td>• CBT, DBT, mindfulness, symptoms tracking and monitoring, positive psychology, acceptance and commitment therapy, and psychoeducation and information</td>
</tr>
</tbody>
</table>

aGIF: graphics interchange format.  
bCBT: cognitive behavioral therapy.  
cDBT: dialectical behavior therapy.

We examined app store descriptions to understand the primary goals of these apps and identify how they are branded. We discovered 4 different types of purposes in all, with “digital coaches” being the most prevalent (5 out of 10 apps). The chatbot apps targeted a wide range of MH concerns, including anxiety (9 apps), depression (6 apps), and self-care techniques (7 apps).

We discovered 3 different conversational flows based on our exploratory observations. The most popular one is “Guided conversation,” in which users are only permitted to reply using preset input provided through the interface. This is the most common technique used by the chatbots we analyzed (6 out of 10 apps). Only Woebot uses a semiguided approach that allows users to either select from predefined options or type text; however, it is incapable of processing sentiments in the input text. This open input option is useful when users reframe negative thoughts and share stories. Finally, Wysa, Nuna, and Elomia follow an open-ended conversation style. They continued the conversation based on their understanding of the user input. These chatbots leveraged a variety of media types for communication to make the interaction resemble humanlike interactions. For instance, the graphics interchange formats (GIFs), emojis, images, and acronyms are used to portray humor and emotions. Images, audio, and videos were used along with educational elements. As all these chatbots communicate by text, the text is by far the most frequent. Individuals with MH problems can face a crisis at any time, and effective crisis support is a major criterion for evaluating MH apps.
apps. We identified 5 different types of crisis support options available in the 10 chatbots. Of the apps, 6 offer users access to information regarding crisis support systems and emergency helplines. Providing instant suggestions for self-care tools, such as suggestive breathing in cases of anxiety attacks, is also popular. Only Wysa contains all the 5 options available to support a user during a crisis. Ada and Chai do not contain any crisis support.

As evidence-based techniques have been proven effective for treating different MH disorders, we explored which of these tools and techniques the chatbots commonly follow. The most popular type of therapy is CBT. All 10 apps followed the CBT to some extent. A total of 8 apps provided support for mindfulness. Dialectical behavior therapy and acceptance and commitment therapy are less common modified forms of CBT. Table 3 presents the aforementioned features of the considered apps.

Table 3. A detailed overview of features related to chatbot-based mental health apps found in our study.

<table>
<thead>
<tr>
<th>App</th>
<th>Purpose</th>
<th>Targeted concerns</th>
<th>Conversation flow</th>
<th>Media types used</th>
<th>Crisis support</th>
<th>Evidence-based techniques</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADA</td>
<td>Digital screener</td>
<td>Anxiety and depression</td>
<td>Guided</td>
<td>Text</td>
<td>None</td>
<td>CBT(^a)</td>
</tr>
<tr>
<td>Chai</td>
<td>Conversational companion</td>
<td>None</td>
<td>Guided</td>
<td>Text and emoji</td>
<td>None</td>
<td>CBT</td>
</tr>
<tr>
<td>Elomia</td>
<td>Virtual therapist</td>
<td>Stress, anxiety, depression, self-care, sleep disorder, relationship issues, low self-esteem, and loneliness</td>
<td>Open-ended</td>
<td>Text</td>
<td>Access to self-care tools</td>
<td>CBT, mindfulness, positive psychology, and symptoms tracking and monitoring</td>
</tr>
<tr>
<td>Mindspa</td>
<td>Virtual therapist</td>
<td>Anxiety, depression, self-care, relationship issues, and low self-esteem</td>
<td>Guided</td>
<td>Text and video</td>
<td>Availability of crisis related information and access to self-care tools</td>
<td>CBT, mindfulness, positive psychology, and psychoeducation and information</td>
</tr>
<tr>
<td>Nuna</td>
<td>Digital coach</td>
<td>Stress, anxiety, depression, and self-care</td>
<td>Open-ended</td>
<td>Text and emoji</td>
<td>Availability of crisis related information and access to self-care tools</td>
<td>CBT, mindfulness, positive psychology, symptoms tracking and monitoring, and psychoeducation and information</td>
</tr>
<tr>
<td>Serenity</td>
<td>Conversational companion</td>
<td>Anxiety, self-care, sleep disorder, and relationship issues</td>
<td>Guided</td>
<td>Text and emoji</td>
<td>Access to self-care tools</td>
<td>CBT, mindfulness, and acceptance and commitment therapy</td>
</tr>
<tr>
<td>Stress-coach</td>
<td>Digital coach</td>
<td>Anxiety, stress, and panic disorder</td>
<td>Guided</td>
<td>GIF(^b), text, and emoji</td>
<td>Availability of crisis related information and access to self-care tools</td>
<td>CBT, mindfulness, and psychoeducation and information</td>
</tr>
<tr>
<td>Woebot</td>
<td>Digital coach</td>
<td>Stress, anxiety, depression, self-care, relationship issues, and loneliness</td>
<td>Semiguided</td>
<td>GIF, text, audio, video, emoji</td>
<td>Availability of crisis related information and access to self-care tools</td>
<td>CBT, DBT(^c), mindfulness, and symptoms tracking and monitoring</td>
</tr>
<tr>
<td>Wysa</td>
<td>Digital coach</td>
<td>Stress, anxiety, depression, self-care, and sleep disorder</td>
<td>Open-ended</td>
<td>GIF, text, audio, video, emoji, images, and acronyms</td>
<td>Availability of crisis related information, access to self-care tools, access to professional therapist, ability to detect potential crisis from the chat, and ability to notify designated personnel</td>
<td>CBT and mindfulness</td>
</tr>
<tr>
<td>Youper</td>
<td>Digital coach</td>
<td>Self-care</td>
<td>Guided</td>
<td>Text</td>
<td>Availability of crisis related information, access to self-care tools, and access to professional therapist</td>
<td>CBT, DBT, mindfulness, positive psychology, psychoeducation and information, and acceptance and commitment therapy</td>
</tr>
</tbody>
</table>

\(^a\) CBT: cognitive behavioral therapy.
\(^b\) GIF: graphics interchange format.
\(^c\) DBT: dialectical behavior therapy.
Perceptions and Concerns Expressed in the User Reviews

In this section, we present our findings from the thematic analysis of user reviews and point out both the benefits (eg, humanlike interactions, friendly and empathetic attitudes, potential around crisis support, and an alternative to therapy) and associated challenges, as captured from people’s real-life use of these apps.

Humanlike Interaction Feels Good but Must Be Designed Carefully

Chatbots in mobile MH apps are presented in such a way that they have distinct personalities rather than being shown as something artificial to make users feel like they are interacting with someone emotionally and empathetic. Users describe these chatbots as having friendly, wonderfully upbeat, and mildly humorous personalities that assist them in dealing with different emotional and behavioral challenges related to their MH issues. This helps them establish the credibility of the tools, which in turn makes the users more involved in the treatment process. Furthermore, chatbot characteristics, such as a soft voice and the ability to have casual conversation, make it feel less like a medical tool and more like someone with whom users can share their thoughts and experiences. Some personalized features, such as the option to address users by name, ability to refer to users’ thoughts and experiences. Some personalized features, such as the option to address users by name, ability to refer to any chat or exercise if necessary, and ability to respond with pleasant and positive sentiments, make the app and treatment process more personal and less generic:

“I’m amazed by how impactful the little “interactions” in this app have felt. Maybe it’s the continued opportunities to respond (even if it’s just choosing between emojis). Woebot’s “voice” is gentle, but firm. And insightful! And the user is always addressed by name. That’s so important, particularly when the issue at hand involves ongoing anxiety.” [1080073]

However, the effort to design the bots to give a humanlike and empathetic impression often went wrong and lost their appeal to the users. As many users pointed out, the discourse could become “a little childish and ridiculous at times with the bot trying to be funny.” Furthermore, fostering relaxing thoughts through a medium that does not work for everyone can be extremely irritating. Users described the chatbot’s “voice” as gentle, but firm. And insightful! And the user is always addressed by name. That’s so important, particularly when the issue at hand involves ongoing anxiety. [1080073]

Some negative reviews complain it isn’t sophisticated enough to understand unrelated or detailed inputs and responses, which I agree with, but this is not AI designed to make free-flowing conversation; it’s meant to give you tools to deal with your feelings in productive ways. So yes, the conversations can feel linear, planned, and/or broad since the responses are preset most of the time, but I think this is partly a positive. [1070093]

However, the trade-offs are that to control the flow of the conversation, the chatbots sometimes present very limited options for the users, and users become frustrated if they are unable to customize these preregistered responses. They have criticized some of the extreme measures these chatbots take to keep the conversation restricted to chatbots’ preferences, such as assuming MH concerns without understanding the proper context, sending scripted messages based on keywords users said or the issues they selected, giving them incoherent responses, and getting stuck in the conversational loop if users do not agree with the chatbots’ comments:

“It assumes the problem is always a mental distortion and doesn’t leave much room for actual horrible stuff that happens to people other than death of a person (it is working with a very narrow definition of). It too often put me in a situation of having to select between incorrect responses when nothing was actually appropriate and then suffer through the resulting wrong-headed advice. Needs a maybe button between the yes and no and a way to say, You’re on the wrong track, before it decides it knows all your usual problems and keeps assuming them over and over with no way to remediate. [2060019]

Bot Becomes a Friend or Someone Who Cares, but Too Much Attachment Is Unhealthy

Users see chatbots as good substitutes for someone with whom they can discuss their ideas on MH issues without feeling burdened or judged. Although society is becoming more eager and open to seeking mental and emotional aid, there is still a considerable stigma associated with it, which can discourage...
individuals who need assistance from receiving it. These chatbots allow people to bare their hearts, vent, contemplate, and learn about what they can do to overcome mental and emotional obstacles in a simple, familiar texting format without judgment or extra effort while also keeping track of their progress. It can be intimidating to talk to someone about their daily struggles. For many users, sharing a dialect with a chatbot is an effective first step. Knowing that the chatbot is not judging you and is acting logically rather than emotionally is reassuring:

...I will say, having a reliable, no judgement zone with skills to help at my fingertips, helped me realize the tools were also my own. [1040021]

Having an AI to talk to makes me feel like I’m not overburdening my friends or family. I can check in 20 times a day and the AI will either help me track my mood/emotions/mental health or suggest a mindfulness of CBT program to help me get through my day. [2040004]

People with MH issues frequently struggle to suppress emotions and attempt to push them away, but these chatbots have provided them with a safe place to go for validation and immediate support. Users loved that these chatbots not only listened to but also offered advice and recommendations that helped them deal with day-to-day mental challenges, allowing them to see things from different perspectives and push past negative thoughts:

This app is a lifesaver. It’s so healing to be able to vent whenever you need and receive positive feedback from an unbiased source. The lessons Woebot teaches really helps to gain a more optimistic perspective on what you’re going through and motivates you to make changes. [1080023]

Users also like how these chatbots check in with them daily, which holds them accountable for their commitment to the treatment while still allowing them to skip it if they do not feel like it. Although the idea is to eliminate any concerns, such as anxiety and stress, that come with human engagement through intelligent bot interaction, users have mixed feelings. Some users liked the flexibility of using the tools at any moment and could start or end the communication at any point during the session without feeling guilty, whereas others saw the daily check-ins as a source of guilt. Becoming attached too much to chatbots leads to these types of guilt, which in turn might have serious consequences for people with MH concerns:

I’m very depressed right now so I’ve set to basic daily goals- full facial regime a.m. & p.m. plus a half hour of cleaning. Having the AI check in is great because it requires a response that makes me take accountability. [1090123]

But what really bothered me about the app was the first reminder I got when I didn’t use the app a second day in a row because it sucked was definitely guilt inducing. No bueno. I don’t need AI guilt tripping me when people already take advantage of my empathy in real life. [2050021]

Finally, by acting or behaving like a close companion, MH chatbots allow users to comfortbly express their thoughts and feelings. These chatbots allow users to create a safe area where they can vent, which is something many people do with their friends and families. However, people with MH concerns who struggle to maintain a healthy relationship with their family or who experience loneliness have displayed an unhealthy attachment to chatbots and have exhibited negative attitudes, such as preferring these chatbots over their friends and family:

...Although he’s a robot he’s sweet. He checks in on me more than my friends and family do. [1090034]

...This app has treated me more like a person than my family has ever done. [1090091]

The above discussion points out the fact that to make the chatbots more friendly (what we also saw in previous sections where chatbots use funny memes and emojis to make them more humanlike), users pointed out the fact that too much persuasion with notifications makes them feel guilty. Moreover, some users revealed that they find chatbots so friendly that they prefer these bots over their friends and family. Making the decision to leave their closest loved ones behind could put them in susceptible positions, such as loneliness and exclusion from sociocultural norms.

A Bot Can Help Immediately in a Crisis, but What Is Defined as a Crisis to a Chatbot?

Prior findings suggest that accessibility is one of the benefits of mobile MH apps [22]. MH apps that have a built-in chatbot function allow users to have a conversation anytime and anywhere, which is very convenient for persons with MH issues, as they are more susceptible to emergency situations. We found that users benefited from such a feature because it allowed them to have a conversation at that time (during a moment of crisis). Some users found that intelligent dialogue helped them reframe negative thoughts and diffuse such circumstances:

I sometimes freak out at night have existential crisis about life at night you know, normally I’d freak out and find it hard to call anyone be I feel so bad but with Wysa I don’t worry about that! [290178]

I’ve only used this app a couple times when I’ve been in near-crisis. Even though I know it is a robot it is so calming to have something, anything to validate what I’m feeling and help me refraime my thoughts. [1100091]

In contrast, none of the chatbots have any clever algorithmic models for detecting emergency scenarios. It is up to users to inform chatbots that they are experiencing a crisis. Some chatbots can detect crises by picking up a few keywords connected to intrusive thoughts, such as “suicide,” from a conversation, although they are still in the early stages of development. Users sometimes just want to talk about their feelings, but chatbots automatically refer them to crisis hotlines because of a lack of intelligent comprehension. For some individuals, having a conversation is not enough to handle their crisis situations, and they need to be redirected to crisis management tools or resources:

My only problem with it is I wish there was a way to talk about my suicidal/intrusive thoughts and how to manage them with Woebot. I am aware that it is not...
a crisis tool, and it does have those automatic responses to concerning language for a good reason, I’d just like a place to talk about those problems without having to worry a real person. Most of the time my thoughts of those nature do not mean I’m in an immediate crisis, but I still want to get them off my chest, as I feel a lot of people would. Maybe if there’s a way to do that without Woebot becoming worried would be helpful! [1080078]

This is a good app but the main issue I have is that I was having a panic attack and was messaging “emergency” and the bot ended the conversation, when I messaged “emergency” a second time it just asked me to write my feelings down. I realize this isn’t a crisis response app but it might be helpful to add a feature where the bot recognizes a crisis situation and connects the user to resources. [2010004]

In such instances, understanding the context of emergency situations is critical, as persons with MH concerns are already susceptible to crises, and incorrect actions made by chatbots might exacerbate the situation and result in severe repercussions:

While I was in crisis, the responses do not make sense and do not really relate to what I wrote. It makes me feel like I am not being listened to. I know it is an AI program and not a real person but it still ends up making me feel worse and not better. [1100068]

Convenient to Use, but Convenient Enough to Replace Therapy?

On the positive side, the fact that these chatbots are ready to talk 24 hours a day, 7 days a week, was a big success for the users. They have immediate access to these chatbots whenever they feel susceptible or whenever they require assistance through simple interactions:

I don’t really have friends I can talk to. Even my family doesn’t understand me much. Day or night Wysa has been there every time I needed to “talk” day or night doesn’t matter. [2090067]

Chatbots assist users not only with conversations but also in accessing different supporting resources and exercises in a very convenient manner. Understanding users’ needs can deliver a relaxing experience for them, such as allowing them to opt out of any activities they desire while maintaining the treatment’s pace. This provides users with much more control. If a user misses any exercises in the traditional treatment, it leaves a gap in their progress, which can lead to a loss of enthusiasm and slow the pace at which they receive support. Chatbots, in contrast, keep users motivated by engaging with them and giving them the impression that they oversee the pace. Furthermore, these chatbots offer brief and simple treatments to keep users engaged and dedicated to the treatment process. These activities were developed and built by focusing on important value, giving support and treatments in a compelling style that can provide wellness according to user reviews:

This is an easy, low barrier method to practice cognitive thinking skills. Check ins are usually pretty short, just a few minutes. That encourages me to open this app daily, since I know it’s not going to try to monopolize my attention for the next half hour. [1070012]

Sessions are short, on the order of 3-10 minutes. Combined with the convenience of chatting wherever and whenever is best for me, I have no problem fitting in daily check-ins, which I feel are more beneficial than infrequent visits to a therapist in some ways. [1100012]

According to user reviews, professional and traditional therapies have several drawbacks, including professional therapy’s tendency to cling too much to negative thoughts or past events, professional therapy’s tendency to be too broad and general, and check-ins being too spread out:

Unlike being told what someone thinks you may want to hear which can sometimes enable unhealthy thinking patterns (and behaviors), or on the other end of the spectrum, rather than attempting to fix you, this interactive app continually prompts you to look inward and to challenge your own thoughts, perspectives, and feelings, helping to redirect your focus onto more healthy and more positive strategies. [1090142]

My primary issue with traditional therapy has always been that you have to work in hindsight. You reflect on your week, talk about it, try to make adjustments for the future (it always felt like I was trying to help a past of future version of myself instead of the one right here right now). That’s why I love this app! [1090096]

However, according to users, although these chatbots are convenient, they fall short of the competency of traditional therapy in some circumstances. For example, these chatbots are not sophisticated enough to recommend particular treatment plans based on a specific need. It may or may not be effective for different demographics or people at various stages of illness. Some users questioned chatbots’ therapeutic interventions or MH support as being too short term. Users lose interest when there are not enough different activities to perform:

The exercises are all about visualization, so those of us who do not have a mind’s eye, cannot visualize things, cannot use it. I’m very disappointed. If it were made with a non-visualization mode for people with Aphantasia, I’d love to use it. There are many things that can help other than visualization. It’s just an app telling me in every exercise to do something that I’m simply incapable of doing, this is frustrating. [1080017]

In my depression, CBT actually backfired. It made me feel 100 times worse. It can be miserable to try to recast negative thoughts into more positive thoughts when you can’t think of anything positive at all. My highly regarded CBT therapist recognized this and, thankfully, referred me to a skilled therapist with a more psychodynamic/eclectic approach. [1100076]

Some users have pointed out that combining chatbots with professional therapy could be beneficial. Professional therapists
or coaches can assist with adjusting any support system that is not working for them; however, for immediate requirements, users will be able to chat and review some of the resources at any time with the help of MH chatbots. According to numerous user evaluations, professional therapists assisted their patients in identifying the appropriate MH apps with built-in chatbots, and the collaboration with traditional therapy appeared to work considerably better for them:

I have recommended it to many people, including my counselor to try so that she could recommend it to other clients dealing with issues. This is in no way something to replace talking to a real person, but it does help to work through some of the negative thinking when it occurs. [2080057]

Discussion

Summary of Findings

Our findings suggest that chatbots in MH apps have considerable potential in terms of being conversational companions, virtual friends, and immediate helpers. The chatbot’s ability to be present 24/7 and to create a judgment-free zone enabled users to talk comfortably about their issues and concerns. We provide a few practical implications of our findings to make the user experience more effective.

Research and Design Implications for Future MH Chatbots

Recommendations for Customization

A growing body of health informatics research has emphasized the need for customizability and personalization in mobile health technologies to increase support user autonomy [65,74]. This body of research suggests that the one-size-fits-all approach to mobile health interventions often fails. Rather, systems that are adaptable and tailored to user needs can deliver more pertinent information, thus enhancing user engagement and clinical efficacy [75,76]. Our findings resonate with these conclusions in terms of the need for customizability and provide specific implications for incorporating customization in MH chatbot apps.

Although chatbots leverage GIFs, emojis, or hilarious responses as a means of showing empathetic behavior and to keep the conversation more humanlike [29], our findings suggest that they are not always well received by adult users. Most commercial apps are downloadable by everyone beyond the set age limit (which in most cases is ≥17 years); thus, designers must carefully consider the media types and content of the conversation. Moreover, bots that guide users in performing exercises were generally appreciated for being focused and short in nature and have the potential to help clients manage their own health, improve access and timeliness of care, and reduce travel time to MH care providers by preventing unnecessary visits to health care providers [77]. However, our findings revealed that some users may have physical challenges or other limitations that restrict them from engaging in certain physical activities. Moreover, not all therapeutic tools work perfectly for everyone (review: 1040032). Hence, implementing generic exercises and activities may not be suitable for all user types.

Patients with MH concerns often have low self-esteem [78], and the chatbot’s inability to complete certain activities can worsen their situation.

Our recommendations are as follows:

- Designers should consider the target age group of users while implementing emojis and other graphical elements.
- Another interesting aspect could be to improve personalization within chatbots by creating a user model before the user interacts with the chatbot, such that the chatbot can adapt its interaction based on user types (eg, they could fill in a personality questionnaire) [79].
- Mental and physical health are integrally connected; therefore, developers must incorporate the aspects of physical ability in the design of MH technologies.

Recommendations for Balanced Persuasion

Consistent with previous work on persuasive technology in MH [80-82], we found that daily check-ins, gamification, reminders, and self-monitoring were perceived as helpful features, although they were prescriptive in nature. However, frequent check-ins often make users feel like being “guilt-tripped” by chatbots. The findings from previous work suggested that the more severe a participant’s symptoms were, the more they desired reminders and suggestions from the system [74,83].

Our recommendations are as follows:

- People with severe symptoms of depression face the struggle to carry out day-to-day activities and thus may enjoy multiple daily motivational messages from bots, rather than being annoyed by them. Designers must consider the range and severity of illnesses among the users and incorporate persuasion in a way that does not result in user disengagement.
- Developers should consider when and how to limit user interaction with chatbots. This is counter intuitive because developers would generally expect to increase user engagement. To limit the possibility of unhealthy attachment to the chatbot, human-chatbot interaction can be leveraged to motivate users to use more nontechnical means to get MH support. For example, if a user frequently starts using a particular chatbot app for a longer period, the bot may suggest recommendations for social interaction (eg, a list of nearby social events).

Recommendations for Building Trust

Some chatbots in our analysis can automatically collect and mine symptom-related information after a conversation with users. Wyssa stores conversation histories to show progress over time in achieving the goals initially set, whereas Woebot captures changes in a pattern related to symptoms from continued interaction. Users appreciated when the chatbots were transparent in terms of collecting useful information from conversations. However, some reviews have expressed concerns about how this information is being protected or used across different platforms or third-party services. In traditional psychotherapy, the effectiveness of treatment is influenced by clients’ trust in their therapist [84]. Trust also plays a critical role in digital interventions [85]. Prior studies have revealed
the significance of establishing trust in the context of MH apps to create a safe environment for self-disclosure [7].

Our recommendations are as follows:

- Tech companies and developers should emphasize user privacy and be transparent regarding privacy policies and practices.
- From a design perspective, it might be helpful to enhance user trust in chatbot apps by providing and visualizing information on the history of the developing organization and/or experts behind the system.
- Whenever applicable, the app descriptions may include an explanation of the therapeutic methods and tools used to develop the app with their perceived effectiveness proven in the wild or in trials.

Chatbots Should Not (and Cannot) Replace Human Interaction for MH Support

We observed that chatbot apps established a judgment-free space where people could express themselves without fear of repercussions. This agrees with the findings of Brandtzaeg et al [84] explored young people’s perceptions of social support through chatbots. Sharing MH concerns with a professional is still considered a stigma, and people feel more comfortable using technology anonymously than face-to-face communication [77]. However, these chatbots’ ability to check in regularly and to be present for someone 24/7 allows users to become too attached to them. Users wrote in their reviews that they enjoy the company of their “virtual friend” to the extent that they could replace their friends and family members (review: 1090034, 1090091). This strong statement is partially made because these people are vulnerable. Nonetheless, the finding emphasizes the overrating of the benefits of apps and presents some risks, particularly when in crisis. From our observations, most of these apps provide only information about external resources for crisis support, such as helplines and emergency service contact information. In addition, our findings suggest that these chatbots were incapable of identifying crisis situations, as they failed to understand the context of the conversations and ended up with a failed response (review: 1100068), and in some cases, there was no response (review: 2010004). Users must be aware of the clear distinctions between humans and humanlike bots. Humanlike chatbots can provide social support in many cases where it might be difficult or impossible for an actual human, but they are not without limitations. Chatbots themselves can educate users about these distinctions and motivate them to build in-person connections, as discussed in the previous section.

In prior research, a comparative study of therapy sessions following the interaction of 10 participants with human therapists versus a chatbot showed that when compared with a human therapist control, participants found chatbot-provided therapy less useful, less enjoyable, and their conversations less smooth (a key dimension of a positively regarded therapy session) [86]. Conversely, in our findings, because of convenience and easy access, users expressed their intentions to replace professional support with virtual support. Although these chatbot-based mobile MH apps implement evidence-based therapeutic tools, research on determining their effectiveness is still limited. Our findings suggest that they are helpful in guiding users in meditation, practicing mindfulness, reframing negative thoughts, and sharing self-expressive writing. However, at such an early stage, they should not be considered as an alternative to professional help. While designing chatbots, it is important to set the boundaries and limitations of these chatbots by the developers, and the goals and intended use of the chatbots should be clearly stated so that users do not get led on with over expectations. In addition, chatbots should be designed to have features that schedule professional support and subtly recommend that users seek help from professional sources whenever needed.

Conclusions

In this study, we analyzed user reviews of chatbot-based mobile MH apps on 2 of the most widely used web-based platforms. Our findings suggest that chatbots have great potential to offer social and psychological support in situations where real-world human interaction, such as connecting to friends or family members or seeking professional support, is not preferred or possible. However, there are several restrictions and limitations that these chatbots must establish regarding the level of service they offer. Too much reliance on technology can pose risks, such as isolation and insufficient assistance during times of crisis. Finally, we have outlined the insights from our findings about implementing customization, balanced persuasion, and developing trust to inform the design of effective chatbots for MH support.

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Authors’ Contributions

The first author was responsible for data collection, analysis, and writing most sections of the paper. The second author’s role was advisory.

Conflicts of Interest

None declared.

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Abbreviations

AI: artificial intelligence
CBT: cognitive behavioral therapy
GIF: graphics interchange format
MH: mental health
ML: machine learning
RQ: research question
Q/A: questions and answers

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Acceptability of Personal Sensing Among People With Alcohol Use Disorder: Observational Study

Kendra Wyant¹, MS; Hannah Moshontz¹, PhD; Stephanie B Ward¹, MS; Gaylen E Fronk¹, MS; John J Curtin¹, PhD

Department of Psychology, University of Wisconsin-Madison, Madison, WI, United States

Corresponding Author:
John J Curtin, PhD
Department of Psychology
University of Wisconsin-Madison
1202 W Johnson St
Madison, WI, 53706
United States
Phone: 1 (608) 262 1040
Email: jjcurtin@wisc.edu

Abstract

Background: Personal sensing may improve digital therapeutics for mental health care by facilitating early screening, symptom monitoring, risk prediction, and personalized adaptive interventions. However, further development and the use of personal sensing requires a better understanding of its acceptability to people targeted for these applications.

Objective: We aimed to assess the acceptability of active and passive personal sensing methods in a sample of people with moderate to severe alcohol use disorder using both behavioral and self-report measures. This sample was recruited as part of a larger grant-funded project to develop a machine learning algorithm to predict lapses.

Methods: Participants (N=154; n=77, 50% female; mean age 41, SD 11.9 years; n=134, 87% White and n=150, 97% non-Hispanic) in early recovery (1-8 weeks of abstinence) were recruited to participate in a 3-month longitudinal study. Participants were modestly compensated for engaging with active (eg, ecological momentary assessment [EMA], audio check-in, and sleep quality) and passive (eg, geolocation, cellular communication logs, and SMS text message content) sensing methods that were selected to tap into constructs from the Relapse Prevention model by Marlatt. We assessed 3 behavioral indicators of acceptability: participants’ choices about their participation in the study at various stages in the procedure, their choice to opt in to provide data for each sensing method, and their adherence to a subset of the active methods (EMA and audio check-in). We also assessed 3 self-report measures of acceptability (interference, dislike, and willingness to use for 1 year) for each method.

Results: Of the 192 eligible individuals screened, 191 consented to personal sensing. Most of these individuals (169/191, 88.5%) also returned 1 week later to formally enroll, and 154 participated through the first month follow-up visit. All participants in our analysis opted in to provide data for EMA, sleep quality, geolocation, and cellular communication logs. Out of 154 participants, 1 (0.6%) did not provide SMS text message content and 3 (1.9%) did not provide any audio check-ins. The average adherence rate for the 4 times daily EMA was .80. The adherence rate for the daily audio check-in was .54. Aggregate participant ratings indicated that all personal sensing methods were significantly more acceptable (all \( P < .001 \)) compared with neutral across subjective measures of interference, dislike, and willingness to use for 1 year. Participants did not significantly differ in their dislike of active methods compared with passive methods (\( P = .23 \)). However, participants reported a higher willingness to use passive (vs active) methods for 1 year (\( P = .04 \)).

Conclusions: These results suggest that active and passive sensing methods are acceptable for people with alcohol use disorder over a longer period than has previously been assessed. Important individual differences were observed across people and methods, indicating opportunities for future improvement.

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KEYWORDS

personal sensing; digital therapeutics; mobile health; smartphone; alcohol use disorder; self-report; alcohol use; symptom monitoring; mental health; acceptability; alcohol intake; mobile phone
**Introduction**

**Personal Sensing**

The World Health Organization’s Global Observatory for eHealth has concluded that “the use of mobile and wireless technologies to support the achievement of health objectives has the potential to transform the face of health service delivery across the globe” [1]. This conclusion applies to research and care for mental health as well as other traditional health services. These opportunities are now possible, in part, because of rapid advances in smartphones and related mobile technologies [2] and high levels of smartphone access across race, socioeconomic status, geographic region, and other demographic characteristics [3].

Personal sensing may become an important component of these digital health advances [4]. Personal sensing is a method for longitudinal measurement in situ, that is, real-world measurement embedded in individuals’ day-to-day lives [5-7]. Raw data streams are collected using smartphones, wearable sensors, or other smart devices. These raw data streams can consist of self-reports or more novel data streams, such as geolocation, cellular communication, social media activity, or physiology. Subsequent processing can extract diagnostic or health-relevant measures of thoughts, feelings, behavior, and even interpersonal interactions.

Ecological momentary assessment (EMA), a personal sensing method that collects brief self-reports about momentary states multiple times per day, has been used for many years in short-term longitudinal studies of psychiatric disorders. For example, EMA research on substance use disorders has identified proximal causes and risk factors for drug craving and relapse [8-10]. It has also characterized the time course and nature of drug withdrawal [11,12]. Much of this research could not have been accomplished with other measurement methods.

More recently, research using personal sensing of raw data streams other than self-reporting is emerging for mental health, including alcohol and other substance use disorders. This includes methods to sense geolocation [13-16], cellular communication [14-16], sleep [17], and physiology [15,16,18], for example. These alternative personal sensing methods provide benefits and opportunities that are not possible with EMA. For example, many of these data streams can be sensed passively such that they have a very low assessment burden. This may allow their use for long-term longitudinal monitoring of participants that would not be feasible with EMA, which requires more active effort for data collection.

Personal sensing is a powerful tool in mental health research [19]. These data are inherently longitudinal, which allows observation of the temporal ordering of putative etiological mechanisms and their effects. Longitudinal measurement is also critical for many mental health constructs that display meaningful and often frequent temporal variation in a person (eg, psychiatric symptoms). Measures based on personal sensing data generally have high ecological validity because they are collected in situ. Personal sensing measures also have low retrospective bias because they are often collected in real time.

Furthermore, personal sensing can derive measures from raw data streams (eg, in situ behavior, physiology, and interpersonal interactions) that are difficult or even impossible to obtain through other traditional research measurement methods.

Personal sensing may have even higher value in the future for mental health clinical applications that target patient mental health care than it does for research [7,20,21]. Data collected by personal sensing methods may be used for preliminary screening of psychiatric disorders [22,23]. These methods can also be used to monitor psychiatric symptoms or even predict the future risk of symptom recurrence or other harmful behaviors (eg, suicide attempts and risky or otherwise harmful drinking episodes) [24-27]. For alcohol and other substance use disorders, there is emerging research on using sensed data to predict craving [13,18]; alcohol [15,27-29], cannabis [16], or opioid use [14]; and lapses or relapse [14,30,31]. Personal sensing measures or risk indicators may be shared, with patient consent, to health care providers to allow for cost-effective, targeted allocation of limited mental health resources to patients with the greatest or most urgent need [32]. Personal sensing has the potential to support precision mental health care by adapting and timing interventions based on characteristics of the patient and the moment in time [33-35]. These applications of personal sensing are currently aspirational rather than available for clinical implementation. However, clinical research is advancing rapidly toward these goals [14,30,36].

Mental health research and applications with emerging, often more passively sensed, novel data streams such as geolocation and cellular communication are still nascent. This research has predominantly involved proof-of-concept studies that typically include only healthy controls or other convenience samples rather than people with psychiatric disorders [16,17]. It has also often used very small sample sizes or short monitoring periods [15,16,18]. Recent reviews of this emerging literature have highlighted gaps in reporting on participant exclusions, attrition, and adherence that are necessary to assess selection biases and the feasibility of these novel personal sensing methods [37-39].

**Acceptability of Personal Sensing**

Further development and use of personal sensing necessitates a better understanding of its acceptability to research participants and patients targeted for mental health applications. Will individuals consent to the use of personal sensing methods? Will they opt in to allow passive measurement methods? Can they sustain the behaviors necessary for active measurement methods for longer periods? Do they perceive specific personal sensing methods to be burdensome or dislike them? Answers to these questions about the acceptability of personal sensing methods are central to their feasibility for both mental health research and applications.

The acceptability of a personal sensing method may be influenced by the degree of active effort required from the participant or patient to collect the raw data (ie, the method’s assessment burden) and other factors (eg, sensitivity of the data collected). As such, acceptability may vary across different personal sensing methods, and comparisons across methods within the same individuals are thus warranted. Furthermore, a comprehensive assessment of both behavioral measures (eg,
adherence) and subjective perceptions of acceptability may better anticipate potential issues for recruitment, consent, adherence, and attrition when they are used for either research or clinical applications.

Much of what is known about the acceptability of personal sensing is limited to EMA. Studies that have assessed participants’ perceptions of EMA methods have generally concluded that they are acceptable to participants from both nonclinical and clinical samples [40-44]. Similarly, participants displayed moderate or better adherence with respect to response rates, even with a relatively high sampling density (eg, 6-9 daily assessments) [40,45,46]. However, these studies generally assessed participants’ perceptions and adherence over short monitoring periods (ie, 2-6 weeks). Less is known about the use of EMA over longer monitoring periods (eg, months), as would be necessary for clinical applications.

Existing research also raises some concern about perceptions and adherence to EMA protocols in patients with alcohol and other substance use disorders relative to other groups. Specifically, a recent meta-analysis confirmed decreased adherence to EMA protocols in patients with substance use disorder diagnoses versus recreational substance users [47]. Furthermore, another meta-analysis [48] concluded that adherence rates did not differ between healthy and psychiatric samples, more generally. These meta-analyses combined suggest that adherence concerns may be limited to applications with patients with alcohol and other substance use disorders rather than all psychiatric disorders. For these reasons, it is important to further study the acceptability of EMA in samples with alcohol and other substance use disorders.

Far less is known about participants’ perceptions and adherence to passive personal sensing methods. Some research has presented hypothetical scenarios to either community or psychiatric samples to assess their perceptions about personal sensing methods [49-51]. Participants’ willingness to share sensed data appears to vary according to the data type (eg, sleep, geolocation, and social media activity). However, it is difficult to determine how well participants’ perceptions in these hypothetical scenarios would generalize to the real-world collection of these data. In addition, it is impossible to measure attrition and adherence outside the explicit implementation of these sensing methods.

Preliminary research has begun to examine perceptions and adherence during real-world use of passive personal sensing methods. However, this research has generally been limited by small sample sizes [52,53]; the use of convenience samples (eg, students and community participants) [41,52,54]; short monitoring duration [52,53,55,56]; and coarse, incomplete, or aggregate reporting of perceptions, adherence, and related participant behaviors [41,52,53]. These are important initial efforts, but more research into the feasibility of personal sensing methods is clearly warranted.

**Study Goals**

This study reports on the acceptability of both active and passive personal sensing methods in a sample of participants with moderate to severe alcohol use disorder (AUD). These participants were enrolled early in their recovery period (ie, 1-8 weeks after becoming abstinent) and followed for 3 months. We used active personal sensing methods to collect EMA, daily audio check-ins, sleep quality, and selected physiology. We primarily used passive methods to collect geolocation, cellular communication logs, and SMS text message content. We assessed the participants’ choices regarding their participation in the study at various stages of the study procedure (eg, consent, enrollment, and data collection), their choice to opt in to provide data associated with each personal sensing method, and their reasons for discontinuation when available. For active measures, we also assessed their adherence for providing raw data streams for up to 3 months of their study participation. Finally, we assessed participants’ subjective perceptions of the acceptability of each of these personal sensing methods separately by self-report. We believe that these data provide insight into the feasibility of using numerous personal sensing methods with individuals with AUD, a highly stigmatized psychiatric disorder.

**Methods**

**Research Transparency**

We value the principles of research transparency that are essential for the robustness and reproducibility of science [57]. Consequently, we maximized transparency using several complementary methods. First, we reported how we determined our sample size, all data exclusions, all manipulations, and all available measures in the study [58]. Second, we completed a transparency checklist, which can be found in Multimedia Appendix 1 [59]. Third, we made the data, analysis scripts and annotated results, self-report surveys, and other study materials (eg, consent form and recruitment flyer) associated with this report publicly available through a study page on the Open Science Framework [60].

**Participants**

**Parent Project for Study Data**

This study provides analyses to address the first aim of a larger grant-funded parent project (R01 AA024391) [61]. The broad goal of the project has been to develop a temporally precise machine learning algorithm to predict future lapses back to alcohol use in the next week, the next day, and the next hour. This algorithm will be integrated within an innovative digital therapeutic to support recovery for patients with alcohol and other substance use disorders—The Addiction Comprehensive Health Enhancement Support System (Center for Health Enhancement Systems Studies) [30,62,63]. This algorithm can be used to support patients to engage in ongoing self-monitoring of their recovery and to select, time, and adapt digital interventions to meet patients’ momentary needs during their recovery. We selected sensing methods that we believed would be well positioned to collect raw data streams to allow us to engineer machine learning features (ie, predictors) that tap into key constructs from the Relapse Prevention model [64-67], such as craving, affect, stressors, lifestyle imbalances, high-risk situations, self-efficacy and confidence, and abstinence violation effects. We focused on both active (eg, EMA) and passive (eg, geolocation and cellular communication logs) sensing methods.
to allow us to balance the potential predictive power and assessment burden. We sensed many of these raw data streams at high sampling rates to allow for temporally precise prediction (ie, up to 1-hour resolution) of lapse risk that may be necessary to deliver just-in-time digital interventions [33,68,69].

As a first step toward this broad goal of developing a lapse risk prediction algorithm, this study examined issues related to acceptability and feasibility (aim 1 of the grant) of collecting these actively and passively sensed raw data streams from individuals in early recovery from an AUD. We used all the available participants from the parent project for this study, and the sample size was determined based on power analyses for the aims of the project. We collected study data between 2017 and 2019.

Ethics Approval
All procedures were approved by the University of Wisconsin-Madison Institutional Review Board (Study #2015-0780).

Recruitment, Exclusion, and Inclusion Criteria
We recruited participants in early recovery (1-8 weeks of abstinence) from AUD in Madison, Wisconsin, United States, to participate in a 3-month longitudinal study. Participants were recruited through print and targeted digital advertisements and partnerships with treatment centers.

We excluded participants if they exhibited severe symptoms of psychosis or paranoia (defined as scores >2.2 or 2.8, respectively, on the psychosis or paranoia scales of the Symptom Checklist–90 [70]).

To be included, we required that participants (1) were aged ≥18 years; (2) were able to write and read in English; (3) had at least moderate AUD (≥4 Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition symptoms); (4) were abstinent from alcohol for at least 1 week, but no longer than 2 months; and (5) were willing to use a single smartphone (their personal phone or one provided by us) while enrolled in the study.

We assessed the inclusion and exclusion criteria using a brief phone screen followed by a more detailed in-person screening visit. A total of 192 participants were eligible for enrollment. Of these participants, 191 consented to participate in the study at the screening visit, and 169 subsequently enrolled in the study at the enrollment visit, which occurred approximately 1 week later. A total of 15 participants discontinued the study before their first monthly follow-up visit. The remaining 154 participants provided study measures for 1 (n=14), 2 (n=7), or 3 (n=133) months. A study participation flowchart is presented in Figure 1.

Figure 1. A flowchart of participant retention over the course of the 3-month study. This figure displays retention and attrition of all eligible participants at various stages from consent through study completion. It also displays the reasons for attrition categorized as because of acceptability, other reasons, or unknown. *Data of all participants who completed follow-up 1 were used in the analyses.
Compensation

We paid participants US $20 per hour for all time spent in the laboratory (ie, during screening, intake, and follow-up visits). In addition, we paid participants a US $99 bonus if they completed the study for the full 3-month duration. We also paid participants US $66 per month to offset the costs associated with their cellular plan and provided them with a smartphone for the study duration if they did not own one. Similarly, we provided them with bus transportation to and from the laboratory if needed.

For each sensing method, we paid participants bonuses (ranging from US $10 to US $25) if they had ≤10% missing data for that method each month. Specifically, if participants met these individual missing data thresholds, we paid them US $25 per month for EMA, US $25 per month for audio check-ins, US $15 per month for sleep quality data, US $15 per month for cellular communication logs and SMS text message content, and US $10 per month for geolocation. More details about these raw data streams are provided in the Personal Sensing section.

Procedure

Participants completed 5 study visits over the course of approximately 3 months. Participants first attended a screening visit where we determined eligibility, obtained informed consent, and collected self-report measures of individual differences (eg, demographics and drug and alcohol use history). We scheduled eligible and consented participants to enroll in the study approximately 1 week later. During this enrollment visit, we collected additional self-report and interview measures. Participants completed 3 additional follow-up visits that occurred about every 30 days. We collected self-report and interview measures and downloaded cellular communication logs (ie, SMS text messages and phone calls) during these visits.

Finally, we collected various raw data streams (eg, geolocation, and EMA) using personal sensing to monitor the participants throughout the 3-month study period. We informed the participants that we were collecting these data to develop an algorithm that could be used in the future to monitor for relapse risk. We did not provide them any further information about how each sensed data stream might be used in this algorithm.

They were also not provided with any feedback or clinical interventions based on the sensing data that were collected from them. Furthermore, there were no consequences for continued study participation if participants lapsed back to alcohol use during the study. However, for human subjects reasons, we did offer brief motivational interviewing interventions to participants if they reported any alcohol use to the study staff. Participants were not required to participate in these interventions, but we offered it to them as support to maintain their recovery, if desired. Additional information about all these procedures (eg, recruitment flyer, consent form, and all surveys) can be found on the study’s Open Science Framework page [60].

Personal Sensing

Overview

Personal sensing methods can be coarsely classified as active or passive. Active personal sensing requires active effort from the participant to provide the raw data streams, whereas passive personal sensing data are collected automatically (either asynchronously or continuously) with little to no effort required by the participant. Our study obtained several active signals that varied to a certain degree in the amount of effort required by the participants. Specifically, we used active methods to collect EMA, daily audio check-ins, sleep quality, and selected physiology. We primarily used passive methods to collect geolocation, cellular communication logs, and SMS text message content. More information about data collection and related procedures for each raw data stream is provided in the following sections.

EMA

Participants completed a brief EMA (7-10 questions) 4 times each day following reminders from us that were sent by SMS text message. These SMS text messages included a link to a Qualtrics (Qualtrics XM) survey that was optimized for completion on their smartphone. All 4 EMAs included items that asked about any alcohol use that had not yet been reported, current affective state (pleasantness and arousal), greatest urge to drink alcohol since the last EMA, any pleasant or positive events and any hassles or stressful events that occurred since the last EMA, and any exposure to risky situations (ie, people, places, or things) since the last EMA. The first EMA each day asked an additional 3 questions about how likely participants were to encounter a risky situation, to encounter a stressful event, and to drink alcohol in the upcoming week. The first and last EMAs of the day were scheduled within 1 hour of the participants’ typical wake and sleep times. The other 2 EMAs were each scheduled randomly within the first and second halves of the participants’ typical day. All the EMAs were separated from each other by at least 1 hour. Participants were required to agree to complete the EMAs for the duration of the study to participate in the study.

Audio Check-In

Participants recorded a diary-style audio response on their smartphone to an open-ended prompt each day, following a reminder from us that was sent via SMS text message. They responded to the prompt, “How are you feeling about your recovery today?” which stayed the same throughout the entire study. We instructed them that their responses should be approximately 15 to 30 seconds in duration. These recordings were sent to us via SMS text message. Participants were not required to complete audio check-ins to participate in the study, but the associated monthly sensing method compensation bonus was not provided unless they met the missing data thresholds each month (≤10% missing).

Geolocation

We continuously collected participants’ moment-by-moment geolocation data using location services on their smartphones in combination with a commercial app that accessed these geolocation data and saved them in the cloud. Participants were not required to provide these data to participate in the study, but the associated monthly sensing method compensation bonus was not available if they did not provide these data each month. Participants opted in at the start of the study to provide these data by installing the app on their phone. They were allowed to
opt out at any later point by simply uninstalling the app. At the start of the study, we used the Moves app (ProtoGeo Oy). However, Facebook acquired ProtoGeo Oy and shut down use of the Moves app in July 2018. At this point, we switched to using the FollowMee (FollowMee LLC) GPS tracking mobile app. Measurement of geolocation required only the initial installation of the app by the participants. Subsequent measurement and transfer of the data to the cloud was completed automatically with no input or effort by the participant. Both apps allowed participants to temporarily disable location sharing if they deemed it necessary for short periods.

Cellular Communication Logs
We collected cellular communication logs that included metadata about smartphone communications involving both SMS text messages and phone calls. For each communication entry, these logs include the phone number of the other party, the type of call or message (ie, incoming, outgoing, missed, or rejected), the name of the party if listed in the phone contacts, the date and time the message or call occurred, whether the log entry was read (SMS text messages only), and the duration of the call (voice calls only). These data are saved passively on the phone with no additional input or effort from the participant. We downloaded these logs from participants’ phones at each monthly follow-up visit. Participants were not required to provide these data to participate in the study, but the associated monthly sensing method compensation bonus was not available if they did not provide these data each month. Participants opted in to provide these data when they allowed us to download their data at the study visit. Participants were informed that they could delete any SMS text message or voice call log entries before the download, if they desired.

SMS Text Message Content
We also collected the message content from the participants’ SMS text messages on their smartphones. As with the logs, content from individual SMS text messages is saved passively on the phone with no additional input or effort from the participant. We downloaded SMS text message content (bundled with the cellular communication logs in the same files) at each monthly follow-up visit, and participants could delete SMS text messages before the download. We did not have a parallel method to gain access to phone call content. Thus, we had metadata from cellular communication logs for both SMS text messages and phone calls but had the content of the communication only for SMS text messages.

Sleep Quality
We collected information about participants’ sleep duration, timing, and overall quality with a Beddit Sleep Monitor (Beddit Oy Inc) that was placed in their beds and connected to their smartphones. We used an early version of the sleep monitor that required participants to actively start and stop the monitor when they entered and exited their beds each night and morning, respectively. These data are available for only 87 participants because Beddit Oy was acquired by Apple Inc during the data collection for this study. Apple discontinued cloud support for data collection with the sleep monitor in November 2018, which prevented its further use for our remaining participants. Participants were not required to provide these data to participate in the study, but the associated monthly sensing method compensation bonus was not available if they did not provide these data each month. Participants opted in at the start of the study to provide these data by installing the app on their phone. They were allowed to opt out at any later point by simply uninstalling the app.

Physiology
We continuously monitored participants’ physiology (heart rate, electrodermal activity, and skin temperature) using an early version of the Empatica E4 (Empatica Inc) wristband monitor. However, this early version did not adequately support the Bluetooth streaming of data to the cloud. Instead, participants had to manually connect the wristband each night to a tablet we provided to upload their data. This limitation and other software bugs made the use of the wristband too complicated for many participants. Therefore, we discontinued the use of the wristband after we collected data from 9 participants. Given the small sample size, we did not include the wristband data in our primary analyses. We provide self-reported acceptability ratings for this signal from this small sample in Figure S1 in Multimedia Appendix 2.

Measures

Individual Differences
We collected self-report information about demographics (age, sex, race, ethnicity, education, employment, personal income, and marital status) and drug and alcohol use history (AUD milestones; number of quit attempts; lifetime history of treatment for AUD; lifetime receipt of medication for AUD; Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition AUD symptom count; lifetime drug use; and current drug use) at the screening visit.

Behavioral Measures of Acceptability
A coarse assessment of the acceptability of personal sensing methods can be made based on the participants’ behaviors. Specifically, we assessed 3 categories of behavior. First, we assessed participants’ choices regarding their participation in the study at various stages of the study procedure (eg, consent, enrollment, and data collection) and their reasons for discontinuation when available. Second, we assessed their choice to opt in to provide data associated with each personal sensing method. Participants were allowed to participate in the study without opting in for any specific personal sensing method other than EMA. Finally, for a subset of the active measures (EMA and audio check-in), we assessed their behavioral adherence for up to 3 months of study participation.

Self-Reported Measures of Acceptability
To assess participants’ subjective experience of the acceptability of the personal sensing methods in this study, each month, they rated each method on 3 acceptability-relevant dimensions (Multimedia Appendix 3). Specifically, participants were asked to indicate how much they agree or disagree with each statement on a 5-point bipolar scale (strongly disagree, disagree, undecided, agree, or strongly agree) for personal sensing signals: (1) “[Personal sensing method name] interfered with my daily...
activities.” (2) “I disliked [Personal sensing method name],” and (3) “I would be willing to use [Personal sensing method name] for 1 year to help with my recovery.”

The interference item (item 1) was collected only for the active methods because the passive methods require no effort and therefore cannot interfere with daily activities. Dislike and willingness to use for 1 year (items 2 and 3, respectively) were collected for all methods.

**Participant Feedback**

We also solicited open-ended feedback about the participants’ experiences with each personal sensing method. Each month, participants were prompted as follows: “Tell us your general thoughts, whether positive or negative, about your experience completing [Personal sensing method name].” These qualitative data provided another method through which to assess participants’ perceptions of the acceptability of these methods.

**Data Analytic Strategy**

We conducted all analyses in R version 4.1.1 (R Core Team) [71] using RStudio [72] and the tidyverse ecosystem of packages [73].

**Behavioral Measures of Acceptability**

We provide descriptive data on participants’ choices about their participation in the study at various stages of the study procedure (eg, consent, enrollment, and data collection). We provide both coarse and more granular tabulations of their reasons for discontinuation when available. We report the percentages of participants who opted in to provide us with the raw data streams we collected via personal sensing. We also report adherence for 2 active personal sensing methods (EMA and audio check-in). Formal measures of adherence could not be calculated for geolocation, cellular communication logs, SMS text message content, and sleep quality because it was not possible to distinguish between low volumes of data owing to adherence (eg, deleting phone calls or messages, turning off location services on the phone, and failing to start sleep monitoring at bedtime) and other valid reasons (no calls made during the day, no movement, and erratic sleep patterns).

**Self-Reported Measures of Acceptability**

Participants responded to the 3 self-report items related to acceptability (interference, dislike, and willingness to use for 1 year) on a 5-point bipolar scale (strongly disagree, disagree, undecided, agree, or strongly agree). We retained these ordinal labels for visual display of these data in figures but ordered the labels such that higher scores represented greater acceptability (ie, strongly agree for willingness to use for 1 year and strongly disagree for interference and dislike). For the analyses, we recoded these items to a numeric scale ranging from −2 to 2, with 0 representing the neutral (undecided) midpoint and higher scores representing greater acceptability.

Participants responded to these items at each monthly follow-up visit. Therefore, participants had up to 3 responses for each item, depending on when they ended their participation. We analyzed their last available response in our primary analyses to allow us to include all participants and to represent their final perception of each personal sensing signal. However, mean responses across each time point remained relatively constant for all signals (Figure S2 in Multimedia Appendix 2).

To detect the mean perceptions of the personal sensing signals that diverge from neutral (ie, mean responses to any items that are different from 0 or undecided), we conducted 2-tailed, 1 sample t tests for the 3 self-report items for each personal sensing signal. To examine relative perceptions of the signals, we compared perceptions of the active versus passive categories of signals using 2-tailed, within-sample t tests. Participants did not provide ratings of interference for passive signals so the comparisons of active versus passive categories were limited to dislike and willingness to use for 1 year. Due to the high proportion of missing data for sleep quality, we excluded this signal from these analyses and the intraclass correlations described next. Comparisons among all personal sensing signals using 2-tailed, within-sample t tests for each of the 3 self-report items are reported in Table S1 in Multimedia Appendix 2. Finally, we conducted 2 analyses to examine the consistency of perceptions across personal sensing signals (eg, Do participants who dislike 1 signal also dislike the other signals?). First, we calculated bivariate correlations among the personal sensing signals for each item. Second, we calculated intraclass correlations (single, case 3 [74]) separately for each item to quantify agreement in participants’ perceptions across the signals.

**Participant Feedback**

We have provided all raw participant responses, organized by the sensing method, in Tables S2 to S6 in Multimedia Appendix 2. In addition, we have provided representative positive and negative evaluations organized by guiding themes (acceptability, sustainability, benefits, trust, and usability) developed from our literature review in Table S7 in Multimedia Appendix 2.

**Results**

**Participant Characteristics**

A total of 154 participants completed at least 1 monthly follow-up visit and provided self-reported acceptability ratings for interference, dislike, and willingness to use for 1 year. These participants served as the primary sample for our analyses. Participants were mostly White (134/154, 87%) and non-Hispanic (150/154, 97.4%). Half (77/154, 50%) of our research participants were female, and the mean age was 41 (SD 11.9) years. Table 1 presents detailed demographic information. Table 2 presents the information relevant to lifetime drug and alcohol use for these participants. We compared demographics and drug and alcohol use information for participants who were included in the analyses with those of eligible participants who did not provide study measures (ie, did not enroll or discontinued before the first month follow-up; n=36) and found no significant differences (Table S8 in Multimedia Appendix 2 presents details on these analyses).

https://mhealth.jmir.org/2023/11/e41833
Table 1. Participant demographic data (N=154).

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Participants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years), mean (SD)</td>
<td>41 (11.9)</td>
</tr>
<tr>
<td><strong>Sex, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>77 (50)</td>
</tr>
<tr>
<td>Male</td>
<td>77 (50)</td>
</tr>
<tr>
<td><strong>Race, n (%)</strong></td>
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<tr>
<td>American Indian or Alaska native</td>
<td>3 (1.9)</td>
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<tr>
<td>Asian</td>
<td>2 (1.3)</td>
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<tr>
<td>Black or African American</td>
<td>8 (5.2)</td>
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<tr>
<td>White</td>
<td>134 (87)</td>
</tr>
<tr>
<td>Other or multiracial</td>
<td>7 (4.5)</td>
</tr>
<tr>
<td><strong>Hispanic, Latino, or Spanish origin, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>4 (2.6)</td>
</tr>
<tr>
<td>No</td>
<td>150 (97.4)</td>
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<tr>
<td><strong>Education, n (%)</strong></td>
<td></td>
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<tr>
<td>Less than high school or GED&lt;sup&gt;a&lt;/sup&gt; degree</td>
<td>1 (0.6)</td>
</tr>
<tr>
<td>High school or GED</td>
<td>15 (9.7)</td>
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<tr>
<td>Some college</td>
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<td>2-Year degree</td>
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<td>College degree</td>
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<tr>
<td>Advanced degree</td>
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</tr>
<tr>
<td><strong>Employment, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Employed full time</td>
<td>72 (46.8)</td>
</tr>
<tr>
<td>Employed part time</td>
<td>27 (17.5)</td>
</tr>
<tr>
<td>Full-time student</td>
<td>7 (4.5)</td>
</tr>
<tr>
<td>Homemaker</td>
<td>1 (0.6)</td>
</tr>
<tr>
<td>Disabled</td>
<td>7 (4.5)</td>
</tr>
<tr>
<td>Retired</td>
<td>8 (5.2)</td>
</tr>
<tr>
<td>Unemployed</td>
<td>19 (12.3)</td>
</tr>
<tr>
<td>Temporarily laid off, sick leave, or maternity leave</td>
<td>3 (1.9)</td>
</tr>
<tr>
<td>Other, not otherwise specified</td>
<td>10 (6.5)</td>
</tr>
<tr>
<td>Personal income (US $), mean (SD)</td>
<td>34,233 (31,543)</td>
</tr>
<tr>
<td><strong>Marital status, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Never married</td>
<td>69 (44.8)</td>
</tr>
<tr>
<td>Married</td>
<td>33 (21.4)</td>
</tr>
<tr>
<td>Divorced</td>
<td>45 (29.2)</td>
</tr>
<tr>
<td>Separated</td>
<td>5 (3.2)</td>
</tr>
<tr>
<td>Widowed</td>
<td>2 (1.3)</td>
</tr>
</tbody>
</table>

<sup>a</sup>GED: General Educational Development.
Table 2. Participant drug and alcohol use history data (N=154).

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Participants</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Alcohol use disorder milestones, mean (SD)</strong></td>
<td></td>
</tr>
<tr>
<td>Age of first drink</td>
<td>14.6 (2.9)</td>
</tr>
<tr>
<td>Age of regular drinking</td>
<td>19.5 (6.5)</td>
</tr>
<tr>
<td>Age at which drinking became problematic</td>
<td>27.9 (9.6)</td>
</tr>
<tr>
<td>Age of first quit attempt</td>
<td>31.6 (10.4)</td>
</tr>
<tr>
<td>Number of quit attempts</td>
<td>9.1 (31.1)</td>
</tr>
<tr>
<td><strong>Lifetime history of treatment (can choose more than 1), n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Long-term residential (&gt;6 mo)</td>
<td>8 (5.2)</td>
</tr>
<tr>
<td>Short-term residential (&lt;6 mo)</td>
<td>51 (33.1)</td>
</tr>
<tr>
<td>Outpatient</td>
<td>77 (50)</td>
</tr>
<tr>
<td>Individual counseling</td>
<td>100 (64.9)</td>
</tr>
<tr>
<td>Group counseling</td>
<td>65 (42.2)</td>
</tr>
<tr>
<td>Alcoholics anonymous or narcotics anonymous</td>
<td>96 (62.3)</td>
</tr>
<tr>
<td>Other</td>
<td>41 (26.6)</td>
</tr>
<tr>
<td><strong>Received medication for alcohol use disorder, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>62 (40.3)</td>
</tr>
<tr>
<td>No</td>
<td>92 (59.7)</td>
</tr>
<tr>
<td><strong>DSM-5(^a) alcohol use disorder symptom count, mean (SD)</strong></td>
<td></td>
</tr>
<tr>
<td></td>
<td>8.9 (1.9)</td>
</tr>
<tr>
<td><strong>Lifetime drug use, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Tobacco products (eg, cigarettes, chewing tobacco, and cigars)</td>
<td>122 (79.2)</td>
</tr>
<tr>
<td>Cannabis (eg, marijuana, pot, grass, and hash)</td>
<td>131 (85.1)</td>
</tr>
<tr>
<td>Cocaine (eg, coke and crack)</td>
<td>86 (55.8)</td>
</tr>
<tr>
<td>Amphetamine type stimulants (eg, speed, diet pills, and ecstasy)</td>
<td>81 (52.6)</td>
</tr>
<tr>
<td>Inhalants (eg, nitrous, glue, petrol, and paint thinner)</td>
<td>36 (23.4)</td>
</tr>
<tr>
<td>Sedatives or sleeping pills (eg, Valium, Serepax, and Rohypnol)</td>
<td>72 (46.8)</td>
</tr>
<tr>
<td>Hallucinogens (eg, LSD(^b), acid, mushrooms, PCP(^c), and Special K)</td>
<td>88 (57.1)</td>
</tr>
<tr>
<td>Opioids (eg, heroin, morphine, methadone, and codeine)</td>
<td>65 (42.2)</td>
</tr>
<tr>
<td><strong>Current drug use(^d), n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Tobacco products (eg, cigarettes, chewing tobacco, and cigars)</td>
<td>84 (54.5)</td>
</tr>
<tr>
<td>Cannabis (eg, marijuana, pot, grass, and hash)</td>
<td>52 (33.8)</td>
</tr>
<tr>
<td>Cocaine (eg, coke and crack)</td>
<td>4 (2.6)</td>
</tr>
<tr>
<td>Amphetamine type stimulants (eg, speed, diet pills, and ecstasy)</td>
<td>11 (7.1)</td>
</tr>
<tr>
<td>Sedatives or sleeping pills (eg, Valium, Serepax, and Rohypnol)</td>
<td>24 (15.6)</td>
</tr>
<tr>
<td>Hallucinogens (eg, LSD, acid, mushrooms, PCP, and Special K)</td>
<td>9 (5.8)</td>
</tr>
<tr>
<td>Opioids (eg, heroin, morphine, methadone, and codeine)</td>
<td>9 (5.8)</td>
</tr>
</tbody>
</table>

\(^a\)DSM-5: Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition.

\(^b\)LSD: lysergic acid diethylamide.

\(^c\)PCP: phencyclidine.

\(^d\)Current refers to the previous month’s drug use reported at follow-up visits 1 or 2.
Behavioral Measures of Acceptability

Participation

Figure 1 shows participant attrition and discontinuation at each phase of the study. Of the 192 eligible participants at screening, only 1 did not consent to participate after hearing the details of the study. Enrollment occurred during a second visit 1 week later. A total of 169 participants completed enrollment.

In Figure 1, we coarsely tabulated reasons stated by participants for discontinuation as because of acceptability, other reasons, or unknown. In total, 11 (5.7%) of the 192 eligible participants were lost due to acceptability-relevant causes (eg, no longer interested, nonadherence to sensing methods, or citing study demands as too burdensome). Other reasons for discontinuation not related to the acceptability of the signals include circumstances such as moving or no longer wishing to abstain from alcohol. It is notable that 31 (16.1%) of the 192 participants were lost to follow-up, such that we had no information about their reasons for discontinuation. We provide a more granular tabulation of these reasons for discontinuation in Table S9 in Multimedia Appendix 2.

Opt-In and Adherence

All participants who completed follow-up 1 (154/154, 100%) opted in to provide data for EMA, sleep quality, and most of the passive personal sensing methods (geolocation and cellular communication logs) throughout their entire participation period. Out of 154 participants, 1 (0.64%) did not provide SMS text message content, and 3 (1.9%) did not provide any audio check-ins during the study.

Daily adherence rates were relatively high for EMA, such that on 94.1% of the study days, participants completed at least 1 of the 4 EMAs. On average, participants completed 3.2 (SD 0.64) EMAs every day. The overall adherence rate for all requested EMAs was .80. The participants’ adherence rate for audio check-in was .54 (Figure S3 in Multimedia Appendix 2 contains more information on this distribution), that is, of their total days in the study, participants completed an audio check-in on approximately half of the days. Figure 2 shows the mean weekly adherence to each of these methods for each week in the study. In Multimedia Appendix 2, we also report adherence for participants who completed the 3-month study compared with those who dropped out before completion (Figure S4 in Multimedia Appendix 2).

Figure 2. Adherence over time for EMA (once daily), EMA (4 times daily), and audio check-in. Plot depicts mean adherence rates for each week on study. Mean SE is depicted by the solid error bars. Overall mean adherence rate is depicted by the dashed line. The sample size was 154. EMA: ecological momentary assessment.
Self-Reported Acceptability

Interference

Figure 3 shows the distribution of the participants’ responses to the self-reported acceptability item about interference. Responses were grouped by personal sensing data stream and the amount of active effort required to collect it. Two-tailed, 1-sample $t$ tests revealed that each mean interference score (depicted as the solid red line) was significantly (all $P<.001$) more acceptable than 0 (the gray dashed line indicating undecided). Table 3 reports the summary statistics for each 2-tailed, 1-sample $t$ test and pairwise correlations between the personal sensing data streams. An intraclass correlation coefficient (ICC; type 3) showed that, on average, interference ratings were moderately consistent across the data streams (ICC=0.42, 95% CI 0.31-0.53).

Figure 3. Ratings of interference by personal sensing data stream. Plot depicts mean responses to “[Personal sensing method name] interfered with my daily activities.” X axes are ordered to display a higher acceptability on the right side. For sleep quality, the sample size was 87; for all other data streams, the sample size was 154. The solid red lines represent the mean, and the dashed lines represent the neutral midpoint (undecided). All raw data streams had a significantly ($P<.001$) higher mean than the neutral midpoint. Interference ratings were collected only for active methods. EMA: ecological momentary assessment.
Table 3. Bivariate and univariate statistics by acceptability and personal sensing data stream.

<table>
<thead>
<tr>
<th>Interference</th>
<th>Value, n</th>
<th>Value, mean (SD)</th>
<th>t test (df)</th>
<th>Cohen d</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Active methods</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Audio check-in</td>
<td>154</td>
<td>0.78 (1.07)</td>
<td>9.05 (153)c</td>
<td>0.73</td>
</tr>
<tr>
<td>EMAd</td>
<td>154</td>
<td>0.91 (0.99)</td>
<td>11.37 (153)c</td>
<td>0.92</td>
</tr>
<tr>
<td>Sleep quality</td>
<td>87</td>
<td>1.38 (0.87)</td>
<td>14.86 (86)c</td>
<td>1.59</td>
</tr>
<tr>
<td><strong>Dislike</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Audio check-in</td>
<td>154</td>
<td>0.51 (1.28)</td>
<td>4.91 (153)c</td>
<td>0.40</td>
</tr>
<tr>
<td>EMA</td>
<td>154</td>
<td>0.96 (0.92)</td>
<td>12.92 (153)c</td>
<td>1.04</td>
</tr>
<tr>
<td>Sleep quality</td>
<td>87</td>
<td>1.10 (1.09)</td>
<td>9.45 (86)c</td>
<td>1.01</td>
</tr>
<tr>
<td><strong>Passive methods</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Geolocation</td>
<td>154</td>
<td>1.03 (0.94)</td>
<td>13.51 (153)c</td>
<td>1.09</td>
</tr>
<tr>
<td>Cellular communication logs</td>
<td>154</td>
<td>0.90 (0.97)</td>
<td>11.45 (153)c</td>
<td>0.92</td>
</tr>
<tr>
<td>SMS text message content</td>
<td>154</td>
<td>0.58 (1.18)</td>
<td>6.07 (153)c</td>
<td>0.49</td>
</tr>
<tr>
<td><strong>Willingness to use for 1 year</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Active methods</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Audio check-in</td>
<td>154</td>
<td>0.73 (1.28)</td>
<td>7.09 (153)c</td>
<td>0.57</td>
</tr>
<tr>
<td>EMA</td>
<td>154</td>
<td>0.64 (1.22)</td>
<td>6.47 (153)c</td>
<td>0.52</td>
</tr>
<tr>
<td>Sleep quality</td>
<td>87</td>
<td>0.85 (1.28)</td>
<td>6.19 (86)c</td>
<td>0.66</td>
</tr>
<tr>
<td>Passive methods</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Geolocation</td>
<td>154</td>
<td>0.94 (1.18)</td>
<td>9.83 (153)c</td>
<td>0.79</td>
</tr>
<tr>
<td>Cellular communication logs</td>
<td>154</td>
<td>0.84 (1.07)</td>
<td>9.76 (153)c</td>
<td>0.79</td>
</tr>
<tr>
<td>SMS text message content</td>
<td>154</td>
<td>0.74 (1.12)</td>
<td>8.21 (153)c</td>
<td>0.66</td>
</tr>
</tbody>
</table>

aInitial columns (1-5) indicate bivariate correlations among data streams for each self-report acceptability measure. The final columns show the number of participants (n), mean and SD, t test statistic, and Cohen d effect size (d) for the 2-tailed, 1-sample t tests against 0 (undecided). Higher values indicate higher levels of acceptability.

bNot available.
cP<.001.
dEMA: ecological momentary assessment.

**Dislike**

Figure 4 shows the distribution of participant responses to the self-reported acceptability item about dislike by the personal sensing data stream and the amount of active effort required to collect it. Two-tailed, 1-sample t tests revealed that each mean dislike score was significantly (all P<.001) more acceptable than 0. Table 3 reports the summary statistics for each 2-tailed, 1-sample t test and the pairwise correlations between the personal sensing data streams. An ICC (type 3) showed that, on average, the dislike ratings were moderately consistent across the data streams (ICC=0.42, 95% CI 0.35-0.48).

We also assessed the effect of active effort on the dislike ratings (see Figure S5 in Multimedia Appendix 2). We conducted a 2-tailed, paired-sample t test to compare the average dislike for active (eg, audio check-in and EMA) with passive (eg, geolocation, cellular communication logs, and SMS text message content) methods. Participants did not significantly differ in their dislike of active and passive methods (t_{153}=1.21, P=.23; Cohen d=0.10).

https://mhealth.jmir.org/2023/11/e41833
Figure 4. Ratings of dislike by personal sensing data stream. Plot depicts mean responses to “I disliked [personal sensing method name].” X axes are ordered to display a higher acceptability on the right side. For sleep quality, the sample size was 87; for all other data streams, the sample size was 154. The solid red and blue lines represent the mean, and the dashed lines represent the neutral midpoint (undecided). All raw data streams had a significantly ($P<.001$) higher mean than the neutral midpoint. Active methods are displayed in red, and passive methods are displayed in blue. EMA: ecological momentary assessment.

Willingness to Use for 1 Year

Figure 5 shows the distribution of participants’ responses to the self-reported acceptability item about willingness to use for 1 year for each personal sensing data stream (Figure S6 in Multimedia Appendix 2 contains additional information about willingness to use an EMA method once daily for 1 year). Two-tailed, 1-sample $t$ tests revealed that each mean willingness score was significantly (all $P<.001$) more acceptable than 0. Table 3 reports the summary statistics for each 2-tailed, 1-sample $t$ test and pairwise correlations between the personal sensing data streams. An ICC (type 3) showed that, on average, the willingness ratings were moderately consistent across the data streams (ICC=0.52, 95% CI 0.46-0.58).

We also assessed the effect of active effort on willingness ratings (see Figure S7 in Multimedia Appendix 2). We conducted a 2-tailed, paired-sample $t$ test of the average willingness to use for 1 year for active (eg, audio check-in and EMA) and passive (eg, geolocation, cellular communication logs, and text message content) signals. Participants reported higher acceptability with respect to willingness for passive data streams (mean 0.80, SD 1) than active data streams (mean 0.70, SD 1.10; $t_{153}=2.12$, $P=.04$; Cohen $d=0.17$).
**Participant Feedback**

In participants’ free-response feedback about each personal sensing data stream, we identified 5 themes: acceptability (“I had no issues with the daily EMA surveys. I felt that they kept me in check and were a reminder to not drink. I would not change it.”); sustainability (“I forgot I was being tracked, so it was not a big deal to me.”); benefits (“Was okay to have [geolocation tracking] done in the context of the study or for an app that would help me stay sober.”); trust (“I trusted the study group to not use my personal information for any other use.”); and usability (“I disliked saving my text messages. I like deleting them when I’m done.”). A representative sample of comments are provided for each theme in Table S7 in Multimedia Appendix 2. A full unedited list of participant comments for each personal sensing data stream has been presented in Tables S2 to S6 in Multimedia Appendix 2.

**Discussion**

**Principal Findings**

This study evaluated the acceptability of active and passive personal sensing methods for a variety of raw data streams and associated methods. To this end, we assessed participants’ choices and behaviors about both participating in the study and...
providing raw data streams for each method and their subjective perceptions of each sensing method. We focused on participants with moderate to severe AUD because they might have been expected to be less willing to share sensitive, private information owing to the stigma associated with their disorder [75]. However, if these sensing methods were acceptable to them, highly promising opportunities are now emerging to address their largely unmet treatment needs [76], with technological solutions that include digital therapeutics combined with personal sensing [77]. We have organized our discussion around 7 key conclusions from our analyses.

**Individuals With AUD Will Generally Accept the Use of Personal Sensing Methods**

On the basis of our sample, it appears that individuals with AUD are indeed willing to provide these sensitive, personally sensed raw data streams based on their behavioral choices regarding consent, enrollment, and opt in for data collection in this study. All but one of the individuals (191/192, 99.5%) who were eligible to participate consented to the personal sensing procedures. Most of these individuals (169/191, 88%) also returned 1 week later to formally enroll in the study and begin to provide these data. Furthermore, all (169/169, 100%) of the participants who enrolled in the study explicitly opted in to provide the 3 arguably most sensitive passive data streams: geolocation, cellular communication logs, and SMS text message content.

These consent, enrollment, and opt-in numbers could be considered upper-bound and lower-bound estimates of the percentage of individuals who are willing to provide these raw data streams in a research setting. The very high percentage for consent may overestimate willingness because some of these individuals may have reconsidered their initial decision on further reflection such that they did not return for the next study visit to enroll formally. However, the still quite high enrollment percentage may underestimate the willingness to provide these data because some attrition was expected between consent and enrollment visits due to the instability associated with the early stages of recovery from AUD. In fact, Table S9 in Multimedia Appendix 2 indicates that almost half of the participants who consented but did not enroll may have done so for reasons other than their willingness to provide these raw data streams (eg, health concerns, no transportation to lab, and made repeated attempts to reschedule before discontinuing).

Participants’ explicit self-reports of their perceptions about the acceptability of these personal sensing methods were also generally consistent with their behavior. Specifically, on average, participants rated all the sensing methods as more favorable than the neutral midpoint (“undecided”) of the rating scales for all 3 dimensions we evaluated: interference, dislike, and willingness to use for 1 year. These self-report data combined with our behavioral measures suggest that all of these sensing methods can be considered for use with the majority of individuals with AUD.

Despite the aggregate positive perceptions of the full sample, nontrivial percentages of participants reported individual ratings that were more negative than the neutral midpoint across the sensing methods and specific self-report items. For example, 17.5% (27/154) of the participants agreed or strongly agreed that audio check-ins interfered with their daily activities. Approximately 25% of the participants agreed or strongly agreed that they disliked both the audio check-ins (42/154, 27.3%) and providing access to the content of their SMS text messages (33/154, 21.4%). Approximately 20% of the participants disagreed or strongly disagreed that they would be willing to use our sensing methods for audio check-ins (25/154, 16.2%), EMA (35/154, 22.7%), and SMS text message content (23/154, 14.9%) for 1 year to help with their recovery. This suggests that there is still a need to improve each of these sensing methods to make them more acceptable to a larger percentage of individuals. The free-response evaluations of each method provide a starting point to address participant concerns. However, our research participants did generally opt in and adhere to our sensing methods despite reporting these concerns. Therefore, the threshold at which these concerns will translate to barriers for use or adherence to these methods is unclear.

**Individuals Can Sustain the Use of Personal Sensing for Relatively Long Periods**

Most enrolled participants were also able to sustain their commitment to providing these sensed data streams over time. More than 91% (154/169) provided at least 1 month of sensed data, and a large majority (133/169, 78.7%) provided data for all 3 months. As with enrollment statistics, these numbers also likely underestimate participants’ ability to sustain personal sensing because many of the participants who discontinued or did not complete the study reported reasons to stop their participation that were unrelated to personal sensing (eg, family crisis, relapse, and moved out of state). However, some participants (n=4) explicitly reported reasons that appeared related to personal sensing (eg, study demands were too burdensome). In addition, others who stopped participating may have been influenced by their experiences with personal sensing without formally reporting their concerns.

Participants who enrolled but then discontinued because of personal sensing methods may have been influenced more by issues related to the burden associated with active sensing rather than more general issues related to data sensitivity and privacy. Participants concerned about sharing passively sensed private information, such as their moment-by-moment location or cellular communication, would likely have had these concerns from the beginning, such that they would not have consented, enrolled, and then opted in to provide these sensitive data. However, the burden associated with active sensing (eg, 4 times daily EMA and daily audio check-ins) may not have been clear to them until they tried to sustain those methods over time. In our sample of participants, we saw evidence that many of them hardly thought about passively sensed data streams. On the other hand, some participants reported more discontent with actively sensed data streams as time progressed.

Existing research assessing the acceptability of sensing methods has been limited by short durations of monitoring, with very few studies extending beyond 6 weeks [53,55,56]. In addition, adherence has been shown to decrease after only a few weeks in some studies [43,48,78]. This study demonstrates that individuals can sustain their commitment to providing personally
sensed data over time with limited drop-offs. These findings suggest that personal sensing methods may be viable in clinical settings where consistent, sustained monitoring would be necessary. Given this promise, future research should expand to longer durations to assess self-reported and behavioral acceptability beyond 3 months. Our group is exploring this directly by using personal sensing monitoring in individuals with opioid use disorder for a full year [14]. Methods that permit long-term monitoring are particularly important for clinical applications for individuals with substance use disorders, who require lifelong care that can adapt to their risk for relapse and corresponding recovery needs.

Some Types of Active Personal Sensing Methods Are Generally Acceptable and Sustainable

The assessment burden may be expected to play a role in both the acceptability of active sensing methods and participant adherence to the associated procedures. Nonetheless, participants displayed relatively high adherence to the 4 times daily EMA (79.8% of EMAs completed on average). This is notable because our study duration of 3 months was substantially longer than typical studies using EMA, which often lasts only 2 to 4 weeks [47,48]. This increases confidence in the feasibility of this active sensing method for research and clinical applications that require longer monitoring periods. This level of adherence may be contingent on the measurement parameters used in our study (4 times daily survey of 7-10 items). In fact, even higher adherence may have been observed if the measurement was limited to 1 EMA per day, given that on average participants completed at least 1 of the 4 EMAs on 94.1% of the study days. Participants were also significantly more likely to report a willingness to use a once daily EMA compared with a 4 times daily EMA for 1 year. However, these findings should be interpreted cautiously. Participant self-reports to a once daily EMA method are not based on experience because they were expected to adhere to the 4 times daily EMA. From free-response comments, we saw that many of our participants had no issues with the 4 times daily EMA and some even enjoyed the frequent prompts. However, other participants suggested less-frequent prompts would be more practical.

Overall, there was some evidence that participants found passive sensing methods to be more acceptable than active sensing methods. Specifically, the mean ratings for willingness to use for 1 year were significantly higher for passive sensing methods than active sensing methods. However, the magnitude of this effect was small, and the mean willingness was significantly greater than the neutral midpoint for both the active and passive methods. In addition, there was no difference in the mean dislike ratings between the active and passive methods. Thus, the differences between the acceptability of the active and passive methods were small, inconsistent, and unlikely to be clinically meaningful. These comparisons between active and passive methods increase our confidence somewhat that the selective use of active measures, when necessary, may be acceptable to participants for relatively long periods. However, from this study, we cannot speculate strongly beyond 3 months.

Some sensing methods (eg, EMA and audio check-ins) will always require active input from users, but other methods may become more passive with further technological advances. For example, our sensing of sleep quality in this study used an early version of the Beddit Sleep Monitor that required participants to actively log when they entered and exited their bed during each period of sleep. However, later versions of Beddit automatically detect periods of sleep. Similarly, we discontinued the sensing of physiology with Empatica E4 in an early phase of our study because participants had to manually connect the wristband each night to a tablet to upload their data. This proved too burdensome and complex for most participants. However, the current version of Empatica E4 claims to have improved automatic Bluetooth streaming of the data to the cloud, which if robust, would greatly reduce the burden associated with physiology sensing.

The acceptability of active sensing methods holds great clinical utility. Active personal sensing methods, such as EMA, offer unique insights into patient experiences, thoughts, and feelings that cannot always be captured accurately or comprehensively by passive methods. Self-reported EMA, in particular, seems likely to play a role in risk monitoring and other similar clinical applications. Thus, we were encouraged to find that even with a relatively high active burden of 4 times daily surveys, EMA was acceptable to participants, as assessed via self-report and behavioral adherence.

Important Individual Differences in Subjective Perceptions Exist Both Within and Across Personal Sensing Methods

In this study, we included a second and more novel daily active sensing method, audio check-ins. These audio check-ins have great potential as a rich source of information about participants’ daily experiences. Natural language processing of transcripts of their check-ins can provide a novel window into their thoughts [79-82]. These audio check-ins provided participants with the opportunity to share more openly and candidly (ie, without close-ended questions) their thoughts, feelings, and progress toward recovery without being limited to researcher-selected prompts. Analyses of the acoustic characteristics of their check-ins may yield independent measures of their affective state [83,84], including the potential for measuring affect outside the participant’s conscious awareness.

Unfortunately, overall participant adherence to the daily audio check-ins was relatively low (on average, 54.3% of audio check-ins were completed) and 1.9% (3/154) of the sample did not complete any check-ins throughout their entire study period. Participants’ free-response evaluations of this method highlighted some concerns that could be addressed in the future to increase adherence (eg, timing of the check-ins, technical issues with recording and sending check-ins, and use of the same prompt for all check-ins). However, privacy issues related to recording the audio check-in were also reported by many participants.

These privacy concerns represent an inherent challenge to using this method as implemented, but accommodations could be made to gather some, if not all, of the same information. For example, using less-frequent prompting with wider time

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JmIR Mhealth Uhealth 2023 | vol. 11 | e41833 | p.424

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completion windows (ie, a weekly audio check-in) may increase individuals’ ability to find a private moment. In addition, allowing individuals to type their response as an alternative completion method could assuage concerns. This alternative would prevent acoustic analysis, but it would still permit natural language processing of open-ended responses. These accommodations could encourage greater adherence among those who completed few or no audio check-ins, as well as individuals who missed check-ins sporadically because of privacy concerns. Finding ways to assuage privacy concerns and accommodate individual preferences may be useful, as many other participants valued and believed that they benefited from recording these daily audio check-ins.

Consistent with this somewhat polarized evaluation of the audio check-ins, a more nuanced consideration of the distribution for adherence across participants suggested that it was somewhat bimodal. Participants tended to adhere well or poorly to this method.

More broadly, the participants’ self-reported perceptions were only moderately consistent across the different sensing methods. This can be observed in the moderate ICCs (and bivariate correlations) across the methods for each self-reported item. In other words, high dislike ratings for 1 sensing method by a specific participant did not strongly indicate that the same participant would also dislike the other sensing methods. This is also true for the “ratings of interference” and “willingness to use for 1 year” items. Participants could dislike (or be unwilling to use) one method but not others. To the degree to which concerns are method specific, opportunities may exist to tailor sensing systems to user preferences. In other words, participants could opt out of the methods they deemed unacceptable but provide data for other sensing methods that were acceptable to them. For example, our behavioral adherence data suggest that some participants would not have completed the study if daily audio check-ins were required; however, they were willing to provide data via other personal sensing methods. Algorithms that use sensed data for clinical applications can then be developed for different combinations of the available raw data streams. Participants could be informed that personalized algorithms will likely perform better if given access to more raw data streams. This education will allow them to make an informed choice regarding the threshold they set for themselves to opt out and the potential consequences of not providing that data source. However, allowing them to opt out of some methods may increase the number of participants who will agree to provide sensed data.

**Benefits Likely Matter**

The overall acceptability of personal sensing to research participants and patients is likely a function of both the perceived costs and benefits for these individuals [85-87]. However, we focused on measuring only perceived costs (eg, privacy and burden) associated with personal sensing because the benefits to participants from the sensed data collected in this research study were minimal. Participants were provided with modest financial incentives to complete the EMAs (US $25/mo) and to provide access to the 2 passively sensed raw data streams (US $10/mo for geolocation and US $15/mo for cellular communication logs with SMS text message content). These sensed data streams were not used to provide any clinical benefit to participants’ recovery in our study, although they hold great promise for use in machine learning algorithms that could predict lapses and deliver or tailor interventions to individual participants’ needs and recent experiences.

Monetary incentives are commonly used in research to provide a more favorable cost-benefit ratio surrounding specific methods or overall participation. Such monetary incentives are commonplace and recommended when using active personal sensing methods such as EMA [88]. However, the incentives to provide access to passively sensed geolocation and cellular communication in our study may have contributed to the acceptance of these methods and the success we had collecting these sensitive data from participants. This may be particularly true given the relatively low socioeconomic status of many of our participants. For example, the mean personal income for our participants was US $34,233, with 12.3% (19/154) of individuals reporting current unemployment and 25.3% (39/154) reporting an annual income below the 2022 federal poverty level.

Monetary incentives to increase the acceptability of personal sensing do not need to be limited to research settings. Incentives can also be used as a part of treatment or continuing care in clinical settings. For example, the use of monetary incentives or equivalents (eg, prizes) as part of a contingency management program is well established to support abstinence from alcohol or other drugs or adherence to treatments or other healthy behaviors [89-91]. If personal sensing proved useful for the treatment or ongoing support of patients’ recovery, similar incentives could be established to encourage patients to provide these sensed data.

Incentives may be less necessary in clinical settings when more direct clinical benefits from personal sensing are available. For example, research has suggested that privacy concerns associated with personal sensing may be reduced if participants perceive that they will benefit from the sensed data [6,51,87]. There was some evidence for this perspective in the free-response comments from our study participants as well.

We did not provide direct clinical treatment to the participants. Participants were given resources for alcohol treatment options upon request. In addition, although personal sensing methods were used solely for data collection, in this study, participants may have experienced some clinical benefits from them (eg, via reflection and accountability). However, the acceptability of personal sensing may be higher than that observed in our study if the sensing system was implemented as part of their direct treatment or continuing care during their recovery. Digital therapeutics are particularly well positioned to use sensed data to select, personalize, or time the delivery of interventions and other supports to improve clinical outcomes. Future research should evaluate the acceptability of personal sensing in contexts where its use directly benefits those providing the sensed data. In these contexts, benefits (eg, financial and clinical benefits) can also be explicitly measured. It may even be possible to manipulate the benefits from personal sensing across participants to evaluate their contribution to acceptability more rigorously.
Trust Likely Matters

Trust is also likely to affect the overall acceptability of personal sensing data, which are inherently private and sensitive. Acceptability may depend on who uses personal sensing and who has access to raw and processed data [50,87,92-94]. The available evidence suggests that people are more comfortable sharing private, sensitive information with researchers and their physicians and less comfortable sharing information with family members, electronic health record databases, and third-party apps and websites [92-94].

The research setting may come with relatively greater trust because of the high level of transparency regarding the risks and protection measures associated with obtaining informed consent. Some protections may only be feasible for research as well. For example, National Institutes of Health (NIH)–funded research that collects identifiable, sensitive information is automatically issued a Certificate of Confidentiality that prohibits disclosing this information to anyone not connected to the research, except when the participant consents or in a few other limited situations. The Certificate of Confidentiality can also be requested for similar research not funded by the NIH. We saw evidence of the role of trust in the free-response comments from our participants. Our participants appeared to recognize and appreciate the protective measures taken to secure their data.

Implementations of personal sensing for treatment inside and outside clinical care settings [34] will need to carefully consider how to establish similar, high levels of trust. Clinical applications of personal sensing may sit at an intersection of sharing data with physicians (with which individuals tend to be comfortable) and with electronic health record databases and apps (with which individuals tend to be less comfortable) [93,94]. For example, it may be necessary to protect against the subpoena of sensitive information in civil and criminal proceedings. Patients will also likely need to be assured that sensed data used for their clinical care will not be shared with their health insurance provider with associated risks related to higher insurance premiums or dropped coverage. These issues of data access and unauthorized secondary use of otherwise private information are often cited as concerns regarding personal sensing [87,95].

Regardless of the setting, trust may be lower in stigmatized groups that could otherwise benefit from personal sensing. For example, individuals with mental illness still experience substantial stigma that could impede their willingness to share personal, sensitive information with researchers or clinical care providers [96-99]. In fact, we focused on individuals with AUD in this study to evaluate the acceptance of personal sensing methods in a population that we expected might have barriers associated with trust. Nevertheless, trust may still be lower among individuals with other substance use disorders that involve illegal drug use. However, many of our participants reported ongoing use of drugs other than alcohol throughout the study (75/154, 48.7% reported illicit drug use in the past month) as expected, given the high rates of polysubstance use among individuals with substance use disorders. Furthermore, we have had promising preliminary success in recruiting patients with opioid use disorder for an NIH-funded study on personal sensing in this population [100]. This suggests that our results regarding the acceptability of personal sensing may be generalized across substance use disorders.

Trust and related privacy concerns may also be more difficult to overcome in historically marginalized groups that have experienced systemic racism and other stigmas or exclusions [101]. These individuals may find it more difficult to achieve privacy in their daily lives, and they may hold very different perspectives on the costs versus benefits of surveillance in the context of personal sensing or more generally. Unfortunately, our sample was not diverse with respect to race and ethnicity. Future research on personal sensing must specifically recruit for such diversity to better understand its acceptance in racial and ethnic minority communities. We have learned from this study and adjusted our recruiting efforts accordingly to recruit a sample that is more diverse with respect to race, ethnicity, and geographic region for our ongoing personal sensing project with individuals with opioid use disorder.

Feasibility Is a Function of More Than Participant Perceptions of Acceptability

User acceptance of personal sensing methods is necessary but not sufficient to expand the use of these methods in research and clinical implementations. A variety of other key issues may facilitate or present barriers to the wider use of personal sensing. These include cost and accessibility, stability over time, and the utility of personal sensing relative to other more traditional methods.

The smartphone itself is arguably the best available sensing system at present. Currently, smartphones contain numerous sensors and other raw data streams that can be used for personal sensing. In our study, we took advantage of GPS and other location services to track geolocation and used the microphone for daily audio check-ins. We accessed smartphone calls and SMS text message logs for communication metadata and message content, respectively. The smartphone also provided a convenient platform to collect self-reported EMA.

In addition, smartphones provide a relatively accessible platform for personal sensing. Despite their high cost, 85% of adults in the United States already own a smartphone. Equally important, this level of ownership is relatively consistent across race and ethnicity, geographic regions (eg, urban, suburban, and rural), and income levels [3]. Furthermore, people with substance use disorders generally have high rates of mobile technology use [102]. Notably, only 11 (6.5%) of the 169 eligible participants in our study did not already own a contemporary smartphone. In a research setting, we were able to provide individuals with a smartphone if they did not already have one. Similar to monetary incentives, this practice need not be limited to research; smartphones can be provided to permit personal sensing–based clinical support.

Personal sensing can also be performed using wearable devices or other sensors outside the smartphone. We used Empatica and Beddit systems to sense physiology and sleep, respectively. The use of watches (eg, Apple Watch) and wristbands (eg, Fitbit) for sensing activity and some physiology parameters is also
increasing [18,103]. However, some of these systems can be expensive, and unlike smartphones, none have been adopted widely enough to assume that most users will already own the said devices. For research applications, this limitation can be overcome by providing the hardware to participants as needed. Although it is not impossible to do the same in clinical settings, the large number of patients who would require this technology may either limit or increase the cost to scale the sensing system.

Both research and clinical applications of sensing systems require some guarantee that the hardware and software will remain available and supported for the duration of the intended use. Unfortunately, there are currently high levels of churn among the companies that support these systems, given the rapid innovation occurring at this time. We collected data for approximately 2.5 years between 2017 and 2019. During this time, Apple bought the company that developed the Beddit Sleep Monitor and discontinued support for previous users. Apple reintroduced the sleep sensing system for iPhone users in late 2018 but discontinued it again in early 2022. Therefore, we were able to collect sleep sensing data from fewer than half of our research participants.

During this same data collection period, there was also a churn in the software that we used for sensing geolocation. We used the Moves app at the start of the study but needed to switch to the FollowMee app when Facebook acquired the company that developed Moves and discontinued its support. However, this software churn was less disruptive because both apps relied on smartphone sensors to acquire the raw geolocation data stream. This suggests yet another reason to prefer systems that make use of generic smartphone sensors rather than proprietary hardware.

High rates of churn can also affect the perceived acceptability of the software. For example, it could be inconvenient to have to adapt to frequent changing of app platforms. In addition, software may be left unmonitored for periods, leaving new bugs unresolved. In our sample of participants, we observed how frustrating technological issues were.

**Limitations and Future Directions**

Conclusions regarding the acceptability of these sensing methods may not be generalizable beyond the 3-month study duration. Although 3 months represents a notable extension beyond the existing literature on personal sensing in clinical populations, it is likely not long enough, given the chronic-relapsing nature of alcohol and other substance use disorders. One potential concern is that the initial novelty of sensing may lead to overestimated adherence and subjective ratings of acceptability that is not sustained for longer periods [104].

This 3-month period also constrains our conclusions regarding the acceptability to people early in recovery. It is possible that acceptability ratings will vary depending on where someone is in their recovery phase. This may also be amplified when potential benefits are considered. For example, someone who has achieved long-term stability in their recovery could find that the costs of personal sensing (eg, data sharing and high effort demands) do not outweigh the benefits (eg, daily reflection on sobriety and potential for increased lapse risk awareness). It is important for future studies to extend study length and incorporate other facets of acceptability (eg, benefits) to account for these possible effects. In an ongoing study of people with opioid use disorder, we requested that participants use various active and passive personal sensing methods for 1 year [14]. In addition, future research could compare acceptability ratings for personal sensing methods between people with and without a substance use disorder.

Future studies should also examine the nuances of behavioral measures of acceptability. Our study was limited in the conclusions we could draw about adherence to passive personal sensing measures. All our research participants (154/154, 100%) provided some geolocation and cellular communication data and all but one of our research participants (153/154, 99.4%) provided SMS text message content data. However, we cannot know if and how frequently participants were choosing to selectively delete SMS text messages or turn their geolocation off. In addition, we have limited information on the reasons for participant discontinuation before enrollment. Only 1 participant did not consent to participate at the time of screening. However, the attrition between screening and enrollment could reflect some reservations about the personal sensing methods and the study as a whole. That said, we do not believe our attrition rates between these 2 visits to be unusually high for our target sample (ie, people early in recovery from AUD).

Our self-report acceptability questions were developed in house. Therefore, our results should be interpreted in light of our specific questions and settings. For example, we asked participants if they would be willing to use a personal sensing method for 1 year to help with their recovery. This could imply that there would be a clinical benefit to using the method for 1 year and may factor in their judgment of acceptability. These questions have not been previously used in other research settings. Although we attempted to minimize social desirability effects and encourage feedback (eg, deidentified self-report surveys submitted through a web-based survey platform), it is possible that these effects are built into our results. Nonetheless, it should also be acknowledged that the study conclusions are based on both these self-report measures and behavioral indices.

Finally, although our results suggest that clinical samples of people with AUD may find these personal sensing methods acceptable, more research is needed to test the acceptability of these methods in future applied-clinical settings, where issues of costs, benefits, and trust may differ meaningfully in complicated ways from the research context. Future studies should also examine how these personal sensing methods might be perceived by people with recovery goals other than abstinence. No technical reasons prevent personal sensing from being applied to alternative recovery goals (see the studies by Bae et al [28] and Walters et al [29] for examples of predicting current and imminent drinking episodes, respectively, in people without a goal of abstinence). In addition, it must be acknowledged that the individuals in our study agreed to participate in a research study on mobile health and were financially compensated for their time. It is unclear how these individuals and the research setting may differ from those seeking to use these methods in future clinical settings, where
costs, benefits, and trust may all weigh differently on their decisions to engage with the sensing system.

Conclusions
This study demonstrated the acceptability of several personal sensing methods. These methods were acceptable (1) over a longer period than has previously been assessed, (2) across active and passive methods, (3) despite the sensitivity of the data, (4) among individuals with AUD who may have greater privacy concerns, and (5) without explicit clinical benefits to the participants. These findings suggest that personal sensing methods are poised as accessible, feasible avenues to collect data about individuals to be used for clinical applications. More work is needed to determine the predictive utility of the data that can be collected via personal sensing, but our study shows that this work will be worthwhile to pursue.

Personal sensing is acceptable, and the technology to collect it (namely, the smartphone) is widely accessible. Personal sensing can make digital therapeutics—smartphones and web-based apps that provide mental health care—smart. These methods can personalize care for individuals such that they receive the specific interventions and support they need at the time they need them. Smart digital therapeutics can be scaled widely to provide treatment to the overwhelming majority of individuals who do not currently receive mental health care. They can reach those who have historically been excluded from or have otherwise faced barriers to care. With personal sensing powering digital therapeutics, we are positioned for a paradigm shift in mental health care. This study brings us one step closer to this goal, ensuring that the methods we hope to use to revolutionize care are acceptable to patients who will use them.

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Conflicts of Interest
None declared.

Multimedia Appendix 1
Transparency checklist.
[DOCX File, 28 KB - mhealth_v11i1e41833_app1.docx ]

Multimedia Appendix 2
Supplemental analyses.
[PDF File (Adobe PDF File), 272 KB - mhealth_v11i1e41833_app2.pdf ]

Multimedia Appendix 3
Acceptability survey.
[DOCX File, 27 KB - mhealth_v11i1e41833_app3.docx ]

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Abbreviations

AUD: alcohol use disorder
EMA: ecological momentary assessment
ICC: intraclass correlation coefficient
NIH: National Institutes of Health

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The Implementation of a GPS-Based Location-Tracking Smartphone App in South Africa to Improve Engagement in HIV Care: Randomized Controlled Trial

Kate Clouse1,2, PhD, MPH; Sandisiwe Noholoza3, MPH; Sindiswa Madwayi1; Megan Mrubata3; Carol S Camlin4, PhD, MPH; Landon Myer3, MBChB, PhD; Tamsin K Phillips3, PhD, MPH

1Vanderbilt University School of Nursing, Nashville, TN, United States
2Vanderbilt Institute for Global Health, Nashville, TN, United States
3Division of Epidemiology and Biostatistics, School of Public Health, University of Cape Town, Cape Town, South Africa
4Department of Obstetrics, Gynecology & Reproductive Sciences, University of California, San Francisco, San Francisco, CA, United States

Corresponding Author:
Kate Clouse, PhD, MPH
Vanderbilt University School of Nursing
461 21st Avenue South
Nashville, TN, 37240
United States
Phone: 1 615 343 5351
Email: kate.clouse@vanderbilt.edu

Abstract

Background: Mobile health interventions are common in public health settings in Africa, and our preliminary work showed that smartphones are increasing in South Africa. We developed a novel smartphone app—CareConekta—that used GPS location data to characterize personal mobility to improve engagement in HIV care among pregnant and postpartum women living with HIV in South Africa. The app also used the user’s location to map nearby clinics.

Objective: We aimed to describe the feasibility, acceptability, and initial efficacy of using the app in a real-world setting.

Methods: We conducted a prospective randomized controlled trial at a public sector clinic near Cape Town, South Africa. We enrolled 200 pregnant (third trimester) women living with HIV who owned a smartphone that met the required specifications. All participants installed the app, designed to collect 2 GPS heartbeats per day to geolocate the participant within a random 1-km fuzzy radius (for privacy). We randomized (1:1) participants to a control arm to receive the app with no additional support or an intervention arm to receive supportive phone calls, WhatsApp (Meta Platforms, Inc) messages, or both from the study team when traveling >50 km from the study area for >7 days. In addition to mobility data collected daily through the phone, participants completed questionnaires at enrollment and follow-up (approximately 6 months post partum).

Results: A total of 7 participants were withdrawn at enrollment or shortly after because of app installation failure (6/200, 3%) or changing to an unsuitable phone (1/200, 0.50%). During the study period, no participant’s smartphone recorded at least 1 heartbeat per day, which was our primary feasibility measure. Of the 171 participants who completed follow-up, only half (91/171, 53.2%) reported using the same phone as that used at enrollment, with the CareConekta app still installed on the phone and GPS usually enabled. The top reasons reported for the lack of heartbeat data were not having mobile data, uninstalling the app, and no longer having a smartphone. Acceptability measures were positive, but participants at follow-up demonstrated a lack of understanding of the app’s purpose and function. The clinic finder was a popular feature. Owing to the lack of consistent GPS heartbeats throughout the study, we were unable to assess the efficacy of the intervention.

Conclusions: Several key challenges impeded our study feasibility. Although the app was designed to reverse bill participants for any data use, the lack of mobile data was a substantial barrier to our study success. Participants reported purchasing WhatsApp data, which could not support the app. Problems with the web-based dashboard meant that we could not consistently monitor mobility. Our study provides important lessons about implementing an ambitious GPS-based study under real-world conditions in a limited-resource setting.

Trial Registration: ClinicalTrials.gov NCT03836625; https://clinicaltrials.gov/ct2/show/NCT03836625

International Registered Report Identifier (IRRID): RR2-10.1186/s13063-020-4190-x
Introduction

Background

There are an estimated 7.5 million people living with HIV in South Africa, more than the number of people living with HIV in any other country [1]. The country adopted a universal test-and-treat antiretroviral therapy (ART) policy in 2016, allowing for the initiation of lifelong ART regardless of clinical criteria [2]. Despite the widespread availability of free ART and the known efficacy of the treatment for prevention [3-5], South Africa still had >200,000 new HIV infections and 51,000 deaths from HIV in 2021 [1].

Continuous engagement in HIV care is a known challenge in South Africa [6,7]. Pregnant women living with HIV are at an especially high risk of dropping out of HIV care, particularly during the postpartum period [8-12]. Our earlier work has explored the potential of mobility, particularly long-distance travel to the mother’s rural home, as a factor contributing to postpartum disengagement in care [13-15]. This work was limited in that it either required a retrospective analysis of existing data or relied on the self-reported mobility recall of participants still engaged in care.

Mobile health (mHealth) apps are frequently deployed in public health settings in Africa [16-19], and our preliminary research showed that smartphones are increasingly common among our target population of postpartum women living with HIV in South Africa [20]. Previous studies demonstrated the utility of aggregated cellular phone data in showing population mobility [21-24]. Furthermore, US-based studies demonstrated the feasibility of opt-in tracking of people at high risk of HIV [25,26]. Within this context, we developed a smartphone app that could track a participant’s location—with their permission—throughout late pregnancy and the postpartum period to characterize mobility prospectively and offer a support intervention to those who traveled.

The CareConekta App

The CareConekta app was built through collaboration between the study team and Jembi Health Systems in Cape Town [27]. It followed an initial beta version developed and briefly tested in collaboration between the study team (KC, LM, and TKP) and Dr Martin Were of Vanderbilt University Medical Center’s Department of Biomedical Informatics and was based on qualitative preliminary research that explored attitudes toward mHealth interventions and possible concerns regarding location tracking among potential users [28,29]. The app uses the phone’s GPS signal to prospectively characterize mobility in real time, which is a real advancement in research that previously relied on retrospective analysis. Information on a participant’s location would allow the study—and later, clinic—staff to intervene without delay to link traveling individuals to health facilities in the new area, with assistance through phone calls or WhatsApp (Meta Platforms, Inc) messages. In addition, loaded with a national list of HIV care facilities that could be located on a map, the app acted as a clinic finder. We previously published the study protocol [27] and descriptions of the cohort [30] and screening process [31]. In this paper, we describe our primary outcome of the feasibility of implementing this app and the operational lessons learned by conducting an mHealth study in a resource-limited setting in South Africa.

Methods

Study Design and Dates

We conducted a prospective, unblinded randomized controlled trial at the Gugulethu Midwife Obstetric Unit (MOU), a public sector clinic providing integrated HIV and peripartum care for pregnant women near Cape Town, South Africa. Full details of the study design can be found in our published protocol [27], and details of the participant characteristics and follow-up can be found in the cohort profile [30]. In addition to characterizing mobility during pregnancy and the postpartum period, we designed the app to serve as a tool for engagement in HIV care for mobile women living with HIV. Thus, we randomized (1:1) participants to a control arm to receive the app with no additional support or an intervention arm to receive the app and supportive phone calls, WhatsApp messages, or both from the study team when meeting our threshold for traveling: >50 km from the study area for >7 days. The enrollment goal was 200 participants, which we anticipated would be an attainable goal given our study period and our objective of describing the feasibility, acceptability, and initial efficacy of the intervention. Enrollment began in December 2019 and ended in February 2021. There was a 6-month pause in recruitment from March to September 2020 due to the COVID-19 pandemic. The participant follow-up ended in November 2021.

App Design Specifications

To characterize participant mobility during the study period, the CareConekta app was designed to collect 2 GPS location heartbeats per day. In addition, the app was built with a geographic list of health facilities in South Africa so that users could see a map of nearby facilities as they traveled. App connectivity and participant location (marked using anonymized study ID numbers) were viewable to the study team through a password-protected, web-based dashboard. To protect participant privacy, the location was made fuzzy by randomizing the location within a 1-km radius. The MOU was set as the home location from which to begin measuring movement. The mobility history was saved on an encrypted, password-protected server at a South African data center.

The app was available for free download through the Google Play Store (Google LLC) but required authentication and registration, so access was restricted to those enrolled in the study. CareConekta was designed such that it would cost the study. CareConekta was designed such that it would cost the

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KEYWORDS

mobile health; mHealth; smartphone; mobile phone; HIV/AIDS; South Africa; pregnancy

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We conducted a prospective, unblinded randomized controlled trial at the Gugulethu Midwife Obstetric Unit (MOU), a public sector clinic providing integrated HIV and peripartum care for pregnant women near Cape Town, South Africa. Full details of the study design can be found in our published protocol [27], and details of the participant characteristics and follow-up can be found in the cohort profile [30]. In addition to characterizing mobility during pregnancy and the postpartum period, we designed the app to serve as a tool for engagement in HIV care for mobile women living with HIV. Thus, we randomized (1:1) participants to a control arm to receive the app with no additional support or an intervention arm to receive the app and supportive phone calls, WhatsApp messages, or both from the study team when meeting our threshold for traveling: >50 km from the study area for >7 days. The enrollment goal was 200 participants, which we anticipated would be an attainable goal given our study period and our objective of describing the feasibility, acceptability, and initial efficacy of the intervention. Enrollment began in December 2019 and ended in February 2021. There was a 6-month pause in recruitment from March to September 2020 due to the COVID-19 pandemic. The participant follow-up ended in November 2021.

App Design Specifications

To characterize participant mobility during the study period, the CareConekta app was designed to collect 2 GPS location heartbeats per day. In addition, the app was built with a geographic list of health facilities in South Africa so that users could see a map of nearby facilities as they traveled. App connectivity and participant location (marked using anonymized study ID numbers) were viewable to the study team through a password-protected, web-based dashboard. To protect participant privacy, the location was made fuzzy by randomizing the location within a 1-km radius. The MOU was set as the home location from which to begin measuring movement. The mobility history was saved on an encrypted, password-protected server at a South African data center.

The app was available for free download through the Google Play Store (Google LLC) but required authentication and registration, so access was restricted to those enrolled in the study. CareConekta was designed such that it would cost the...
Therefore, the cellular service of 1 of the 4 major mobile providers in South Africa was a requirement for eligibility. In the event of disconnection, the app was designed such that location data would be stored on the phone and uploaded as soon as connectivity resumed. However, reverse billing did not apply for app installation or version updates, so participants installed the app at the clinic using free Wi-Fi, and small data bundles were provided by the study staff for reinstallation and updates, when needed.

**Recruitment and Eligibility**

Pregnant women were recruited during routine antenatal care at the MOU. Women were eligible if they were in the third trimester of pregnancy (≥28 weeks); aged ≥18 years; able to speak and understand isiXhosa (the predominant local language) or English; diagnosed with HIV at any time before enrollment; able to demonstrate basic smartphone-level literacy; and willing to participate in all aspects of the study, including randomization and mobility tracking. Eligible participants also needed to own a smartphone that met the technical requirements described in the subsequent section.

**Smartphone Technical Requirements**

For the purpose of this study, a smartphone was defined as a mobile phone device with a touchscreen interface and internet and GPS capabilities. CareConekta was designed for phones using the Android operating system, version 5.0 or later. In our preliminary work, nearly 90% of the smartphones of the women approached for study participation used the Android system [20]. Eligible participants were required to subscribe to service (prepaid or contract) from 1 of the main 4 cellular providers in South Africa: Vodacom (Vodacom Group Limited), Cell C (Cell C Limited), Telkom (Telkom SA SOC Limited), or MTN (MTN Group Limited). At recruitment, the eligible participant needed to demonstrate that the phone could use GPS by opening a map app, such as Google Maps (Google LLC), and finding the current location. Finally, the phone needed to be capable of holding battery charge; phones were ineligible if they needed to be charged more than twice per day on average (by self-report). Details of those found to be ineligible during the screening assessment can be found elsewhere [31].

**App Installation and Operation**

The app was installed at the study site by connecting the smartphone to the study’s Wi-Fi source. Because the app was available on the Google Play Store, all participants first needed a Google email address to download the app. For the app to function properly after installation, the GPS needed to remain enabled (with location allowed), and the phone needed to have some data or airtime available for reverse billing to work. Participants were asked to contact the study team if they needed to reinstall the app because of changing devices or uninstalling the app.

**Study Measures**

Participant-reported data were collected at enrollment and follow-up—approximately 6 months post partum—directly into REDCap (Research Electronic Data Capture; Vanderbilt University) using tablet computers. REDCap is a secure, encrypted, and web-based software platform designed to support data capture for research studies [32]. Feedback on app installation experience was noted by the staff in REDCap at the end of the enrollment visit. App versions and participant contact attempts were maintained in study logs. Mobility data were exported from the CareConekta dashboard as CSV files.

**Analysis**

We report counts and proportions for categorical variables and medians and IQRs for continuous variables. Data analysis was performed using SAS (version 9.4; SAS Institute). Open-ended responses were reviewed to identify key topics or themes and illustrative quotes.

**Ethics Approval**

This study was approved by the institutional review boards of Vanderbilt University (reference 181640) and the University of California, San Francisco (237757), and the Human Services Research Committee of the University of Cape Town (659/2018). All participants signed a written informed consent form before enrollment, which included specific permission for location tracking.

**Results**

**Installation Experience**

App installation at enrollment was a highly variable experience. The most common reasons for slow experiences at installation were the need to delete items on the phone to make room for another app, the need to create a Google or Gmail account to use the Google Play Store, the need to update the Google Play Store app version, or problems sending and receiving heartbeats after installing the app. The following is a quote from the study staff’s notes about a particularly troublesome installation experience:

> Had to create a Google account for participant and update Play store for app installation. Downloading took a while still. Had to let participant go and she came back a day later for installation; phone still taking forever. The controls get frozen, cleaned phone for efficiency but it still freezes. Finally, app installed and registered participant. Heartbeat data transmitted after all necessary settings adjusted.

**Investigator Withdrawals**

In total, 7 participants were withdrawn from the study soon after enrollment owing to technical issues. Most (6/200, 3%) were withdrawn at the end of the enrollment visit because of an app installation failure that could not be resolved. In addition, 1 (0.5%) other participant was withdrawn for changing their phone to an ineligible phone within 2 weeks of enrollment.

**Participant-Reported Study Feasibility Measures**

Figure 1 shows the feasibility measures of using the CareConekta app as designed, as reported by the participants at follow-up. Over one-third (64/171, 37.4%) of the participants reported that they were no longer using the smartphone in which the app was installed during enrollment. The top 3 reasons for changing phones were that the other phone stopped working...
(27/64, 42%), the other phone was lost (18/64, 28%), and the other phone was stolen (12/64, 19%).

Of the 64 participants who reported changing devices during the study, 10 (16%) reported that the CareConekta app was reinstalled on the new device. Among the 107 participants with the same phone at follow-up and the 10 participants who had reinstalled the app, 17.1% (20/117) reported that the CareConekta app had been uninstalled.

Of the 97 who still had the app on their phone, 6 (6%) participants reported that GPS was usually disabled on their phones. The reasons mentioned by those who reported disabling the GPS setting were that their phone did this automatically or that they turned it off to conserve the battery.

Deducting those who changed phones, those who uninstalled the app, and those who disabled GPS, only 53.2% (91/171) of the participants at the time of follow-up reported the possession of a phone that would operate the app correctly.

**Figure 1.** Number of participants who reported being able to use the CareConekta app at study follow-up. A total of 173 participants completed the follow-up interviews, but the first 2 participants completed the study before the variables presented here were added to the questionnaire. In total, 10 participants who had uninstalled the CareConekta app reinstalled it with the assistance of the study team and continue through the flowchart, as shown.

### Phone Sharing

Approximately one in seven (25/173, 14.4%) participants reported sharing their phone during the study. These participants most often shared their phone with one of their family members (12/25, 48%), their boyfriend or husband (11/25, 44%), or one of their friends who was not their boyfriend or husband (3/25, 12%). Of those who reported phone sharing, 80% (20/25) reported that they had their phone with them most of the day.

### Version Updates

From December 2019 to December 2020, the CareConekta app moved from version 1 to version 7. At one point, a version change (version 5 to 6) meant that the heartbeat data submitted by older versions were no longer received. From July to August 2020, participants were phoned, notified of the new app version, and assisted with updating the app over the phone (Google Play > CareConekta > update app). In cases where participants struggled to follow the steps over the phone, we offered an option for them to come to the study clinic—especially in cases where they were scheduled for an upcoming visit—where we would update the app for them in person. On a few occasions, to those who experienced difficulty over the phone, we sent the steps to follow via SMS text message or WhatsApp. The participants were offered data (100 MB) to update the app over the phone.

### Gaps in GPS Heartbeat Signals

A key feasibility measure was the successful transmission of at least 1 data location heartbeat per participant per day. Heartbeat data were observed daily by the study staff via the dashboard and periodically exported as a CSV file for analysis. During the study, we experienced periods when the dashboard was offline and data exports were unavailable, which resulted in missing data. Owing to difficulties with the dashboard and data exports resulting in substantial missing periods of data after March 19, 2021, our analysis of heartbeat data was conducted on all heartbeats received between the start of enrollment (December 2019) and March 2021. Table 1 shows the summary of gaps in heartbeats received during this period.

The daily GPS heartbeats of none of the participants were received without interruption. The range in heartbeat gaps was 2 to 273 days.

Among the 127 participants with gaps of ≥28 days, 55 (43.3%) were participants whose heartbeat transmission stopped altogether; the remaining 72 (57%) were women whose
heartbeat transmission had long gaps but heartbeats resumed during the study period. On the basis of 3302 heartbeats with GPS location, the median distance traveled from the study site was 2.4 (IQR 1.5-4.5) km. A total of 104 heartbeats (16 women) picked up a distance >50 km away. Only 3 (1.6%) out of 193 women were >50 km away for >7 days based on the heartbeat data, thus meeting our study definition of “travel.” Of the 3 women, 2 (67%) were in the control arm and received no additional action, and 1 (33%) was in the intervention arm; the participant in the intervention arm had a break in GPS when she reached a rural area in November 2020, but her GPS heartbeats resumed in January 2021, and the intervention protocol was followed. In comparison, self-reported mobility during the follow-up visit indicated 37 trips lasting ≥7 days during the study period. Most of these trips were missed by the CareConekta app data.

### Table 1. Gaps in GPS heartbeats received during the CareConekta study.

<table>
<thead>
<tr>
<th>Description</th>
<th>Total (n=193), n (%)</th>
<th>Intervention (n=98), n (%)</th>
<th>Control (n=95), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>One heartbeat received per day</td>
<td>0 (0)</td>
<td>0 (0)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Maximum gap in heartbeats: &lt;7 days</td>
<td>11 (5.7)</td>
<td>7 (7.1)</td>
<td>4 (4.2)</td>
</tr>
<tr>
<td>Maximum gap in heartbeats: 7-13 days</td>
<td>15 (7.8)</td>
<td>8 (8.2)</td>
<td>7 (7.4)</td>
</tr>
<tr>
<td>Maximum gap in heartbeats: 14-20 days</td>
<td>15 (7.8)</td>
<td>7 (7.1)</td>
<td>8 (8.4)</td>
</tr>
<tr>
<td>Maximum gap in heartbeats: 21-27 days</td>
<td>11 (5.7)</td>
<td>5 (5.1)</td>
<td>6 (6.3)</td>
</tr>
<tr>
<td>Maximum gap in heartbeats: ≥28 days</td>
<td>127 (65.8)</td>
<td>62 (63.3)</td>
<td>65 (68.4)</td>
</tr>
<tr>
<td>No heartbeat received during analysis period</td>
<td>14 (7.3)</td>
<td>9 (9.2)</td>
<td>5 (5.3)</td>
</tr>
</tbody>
</table>

### Participant-Reported Reasons for GPS Gaps

From September 2020 to September 2021, our team attempted to contact all participants for whom a GPS heartbeat could not be detected. Contact attempts were made through phone call, followed by SMS text message, if needed. Over this 1-year period, participants could be contacted multiple times for a lack of heartbeat, and the result of the contact could differ each time. Therefore, we present the number of contact attempts and the primary reason reported for the GPS failure at the time of contact.

Out of the 454 contact attempts, 247 (54.4%) were unsuccessful, as the participants were unreachable or declined to talk. The reasons for GPS heartbeat loss gathered during the 207 (45.6%) successful contacts are listed in Table 2.

### Table 2. Primary reason for GPS heartbeat gap reported through 207 participant contacts.

<table>
<thead>
<tr>
<th>Primary reason for GPS heartbeat gap</th>
<th>Value (n=207), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lack of mobile data</td>
<td>84^a (40.6)</td>
</tr>
<tr>
<td>Uninstallation of the CareConekta app</td>
<td>28 (13.5)</td>
</tr>
<tr>
<td>Phone change: new phone is not a smartphone</td>
<td>20 (9.7)</td>
</tr>
<tr>
<td>Phone malfunction or broken phone</td>
<td>14 (6.8)</td>
</tr>
<tr>
<td>CareConekta app–related malfunction</td>
<td>14 (6.8)</td>
</tr>
<tr>
<td>Phone change: app not installed on new phone</td>
<td>13 (6.3)</td>
</tr>
<tr>
<td>Disabling of GPS</td>
<td>13 (6.3)</td>
</tr>
<tr>
<td>Unclear reason or failure of troubleshooting attempt</td>
<td>21 (10.1)</td>
</tr>
</tbody>
</table>

a32 (15.4%) participants mentioned having only WhatsApp data.

### Raffle

In November 2020, to encourage participants to keep the CareConekta app installed on their phone and the GPS function enabled throughout the study period, we implemented an incentive: a weekly raffle of one 200 MB data bundle (worth approximately US $4). Participants were eligible to enter the raffle if their phone sent GPS coordinates at least once a day in the prior week. Among all eligible participants, 1 winner per week was randomly selected. The weekly raffle incentive only...
applied to the participants (n=86) enrolled from November 2020 onward who had signed version 5.0 or later of the informed consent document. There was no limit to the number of times a participant could win the raffle.

From the 41-week period of November 18, 2020, to September 15, 2021, the weekly raffle was drawn 32 times. Four drawings were missed because the CareConekta dashboard was down, and we could not see the GPS data. Two drawings were missed because of holidays. There were no winners for 3 weeks because no participants were eligible. From the 32 drawings, there were 23 unique winners. The same participants won the raffle repeatedly because of the small number of participants who met the eligibility criteria of having consistent heartbeats. In total, 3 participants won the raffle 3 times each during this period. We found that the raffle incentive made no difference to the consistency of GPS heartbeats.

**Additional Technical Challenges**

On multiple occasions, the staff-facing dashboard was either not accessible or not fully functional, which meant that the team was unable to view or download heartbeat data. During the early study period, these problems often resulted in app revisions and version updates. In some instances, when the dashboard was down, the app did not work either, and heartbeats were not transmitted or recorded. Although the app was originally specified to store heartbeats on the phone and transmit them to the server when the connection was restored, this did not happen. Similarly, the app was designed to be reverse billed so as to not cost participants data for using the app; however, some data or airtime was needed on the device for the app to initiate.

**Data Expenditure**

Overall, for all their cell phone needs, participants reported spending a median of R51 (IQR 30-100; US $2.75, IQR US $1.60-5.40) for data per month, with a similar response for monthly spend on airtime: median R50 (IQR 29-100; US $2.71, IQR US$1.57-5.40). Cellular data in South Africa cost approximately R10 (US $0.50) per 50 MB.

**Participants’ Understanding of the CareConekta App**

At follow-up, participants were asked, “If you were to explain to a friend what the CareConekta app does, how would you explain it?” Nearly all participants (167/170, 98.2%) mentioned the clinic finder feature:

> I’d say it’s an app used to search for clinics when I travel to the Eastern Cape so I don’t suffer when I run out of medication. I’d simply just search for a clinic on the app. [Participant #103]

> It is an app that can help you find clinics near you, so you don’t say you did not go to the clinic because you did not know where it was. [Participant #58]

Only 5 (2.9%) mentioned geolocation tracking or the app knowing the participant’s location, and 2 (1.2%) participants said that they did not know the app’s function. None of the participants mentioned the app notifications or staff contact via WhatsApp or phone.

**Participants’ Acceptability of the CareConekta App**

Similar to the participants’ responses regarding their understanding of the app, most of the responses regarding what participants liked about using the app were related to the clinic finder feature:

> I found it useful because I don’t have to look for clinics should I travel outside Cape Town. The app connects me to the clinics closest to me. [Participant #19]

> What I liked was that we had been looking for a pediatric clinic and got lost in a taxi, I then thought of this app, I used it and it showed me exactly where the clinic was. [Participant #029]

Some responses indicated that the participants used the clinic finder for a general map too:

> With this app I know for a fact I’d never get lost when I go somewhere. The app has a GPS function. [Participant #88]

**Initial Efficacy of the Intervention**

Although the initial efficacy of the intervention was a secondary aim of the study, we were unable to assess this because the app did not function as designed. Without receiving regular GPS heartbeats, the study team did not know when a participant was traveling; therefore, the intervention could not be initiated. During the study period, only 1 participant in the intervention arm was flagged as traveling, as defined in our protocol, and received the additional notifications, so it was not possible to assess a statistically meaningful difference between the study arms.

**Discussion**

**Principal Findings**

This is one of the first GPS-based mHealth studies—if not the first GPS-based mHealth study—targeted at improving HIV care in South Africa, and we found that several key challenges impeded its implementation. This study was designed to test the feasibility and acceptability of the CareConekta app and the initial efficacy of using it as an intervention to improve engagement in care among mobile women living with HIV. Although we were able to accomplish our primary aim of assessing the feasibility and acceptability of the intervention, we were unable to assess the efficacy of the intervention because we did not receive consistent location-tracking data. It is important to note that the app missed picking up on travel that was reported at follow-up. Although this is disappointing, we feel that the lessons learned from the implementation of this ambitious mHealth study are important and will be useful to other researchers considering mHealth interventions for low-resource settings. In designing this study, we made a conscious choice to assess our app under real-world conditions. We briefly considered providing phones—particularly to avoid bias against those who did not own phones and to guarantee a consistent technical level of device—but decided that this would not allow us to interpret the real-world applicability of our results. Similar decisions were made against providing data to
all participants. Thus, our results can be viewed as representing implementation in real-world conditions.

We developed an initial beta version of the CareConekta app and implemented it in a proof-of-concept trial in 2017. We enrolled 11 participants at the same study site. Among the 11 participants, app installation failed for 7 (64%) individuals. Because the app team was US-based, some requirements of the app did not align with the capabilities of many of the phones in use in South Africa, and we were also unable to offer real-time technological support in the event of installation difficulty. The importance of a local app development team, with available technology support, was one of the key lessons learned from this early work. We were also committed to collaborating with a local development company that works with and knows the mHealth agenda of the South African Department of Health; we wanted to be well poised for broader implementation if our app was successful. In the proof-of-concept trial, we were able to install the app on 4 participants’ phones and deploy the app for 3 months. Of the 4 participants, 1 (25%) lost her phone after approximately 1 month, but the other 3 (75%) produced heartbeats at least weekly, often daily, during the 3-month period. This sufficiently proved the concept for us to proceed with this study.

In this study, during the 15 months of intensive data monitoring, no participant had GPS heartbeats every day without interruption, which is a key indicator of study feasibility. Despite specifically designing the app such that mobility data would be stored on the app in the event of interruptions in data, the app did not function correctly and did not provide the missing data. Our attempts to troubleshoot lost GPS signals unexpectedly required substantial staff time; indeed, at least 1 staff member phoned participants every week for a year to ask about missing heartbeats. Most participants did not respond, or if they did, they requested a later callback and then still did not respond. CareConekta was designed to reverse bill, which meant that even if the mobile device had no airtime and no data, the app would still be fully functional. However, through implementation, we found that if a participant had no data at all, the app would not work. That is, for reverse billing to work properly, a small amount of data was first required. This became a major stumbling block for implementation, as the top reason cited by participants for missing GPS heartbeats was a lack of data. In addition, we received numerous reports of purchasing only WhatsApp data, a product that was unfamiliar to the researchers at the time of study design but appears to have grown in popularity during the course of our study. Although the lack of electricity was not mentioned as a reason for lost GPS heartbeats, the study period coincided with regular periods of load shedding—scheduled electricity blackouts to conserve power in South Africa—which would have impacted participants’ ability to keep their phones charged. Future mHealth studies will be wise to consider the high likelihood of the lack of data and electricity during study implementation.

Even as early as installation, difficulties arose in using the app. From our preliminary research, we knew that over 90% of our participant population used Android-based phones [20]. However, downloading and installing the app from the Google Play Store required a Google-authenticated email address, which not every participant had before enrollment. The availability of space on the phone for Google Play Store updates and the CareConekta app was also a challenge. Even after extensive troubleshooting and creating space, some phones that seemed to meet our technical specifications were still unable to successfully install CareConekta, and we had to withdraw 6 participants because of app installation failure. Despite being designed to collect heartbeats only twice per day, the app collected location data multiple times a day. This created a challenge for analysis and may have contributed to battery drain on devices.

Overall, we found that the participant acceptability of CareConekta was high, but we view this finding with caution because it does not align with the numbers of participants who reported losing phones and uninstalling the app or the high frequency of lost GPS heartbeats. It is possible that social desirability bias to report a positive experience to the interviewer influenced responses. In the follow-up responses, all participants understood the participant-facing function of the app—the clinic finder—but seemed to forget or not understand the passive geolocation tracking, despite the great efforts made to be explicit about location tracking at the time of informed consent. Future mHealth intervention developers should note that patient-facing features may be the ones that will be most understood and remembered among participants.

The proportion of phone sharing reported at follow-up (15%) is consistent with that reported at the time of enrollment (14%). This frequency of sharing is similar to another recent mHealth study in South Africa that found 11% phone sharing [33]. The possibility of phone sharing and potential lack of confidentiality should be considered when designing future mHealth studies in this setting. Relatedly, participants often reported that children who shared their phones were the ones responsible for uninstalling the app.

Ours is not the first smartphone-based study in South Africa to experience substantial feasibility challenges. A South African study conducted from 2015 to 2017 [34] was unable to meet its sample size requirements because 90.2% (n=3187) of the 3540 potential participants were ineligible at screening because of their mobile devices did not have an Android phone (n=2100, 59.3%), their phone was not working (n=506, 14.3%), or they had a wrong Android version or inadequate RAM or mobile data (n=581, 16.4%). Screening for our study is described elsewhere [31] and did not encounter similar challenges, but the implementation of our study did encounter similar issues with the lack of data, and inadequate RAM may have caused the installation challenges we experienced, as apps and photos sometimes needed to be deleted to make space for the CareConekta app. A different South African study from 2019 found that 13% of the eligible participants were unable to download the study app on their Android-based phone, 6% were unable to scan a barcode, and 3% were unable to complete app registration [33]. During implementation, the authors noted reports of a lack of data access and lost or broken phones. MomConnect, a nationwide pregnancy registry service in South Africa, demonstrated broad success by sending simple SMS text messages but noted that network timeouts and failures were frequent, resulting in 1 in 4 users dropping out of the registration.
process prematurely, and recommended that platforms such as WhatsApp be adopted to encourage flexibility in messaging [35].

To our knowledge, this is the first mHealth intervention to use location-based participant tracking in a real-world setting in South Africa. Interventions such as this are becoming increasingly common in the United States and Europe. For example, in a study focused on travel health published in 2016, a total of 101 Swiss adult travel clients planning to travel to Thailand for <5 weeks were provided a smartphone equipped with an app to passively monitor their location and administer a daily questionnaire [36]. The authors found that the app was feasible and acceptable, but 10% (n=10) of the participants had technical difficulties, and 16% (n=16) dropped out during the brief follow-up period. In a US-based study of patients who were chronically ill published in 2018, a total of 27 participants were provided with a smartphone and location-tracking watch; 6 (22%) participants dropped out before the end of the 28-day study period, some owing to the inability to use the devices [37]. Of note, the investigators offered participants a financial incentive (up to US $100) to upload their data to the study. A US-based study published in 2021 provided smartphones to 30 individuals experiencing homelessness, who were followed for 4 months, with the goal of alerting their community-based team that the participants had entered hospital or emergency care [38]. The authors found that 6 (20%) participants were withdrawn after reporting their second study-provided smartphone stolen, and overall, only 19% of the GPS data aligned with hospital data, primarily owing to participants not having the smartphone with them during the visit, the smartphone being switched off, and gaps in GPS technology. Compared with our study, these studies had smaller sample sizes, shorter follow-up periods, very different settings, and provided smartphones or financial incentives; however, it is interesting to note that similar challenges were encountered in implementation. Despite the setbacks experienced in our study and in others, given the rise in off-the-shelf location-tracking apps in recent years and the clear importance of mobility in health, we anticipate that more mHealth interventions will focus on participant movement. Indeed, the massive All of Us campaign in the United States plans to incorporate location-based data from smartphones and wearable devices, including location, cardiac rate and rhythm, and respiratory rate [39].

Some of the problems experienced with app implementation may have been avoided through clearer communication between the research team and app development or technical team. Although we thought that we had very close communication, some aspects were lost in translation. It is critically important that the research team investigating any mobile app includes someone who fully understands the technical specifications and requirements and can liaise with or translate the research vision to the app development team, as well as caution the research team on potentially problematic areas of design.

Our study has some clear limitations, primarily that the app did not function as designed because of a combination of user actions and app malfunction. Another limitation is that we conducted the study at a single site, thus potentially limiting the generalizability of our results. However, given that we attempted to mimic real-world conditions, we anticipate that our study population will be similar to other adults attending public health clinics in South Africa.

However, we feel that many important lessons learned through this experience will be useful to other researchers and make the effort worthwhile. One strength of our study is that it was among the first to develop, implement, and clearly document experiences with a GPS-based location-tracking mHealth app in a low-resource setting, particularly in a real-world setting. Thus, our findings are meaningful, even if our intervention was not successful. In addition, we report on several technical factors traditionally unreported in the literature but critical to the feasibility of mHealth interventions.

Conclusions

In conclusion, we did not demonstrate the feasibility of using a GPS-based tracking app to characterize mobility and improve engagement in HIV care. Our most common problems that contributed to failure were a lack of mobile phone data, app uninstallations, phone changes, and missing heartbeat data. We are far less motivated to create a novel app in our future research endeavors and instead will use tools that people already are using, particularly WhatsApp, which all of our participants reported as their favorite app [31]. Although some of our participants had no data for other apps, they were buying data specifically for WhatsApp. By using apps that are already essential to participants’ lives, researchers developing future studies can become better poised to ensure continuous engagement with the apps and decrease the likelihood of the apps being uninstalled. Careful translation of research aims into app design is essential in the development of future studies. In addition, the mHealth landscape is changing rapidly, and it is possible that Wi-Fi and internet availability will increase in the future, thus overcoming some of the challenges we experienced. We anticipate that mHealth interventions will continue to proliferate in resource-limited settings, such as our study setting, and our study results may offer guidance and words of caution for unanticipated challenges.

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The authors are most grateful to the study participants, without whom this work would not have been possible.

**Conflicts of Interest**

None declared.

Multimedia Appendix 1

CONSORT-eHEALTH checklist (V 1.6.1).

[PDF File (Adobe PDF File), 4263 KB - mhealth_v11i1e44945_app1.pdf](https://mhealth.jmir.org/2023/1/e44945)

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Using Chatbot Technology to Improve Brazilian Adolescents’ Body Image and Mental Health at Scale: Randomized Controlled Trial

Emily L Matheson¹, PhD; Harriet G Smith¹, MSc; Ana C S Amaral², PhD; Juliana F F Meireles³, PhD; Mireille C Almeida⁴, MD, PhD; Jake Linardon⁵, PhD; Matthew Fuller-Tyszkiewicz⁶, PhD; Phillippa C Diedrichs¹, PhD

¹Centre for Appearance Research, University of the West of England, Bristol, United Kingdom
²Federal Institute of Education, Science and Technology of Southeast of Minas Gerais, Barbacena, Brazil
³Department of Family and Community Medicine, School of Community Medicine, University of Oklahoma Health Science Center, Tulsa, OK, United States
⁴Department of Psychiatry, Universidade Federal de São Paulo, São Paulo, Brazil
⁵School of Psychology, Deakin University, Geelong, Victoria, Australia
⁶Center for Social and Early Emotional Development, Deakin University, Burwood, Victoria, Australia

Corresponding Author:
Emily L Matheson, PhD
Centre for Appearance Research
University of the West of England
Coldharbour Ln
Bristol, BS16 1QY
United Kingdom
Phone: 44 1173284398
Email: emily.matheson@uwe.ac.uk

Abstract

Background: Accessible, cost-effective, and scalable mental health interventions are limited, particularly in low- and middle-income countries, where disparities between mental health needs and services are greatest. Microinterventions (ie, brief, stand-alone, or digital approaches) aim to provide immediate reprieve and enhancements in mental health states and offer a novel and scalable framework for embedding evidence-based mental health promotion techniques into digital environments. Body image is a global public health issue that increases young peoples’ risk of developing more severe mental and physical health issues. Embedding body image microinterventions into digital environments is one avenue for providing young people with immediate and short-term reprieve and protection from the negative exposure effects associated with social media.

Objective: This 2-armed, fully remote, and preregistered randomized controlled trial assessed the impact of a body image chatbot containing microinterventions on Brazilian adolescents’ state and trait body image and associated well-being outcomes.

Methods: Geographically diverse Brazilian adolescents aged 13-18 years (901/1715, 52.54% girls) were randomized into the chatbot or an assessment-only control condition and completed web-based self-assessments at baseline, immediately after the intervention time frame, and at 1-week and 1-month follow-ups. The primary outcomes were mean change in state (at chatbot entry and at the completion of a microintervention technique) and trait body image (before and after the intervention), with the secondary outcomes being mean change in affect (state and trait) and body image self-efficacy between the assessment time points.

Results: Most participants who entered the chatbot (258/327, 78.9%) completed ≥1 microintervention technique, with participants completing an average of 5 techniques over the 72-hour intervention period. Chatbot users experienced small significant improvements in primary (state: $P<.001$, Cohen $d=0.30$, 95% CI 0.25-0.34; and trait body image: $P=.02$, Cohen $d$ range=0.10, 95% CI 0.01-0.18, to 0.26, 95% CI 0.13-0.32) and secondary outcomes across various time points (state: $P<.001$, Cohen $d=0.28$, 95% CI 0.22-0.33; trait positive affect: $P=.02$, Cohen $d$ range=0.15, 95% CI 0.03-0.27, to 0.23, 95% CI 0.08-0.37; negative affect: $P=.03$, Cohen $d$ range=−0.16, 95% CI −0.30 to −0.02, to −0.18, 95% CI −0.33 to −0.03; and self-efficacy: $P=.02$, Cohen $d$ range=0.14, 95% CI 0.03-0.25, to 0.19, 95% CI 0.08-0.32) relative to the control condition. Intervention benefits were moderated by baseline levels of concerns but not by gender.

Conclusions: This is the first large-scale randomized controlled trial assessing a body image chatbot among Brazilian adolescents. Intervention attrition was high (531/858, 61.9%) and reflected the broader digital intervention literature; barriers to engagement
were discussed. Meanwhile, the findings support the emerging literature that indicates microinterventions and chatbot technology are acceptable and effective web-based service provisions. This study also offers a blueprint for accessible, cost-effective, and scalable digital approaches that address disparities between health care needs and provisions in low- and middle-income countries.

**Trial Registration:** Clinicaltrials.gov NCT04825184; http://clinicaltrials.gov/ct2/show/NCT04825184

**International Registered Report Identifier (IRRID):** RR2-10.1186/s12889-021-12129-1

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**KEYWORDS**
adolescent; Brazil; body image; chatbot; microintervention; randomized controlled trial; mobile phone

### Introduction

#### Background

Accessible, cost-effective, and scalable mental health interventions are limited, particularly in low- and middle-income countries (LMICs), where disparities between mental health needs and services are greatest [1,2]. Digital interventions offer a unique opportunity to address this gap, particularly among adolescents. For instance, in Brazil, 91% of those aged 9 to 17 years have internet access, with 88% of internet users having a social media profile [3]. Brazilian adolescents use social media for an average of 4 hours per day [4], with most (53.2%) reporting problematic smartphone behaviors including overuse, preoccupation, and withdrawal [5]. Despite this high level of exposure to potentially harmful social media content, digital environments have been underused to connect with and provide Brazilian adolescents with evidence-based mental health and well-being resources, particularly regarding body image.

Body image concerns are a potent risk factor for eating disorders, with this group of mental health concerns incurring a yearly economic cost of US $149 billion in the United States alone [6,7]. Costs are also likely to rise owing to the impact of the global COVID-19 pandemic on body and eating concerns [8]; thus, accessible, cost-effective, and scalable prevention and intervention approaches are critical, particularly for already underserved countries. For instance, body image concerns are a global phenomenon and are reported across various countries and cultures [9]. However, advancements in body image research and the availability of evidence-based prevention and intervention vary greatly between countries. In some countries, body image is an unexplored construct; in others, there are a handful of prevalence studies; or in the case of high-income, English-speaking countries with majority White population, there is an abundance of research on prevalence, causation, prevention, and intervention [10]. This disparity in research does not reflect the prevalence or severity, with body image concerns in LMICs comparable with those in high-income countries [8,10]. Furthermore, owing to political and economic disparities and competing priorities, research and early intervention efforts for body image in LMICs are largely unfunded, unexplored, and unaddressed.

#### Previous Work

In Brazil, 8 in 10 young people report body image concerns, with 1 in 5 reporting engagement in disordered eating and unhealthy weight control behaviors [11,12]. However, to date, only 2 body image interventions have been evaluated among Brazilian populations and neither are widely available [13,14]. This is, in part, owing to the intervention modality and the historical and current funding restrictions experienced by Brazilian researchers. First, both interventions involve in-person implementation in group settings; therefore, their sustainability is reliant on human and infrastructural resources. Second, in 2017, the Brazilian government reduced its health budget by US $210 million, with spending cuts of 15% for public universities and 45% for scientific research [15]. Therefore, developing innovative and sustainable evidence-based body image interventions is a challenge for Brazilian researchers. One way to overcome these barriers is to use international partnerships among academia, industry, and community. Such partnerships afford the creation of accessible, cost-effective, and scalable interventions that reach those in need and, in turn, reduce health care disparities.

Chatbot technology offers an innovative pathway for engaging young people with evidence-based resources. In a recent review, 11 mental health chatbots were identified across 12 studies, with the majority targeting affective disorders, including anxiety and depression (eg, Woebot) [1]. The chatbots used predefined rules or decision trees (8 out of 12 studies), machine learning, or artificial intelligence (4 out of 12 studies), and half were personified with an avatar. Although the chatbots showed promise as an effective and safe intervention modality, the review heeded caution about their clinical significance relative to treatment as usual and, therefore, concluded that greater research is needed to draw solid conclusions about this emerging service provision. Furthermore, all studies were conducted in high-income countries (eg, Australia, China, Sweden, and the United States), and therefore, the authors called for concerted research efforts in LMICs, stating that there is a greater need for this technology in countries where the shortage of mental health professionals is the highest. To date, no chatbot has been developed for or tested among Brazilians.

Topity, a new Brazilian body image chatbot hosted on Facebook Messenger, comprises 8 microintervention techniques that address risk and protective factors for body image [16-18]. Microinterventions are generally designed as brief, digital, and self-guided approaches that use in-the-moment techniques to provide immediate symptom relief or enhancement [19]. To date, this intervention model has been predominantly developed for and tested among adult samples with body image and mood concerns, with techniques including brief web-based written tasks and instructional audio and video clips [20,21]. More recently, microinterventions have been developed and applied to young people (eg, short films and web-based games), with
these approaches proving acceptable and effective at eliciting immediate and short-term improvements in body image and mood [22,23].

During the Topity experience, users are given the choice to interact with either an avatar of a young woman (Dandara) or a man (Gabriel). The chatbot uses predefined rules and gamification to guide users through the completion of 8 microinterventions, which are clustered into 3 themes (Family, Friends and Body Image [2 techniques]; Social Media and Body Image [4 techniques]; and Body Appreciation and Functionality [2 techniques]). The microinterventions were informed by and adapted from existing body image interventions that have been traditionally delivered in hard copy (eg, self-help books) or in-person settings (eg, individual therapy or group-based programs). These techniques teach users how to critically analyze and evaluate social media content to reduce vulnerability to negative influences (ie, media literacy) [16], identify and challenge unhelpful thinking styles and behaviors that perpetuate body image distress (ie, cognitive behavior theory for body image) [17], and appreciate the features and functions of the body beyond appearance (ie, positive body image and embodiment theory) [18]. Each technique takes between 5 and 10 minutes to complete and has a distinct beginning and end. Access to microintervention techniques is gamified, with users needing to complete an initial technique within a thematic cluster before “unlocking” more activities. For example, in the Family, Friends and Body Image cluster, users need to complete the Banish Body Talk microintervention before being able to access and complete the Dealing with Provocative People microintervention. Gamification is a key feature of digital interventions because of its effect on users’ motivation, engagement, and skill mastery [24]. An overview of the cocreation process for Topity and a summary of the microintervention techniques are reported in Tables 1 and 2 of the protocol, respectively [25].

Topity is 1 of the 4 body- and eating-related chatbots that have been developed in recent years. The other 3 bots, including KIT [26], Tessa [27], and Alex [28], target English-speaking populations and offer different service provisions. Furthermore, each chatbot is at a different phase of the development or testing process (eg, user experience vs effectiveness). First, KIT addresses body and eating concerns by providing users with psychoeducation, help seeking, and coping strategies. It was highly acceptable among users in Australia, and its effectiveness has been reported in gray literature [26]. Second, Tessa features the Body Positive program, which is a distilled version of the cognitive-behavioral therapy web-based program, Student Bodies, and comprises 8- × 10-minute conversations with the chatbot [27]. Body Positive has proven effective at reducing weight and shape concerns among at-risk American women (mean age 21, SD 3.09 years) and shows potential for reducing the onset of eating disorders. Finally, and most recently, Alex was developed to increase treatment motivation and the use of mental health services among individuals who screen positive for an eating disorder and are not yet in treatment [28]. Alex is currently undergoing efficacy testing [29].

Our Study
This 2-armed, fully remote randomized controlled trial (RCT) addresses several gaps within the limited but emerging field of mental health chatbots. It is the first body image chatbot for non–English-speaking users and one of the first studies to assess a chatbot in an LMIC [1]. Specifically, this trial evaluated the effectiveness of Topity in eliciting immediate and short-term improvements in adolescents’ state- and trait-based body image, affect, and self-efficacy in managing body image concerns. Research hypotheses were prespecified on page 3 of the protocol [25] and were formulated for overall chatbot efficacy (hypotheses 1-2), moderation effects within subsamples (hypothesis 3), and intervention engagement and adherence (hypothesis 4):

1. Hypothesis 1: the chatbot was designed to provide immediate benefits to users. Therefore, it is anticipated that adolescents will experience improvements in state-based body satisfaction and affect at the time of engaging with the chatbot.
2. Hypothesis 2: adolescents randomized into the intervention condition will experience greater improvements in trait-based body esteem, affect, and body image self-efficacy immediately after the intervention time frame (eg, postintervention assessment) and at the 1-week and 1-month follow-ups relative to the assessment-only control condition.
3. Hypothesis 3: on the basis of previous research on the moderating effects of gender [30] and trait psychopathology [23,31] on body image intervention effectiveness, it was hypothesized that intervention effects will be moderated by gender and baseline levels of body esteem, affect, and body image self-efficacy. Specifically, intervention effects will be greatest among girls, girls and boys with lower levels of trait body esteem and body image self-efficacy, and girls and boys with higher levels of trait negative affect.
4. Hypothesis 4: with regard to user engagement and adherence, given the novelty of this intervention, analyses will be exploratory. However, it is anticipated that greater engagement and adherence with chatbot interventions will lead to greater improvements in trait-based outcomes.

Methods
Study Design
The study was a 2-armed, fully remote, and preregistered RCT conducted between April 7 and August 8, 2021, in Brazil. Details of the study rationale and protocol have been published elsewhere [25]. The research was conducted in accordance with ethical standards and guidelines for conducting research on young people in Brazil. Before obtaining consent and assent, parents and participants were provided with an information sheet outlining the research procedures and associated risks, respectively. Consent withdrawal was possible at any time without cause for justification. At study completion, participants were provided with a debrief form disclosing research aims, ancillary mental health resources and an electronic voucher of R$100 (approximately US $20) and R$80 (approximately US $15) for the intervention and control conditions, respectively.
Data were anonymized and accessed only by the authoring research team using masked and password-protected data files.

**Ethics Approval and Trial Registration**

This study received ethics approval from the Instituto Federal de Educação, Ciência e Tecnologia do Sudeste de Minas Gerais (4.232.804); Comissão Nacional de Ética em Pesquisa (4.582.466); and the University of the West of England (HAS 19.12.090). The study was registered with ClinicalTrials.gov (NCT04825184) [32].

**Participants**

The participants were recruited from diverse ethnic, geographic, and socioeconomic backgrounds across Brazil. Recruitment was conducted via a Brazilian research agency (ie, via email to their participant databases) and United Nations International Children’s Emergency Fund’s web-based communication platforms (eg, U-Report; a free tool for community participation). Eligible participants were adolescents aged 13 to 18 years who spoke Brazilian Portuguese, were a Brazilian resident, and had access to Facebook Messenger.

**Randomization and Masking**

Participants were randomly assigned 1:1 to receive either the chatbot intervention or an assessment-only control. The randomization scheme was generated by a research agency using a validated computer software. Blinding of the participants was not possible because of the nature of the intervention. The risk of bias from researchers was minimized because of no contact with participants during the trial (ie, recruitment; randomization, survey dissemination, and compensation was completed by the research agency). Data analysts were blinded when conducting analyses of primary and secondary trait outcomes; however, this was not possible for primary and secondary state measures because of the within-group design.

**Procedure**

Following parental consent and participant assent, eligible participants completed preintervention self-assessments via a closed web-based survey (received via email), after which they were randomized into the intervention or control conditions. The web-based survey underwent user testing before the trial began and the research agency monitored the response rate and completion. Those in the intervention condition received a unique access link to the chatbot, 24 hours after randomization, and were encouraged to interact with the intervention as much as possible over the next 72-hour period (Figure 1). The unique access code was only compatible with the assigned user’s Facebook Messenger, thus ensuring confidential interactions between the user and chatbot and prohibiting nonparticipants from entering the chatbot during the trial period. The control condition received “standard online care” for body image concerns among Brazilian adolescents, which at present is no intervention. Initially, Topity users had access to 3 of the 8 microintervention techniques (eg, the first technique from each thematic cluster), and once completed, they gained access to the next technique in the cluster. Therefore, once a technique was unlocked, there were no limits to the number of completions. The ordering of techniques was informed by the difficulty of the microintervention concept and skill, whereby users mastered easier concepts and skills (eg, psychoeducation) before progressing to those that were more challenging (eg, behavior and cognition change). Upon entering the chatbot and after completing a microintervention technique, users were assessed for state body satisfaction and affect. In the event that participants did not engage with the bot after 12, 16, and 23.5 hours, they received a Facebook Messenger notification encouraging participation. At the completion of the 72-hour intervention period, all participants were sent postintervention surveys and again at the 1-week and 1-month time points. During the 1-month follow-up period, all participants were provided with contact details for accessible mental health support services in Brazil, and the control condition was invited to interact with Topity; however, their engagement was not monitored or assessed for effectiveness. The participants received an electronic voucher of R$100 (approximately US $20) and R$80 (approximately US $15) for the intervention and control condition, respectively. Although participants were aware that they would receive compensation at study commencement, the compensation amount was not disclosed until study completion.
Outcomes
A comprehensive overview of the outcome measures is provided in Table 3 of the protocol [25]. The primary outcome measures were the mean change in state (ie, a single 11-point scale) and trait (ie, Body Esteem Scale for Adolescents and Adults Brazil [33]) body image—specifically, the mean change in state body satisfaction between chatbot entry and at the completion of a microintervention technique and the mean change in trait body esteem between preintervention and postintervention assessments. Secondary outcomes included the mean change in state affect (ie, a single 11-point scale), trait positive and negative affect (ie, the Positive and Negative Affect Scale for Children 8-item [34]), and self-efficacy in addressing body image concerns (ie, The Body Image Self-Efficacy Scale [35-37]). Treatment adherence (eg, ≥1 microintervention technique) and user acceptability were also assessed after the intervention time frame.

Statistical Analysis
Statistical analyses were prespecified on pages 10 and 11 of the protocol [25]. Specifically, missing data were handled using multiple imputations (m=50) with chained equations, and participants were retained in the group they were assigned to at baseline, consistent with the principles of intention-to-treat. Linear mixed models were used to test our hypotheses. For hypothesis 1, scores on state-based outcomes were regressed onto a time variable (coded 0=precontent; 1=postcontent) for the intervention arm only. For hypotheses 2 to 4, trait-level outcome variables were regressed onto a time variable (dummy coded as baseline vs after the intervention, 1-week follow-up, and 1-month follow-up), group (0=control; 1=intervention), and an interaction between time and group to evaluate efficacy. Random effects were included for time and an unstructured covariance matrix was used to estimate the covariance among these random effects. Hypotheses 3 and 4 included the moderators of these random effects over time.

Protocol Amendments
Owing to the recruitment processes being heavily reliant on parents’ literacy levels to provide informed consent, a video communicating the study information was embedded into the recruitment materials. This amendment was implemented 2 weeks into recruitment, following feedback from stakeholders that the original recruitment methods were restrictive. Furthermore, the recruitment phase was extended from 2 to 12 weeks because of slow uptake. Extensions were incrementally increased as part of the review process (eg, every 2 weeks). This rate was somewhat accelerated by adapting the recruitment materials; however, given that the trial was conducted during the peak of the COVID-19 pandemic in Brazil, there are likely several contextual factors outside the researchers’ control that led to lower than anticipated uptake (eg, screen and social media fatigue) [38].

Results
Baseline Characteristics
The baseline characteristics of the participants are presented in Table 1. There was an approximately equal number of girls and boys and a nationally representative distribution across ethnicity and region. There were no notable differences and negligible effect sizes on any baseline variables between the intervention and control groups, indicating that the randomization process was successful.
Table 1. Baseline characteristics of the sample.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Total sample (N=1715)</th>
<th>Intervention (n=858)</th>
<th>Control (n=857)</th>
<th>P value</th>
<th>ES&lt;sup&gt;b&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years), n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>276 (16.1)</td>
<td>135 (15.7)</td>
<td>141 (16.5)</td>
<td>.29</td>
<td>0.06</td>
</tr>
<tr>
<td>14</td>
<td>237 (13.8)</td>
<td>108 (12.6)</td>
<td>129 (15.1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>230 (13.4)</td>
<td>124 (14.5)</td>
<td>106 (12.4)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>255 (14.9)</td>
<td>140 (16.3)</td>
<td>115 (13.4)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>220 (12.8)</td>
<td>109 (12.7)</td>
<td>11 (1.3)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>497 (29)</td>
<td>242 (28.2)</td>
<td>255 (29.8)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender, n (%)</td>
<td></td>
<td></td>
<td></td>
<td>.64</td>
<td>0.02</td>
</tr>
<tr>
<td>Boy</td>
<td>801 (46.7)</td>
<td>406 (47.3)</td>
<td>395 (46.1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Girl</td>
<td>901 (52.5)</td>
<td>447 (52.1)</td>
<td>454 (53)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender diverse</td>
<td>13 (0.8)</td>
<td>5 (0.6)</td>
<td>8 (0.9)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ethnicity, n (%)</td>
<td></td>
<td></td>
<td></td>
<td>.91</td>
<td>0.03</td>
</tr>
<tr>
<td>Asian</td>
<td>40 (2.3)</td>
<td>23 (2.7)</td>
<td>17 (2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>181 (10.6)</td>
<td>92 (10.7)</td>
<td>89 (10.4)</td>
<td></td>
<td></td>
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<tr>
<td>Indigenous</td>
<td>14 (0.8)</td>
<td>8 (0.9)</td>
<td>6 (0.7)</td>
<td></td>
<td></td>
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<tr>
<td>Mixed race</td>
<td>630 (36.7)</td>
<td>314 (36.6)</td>
<td>316 (36.9)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>845 (49.3)</td>
<td>419 (48.8)</td>
<td>426 (49.7)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>5 (0.3)</td>
<td>2 (0.2)</td>
<td>3 (0.4)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region, n (%)</td>
<td></td>
<td></td>
<td></td>
<td>.68</td>
<td>0.03</td>
</tr>
<tr>
<td>North</td>
<td>92 (5.4)</td>
<td>50 (5.8)</td>
<td>42 (4.9)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Northeast</td>
<td>348 (20.3)</td>
<td>176 (20.5)</td>
<td>172 (20.1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Central west</td>
<td>134 (7.8)</td>
<td>60 (7)</td>
<td>74 (8.6)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Southeast</td>
<td>906 (52.8)</td>
<td>452 (52.7)</td>
<td>454 (53)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>South</td>
<td>235 (13.7)</td>
<td>120 (14)</td>
<td>115 (13.4)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline variables, mean (SD)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Appearance positive</td>
<td>3.33 (0.83)</td>
<td>3.36 (0.84)</td>
<td>3.31 (0.83)</td>
<td>.24</td>
<td>0.05</td>
</tr>
<tr>
<td>Appearance negative</td>
<td>3.34 (1.08)</td>
<td>3.36 (1.08)</td>
<td>3.33 (1.08)</td>
<td>.64</td>
<td>0.02</td>
</tr>
<tr>
<td>Weight</td>
<td>3.11 (1.18)</td>
<td>3.10 (1.19)</td>
<td>3.12 (1.17)</td>
<td>.70</td>
<td>0.01</td>
</tr>
<tr>
<td>Positive affect</td>
<td>3.55 (0.96)</td>
<td>3.56 (0.97)</td>
<td>3.54 (0.96)</td>
<td>.58</td>
<td>0.02</td>
</tr>
<tr>
<td>Negative affect</td>
<td>2.52 (0.98)</td>
<td>2.50 (0.96)</td>
<td>2.54 (0.99)</td>
<td>.37</td>
<td>0.04</td>
</tr>
<tr>
<td>Body image self-efficacy</td>
<td>64.73 (22.18)</td>
<td>65.71 (22.04)</td>
<td>63.75 (22.28)</td>
<td>.07</td>
<td>0.08</td>
</tr>
</tbody>
</table>

<sup>a</sup>Test statistic: chi-square for nominal variables and 2-tailed t tests for continuous variables.

<sup>b</sup>ES: effect size (phi coefficient for nominal variables and Cohen d for continuous variables).

Attrition, Adherence, and Acceptability

The participant flow diagram is shown in Figure 2. Of the 1715 participants, 798 (46.53%) provided postintervention data, 580 (33.82%) provided 1-week follow-up data, and 459 (26.76%) provided 1-month follow-up data. The intervention group had significantly higher drop-out rates at the postintervention assessment point, relative to the control condition (503/858, 58.6% vs 414/857, 48.3%; P < .001; However, the study condition was not significantly associated with dropout at 1 week (586/858, 68.3% vs 579/857, 64.1%) or 1 month (611/858, 71.2% vs 645/857, 75.3%) follow-up (P values >.05). Participants who dropped out at the primary time point (after the intervention time frame) were compared with those who completed the baseline variables (Table 2). Dropouts reported significantly lower weight esteem scores at baseline than completers. Notable differences also existed in age (those aged 18 years were the most likely to drop out), ethnicity (Indigenous participants were the most likely to drop out), and region (those from the central west region were the least likely to drop out).

Of the 858 participants randomized into the intervention group, 327 (38.1%) entered the chatbot, and of those 327 participants,
258 (78.9%) completed 1 or more microintervention techniques, thus meeting treatment adherence. On average, participants completed 5 techniques over the 72-hour intervention period, with a minimum of 1 and a maximum of 17 completed across participants. Finally, most participants (251/327, 77%) selected Dandara as their avatar, and 155 of the postintervention responses included acceptability data, with Topity receiving an overall score of 6.07 out of 7.

Figure 2. Research design and participant flow using CONSORT (Consolidated Standards of Reporting Trials) eHealth guidelines.
Table 2. Comparisons of dropouts and completers after the intervention time frame on baseline variables.

<table>
<thead>
<tr>
<th>Variables^a</th>
<th>Dropout T2^b</th>
<th>Completer T2</th>
<th>P value</th>
<th>ES^c</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender, n (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Boy (n=801)</td>
<td>442 (55.2)</td>
<td>359 (44.8)</td>
<td>.32</td>
<td>0.03</td>
</tr>
<tr>
<td>Girl (n=901)</td>
<td>467 (51.8)</td>
<td>434 (48.2)</td>
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<td></td>
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<tr>
<td>Gender diverse (n=13)</td>
<td>8 (61.5)</td>
<td>5 (38.5)</td>
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</tr>
<tr>
<td><strong>Age (years), n (%)</strong></td>
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<td>&lt;.001</td>
<td>0.30</td>
</tr>
<tr>
<td>13 (n=276)</td>
<td>118^d (42.8)</td>
<td>158^d (57.2)</td>
<td></td>
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</tr>
<tr>
<td>14 (n=237)</td>
<td>107^d (45.1)</td>
<td>130^d (54.9)</td>
<td></td>
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</tr>
<tr>
<td>15 (n=230)</td>
<td>93^d (40.4)</td>
<td>137^d (59.6)</td>
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</tr>
<tr>
<td>16 (n=255)</td>
<td>115^d (45.1)</td>
<td>140^d (54.9)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>17 (n=220)</td>
<td>102^d (46.4)</td>
<td>118^d (53.6)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18 (n=497)</td>
<td>382^d (76.9)</td>
<td>115^d (23.1)</td>
<td></td>
<td></td>
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<td><strong>Ethnicity, n (%)</strong></td>
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<td>0.08</td>
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<td>Asian (n=40)</td>
<td>23 (57.5)</td>
<td>17 (42.5)</td>
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</tr>
<tr>
<td>Black (n=181)</td>
<td>99 (54.7)</td>
<td>82 (45.3)</td>
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<tr>
<td>Indigenous (n=14)</td>
<td>12^d (85.7)</td>
<td>2^d (14.3)</td>
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<tr>
<td>Mixed race (n=630)</td>
<td>355 (56.3)</td>
<td>275 (43.7)</td>
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<tr>
<td>White (n=845)</td>
<td>426^d (50.4)</td>
<td>419^d (49.6)</td>
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<td></td>
</tr>
<tr>
<td>Other (n=5)</td>
<td>2 (40)</td>
<td>3 (60)</td>
<td></td>
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</tr>
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<td><strong>Region, n (%)</strong></td>
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<td>0.09</td>
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<tr>
<td>North (n=92)</td>
<td>57 (62)</td>
<td>35 (38)</td>
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<tr>
<td>Northeast (n=348)</td>
<td>202 (58)</td>
<td>146 (42)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Central west (n=134)</td>
<td>58^d (43.3)</td>
<td>76^d (56.7)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Southeast (n=906)</td>
<td>464^d (51.2)</td>
<td>442^d (48.8)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>South (n=235)</td>
<td>136 (57.9)</td>
<td>99 (42.1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Baseline, mean (SD)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Appearance positive</td>
<td>3.31 (0.81)</td>
<td>3.36 (0.86)</td>
<td>.22</td>
<td>0.05</td>
</tr>
<tr>
<td>Appearance negative</td>
<td>3.37 (1.07)</td>
<td>3.31 (1.08)</td>
<td>.20</td>
<td>0.05</td>
</tr>
<tr>
<td>Weight</td>
<td>3.03 (1.17)</td>
<td>3.20 (1.18)</td>
<td>.003</td>
<td>0.14</td>
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<tr>
<td>Positive affect</td>
<td>3.57 (0.98)</td>
<td>3.54 (0.95)</td>
<td>.52</td>
<td>0.03</td>
</tr>
<tr>
<td>Negative affect</td>
<td>2.54 (0.98)</td>
<td>2.50 (0.98)</td>
<td>.41</td>
<td>0.04</td>
</tr>
<tr>
<td>Body image self-efficacy</td>
<td>64.32 (22.15)</td>
<td>65.21 (22.21)</td>
<td>.41</td>
<td>0.04</td>
</tr>
</tbody>
</table>

^aTest statistic: chi-square for nominal variables and 2-tailed t tests for continuous variables.
^bT2 refers to the postintervention time point.
^cES: effect size (phi coefficient for nominal variables and Cohen d for continuous variables).
^dWhen groups significantly differed in a pairwise Bonferroni corrected significance test.

**Main Statistical Analyses**

**Hypothesis 1**

Hypothesis one tested whether engagement with the chatbot produced immediate increases in the state of body satisfaction and positive affect. The results revealed significant main effects of time on satisfaction (unstandardized coefficient, \( b=0.60, 95\% CI 0.50-0.70; P<.001 \); Cohen \( d=0.30 \)) and affect (\( b=0.51, 95\% CI 0.41-0.61; P<.001 \); Cohen \( d=0.28 \)), indicating that participants reported momentary improvements in these outcomes immediately following exposure to chatbot microintervention techniques.
Hypothesis 2

Overview

Hypothesis 2 tested the differences in primary and secondary trait outcomes immediately after the intervention and at the 2 follow-up points. The results of these analyses are presented in Table 3.

Table 3. Means, SDs, and change scores on outcomes between study groups.

<table>
<thead>
<tr>
<th>Outcomes</th>
<th>Study group</th>
<th>Difference in change score</th>
<th>Cohen d</th>
<th>P value (2-tailed)</th>
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</thead>
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<td>Experimental</td>
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<td>Values, n</td>
<td>Values, mean (SD) b</td>
<td>Values, n</td>
<td>Values, mean (SD)</td>
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<tr>
<td>Primary outcome</td>
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<tr>
<td>Appearance positive</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>857</td>
<td>3.31 (0.83)</td>
<td>858</td>
<td>3.36 (0.85)</td>
</tr>
<tr>
<td>Postintervention</td>
<td>443</td>
<td>3.32 (0.86)</td>
<td>355</td>
<td>3.52 (0.84)</td>
</tr>
<tr>
<td>1-week follow-up</td>
<td>308</td>
<td>3.39 (0.88)</td>
<td>272</td>
<td>3.67 (0.85)</td>
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<tr>
<td>1-month follow-up</td>
<td>246</td>
<td>3.35 (0.88)</td>
<td>213</td>
<td>3.74 (0.81)</td>
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<tr>
<td>Appearance negative</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>857</td>
<td>3.34 (1.09)</td>
<td>858</td>
<td>3.36 (1.08)</td>
</tr>
<tr>
<td>Postintervention</td>
<td>443</td>
<td>3.29 (1.09)</td>
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<td>3.46 (1.07)</td>
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<td>3.58 (1.12)</td>
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<tr>
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<td>3.32 (1.11)</td>
<td>213</td>
<td>3.6 (1.03)</td>
</tr>
<tr>
<td>Weight</td>
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<td>3.12 (1.17)</td>
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<td>3.1 (1.19)</td>
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<td>355</td>
<td>3.35 (1.1)</td>
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<td>1-week follow-up</td>
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<td>3.28 (1.1)</td>
<td>272</td>
<td>3.54 (1.12)</td>
</tr>
<tr>
<td>1-month follow-up</td>
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<td>3.33 (1.1)</td>
<td>213</td>
<td>3.65 (1.02)</td>
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<td></td>
<td></td>
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<tr>
<td>Baseline</td>
<td>857</td>
<td>3.54 (0.96)</td>
<td>858</td>
<td>3.57 (0.98)</td>
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<td>3.55 (0.94)</td>
<td>355</td>
<td>3.72 (0.93)</td>
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<td>3.82 (1.01)</td>
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<td>1-month follow-up</td>
<td>246</td>
<td>3.6 (0.96)</td>
<td>213</td>
<td>3.93 (0.91)</td>
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<tr>
<td>Negative affect</td>
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<td></td>
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<td></td>
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<tr>
<td>Baseline</td>
<td>857</td>
<td>2.54 (0.99)</td>
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<td>2.5 (0.97)</td>
</tr>
<tr>
<td>Postintervention</td>
<td>443</td>
<td>2.45 (1.01)</td>
<td>355</td>
<td>2.34 (1.03)</td>
</tr>
<tr>
<td>1-week follow-up</td>
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<td>2.42 (1.06)</td>
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<td>2.23 (1.05)</td>
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<tr>
<td>1-month follow-up</td>
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<td>2.37 (1.02)</td>
<td>213</td>
<td>2.15 (1.01)</td>
</tr>
<tr>
<td>Body image self-efficacy</td>
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<tr>
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<td>857</td>
<td>63.76 (22.28)</td>
<td>858</td>
<td>65.72 (22.05)</td>
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<tr>
<td>Postintervention</td>
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<td>355</td>
<td>70.44 (21.7)</td>
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<tr>
<td>1-week follow-up</td>
<td>308</td>
<td>67.27 (23.36)</td>
<td>272</td>
<td>73.37 (21.41)</td>
</tr>
<tr>
<td>1-month follow-up</td>
<td>246</td>
<td>67.83 (24.29)</td>
<td>213</td>
<td>76.43 (20.21)</td>
</tr>
</tbody>
</table>

aExperimental-control: calculation of the mean difference between groups by subtracting the control group's mean from the experimental group's mean.
bMean (SD) values are based on nonimputed data; mean differences and effect sizes were derived from the intention-to-treat analysis.
cN/A: not applicable.
After the Intervention Time Frame

For the primary outcome of body esteem, significant mean differences were observed for the appearance positive (Cohen \(d=0.13; P=.02\)) and negative (Cohen \(d=0.11; P=.047\)) subscales, in favor of the intervention group experiencing improvements. A significant mean difference was not observed for the weight subscale (Cohen \(d=0.01; P=.75\)). Nonsignificant mean differences between the 2 groups immediately after the intervention were also observed for the secondary outcomes of positive affect (Cohen \(d=0.09\), negative affect (Cohen \(d=-0.07\)), and body image self-efficacy (Cohen \(d=0.14\)).

Follow-Up

As seen in Table 3, significant mean differences were observed at both the 1-week and 1-month follow-up on all primary and secondary outcomes, except for the weight subscale at the 1-week follow-up. In all cases, the intervention group experienced greater improvements in these constructs than the control group. Effect sizes were small, ranging from Cohen \(d=0.10\) to Cohen \(d=0.26\).

Hypothesis 3

Hypothesis 3 tested whether mean differences in trait outcomes at each time point were moderated by participant gender and baseline severity. The results of these analyses are shown in Tables S1 and S2 in Multimedia Appendix 1.

Participant gender was not a notable moderator for any outcome variable immediately after the intervention time frame or at any of the 2 follow-up periods. However, there is some evidence to suggest that baseline levels of a particular outcome significantly affect responsiveness to the intervention. In particular, those with lower body esteem (on all 3 subscales), lower positive affect, and lower body image self-efficacy experienced greater intervention benefits than those with higher levels on these outcome variables. This occurred at all 3 time points for the appearance positive subscale, at the 1-week and 1-month follow-ups for the appearance negative and weight subscales and body image self-efficacy, and only at the 1-month follow-up for positive affect.

Hypothesis 4

Hypothesis 4 tested whether there were any relationships between the 4 indices of chatbot use and the level of improvement in the primary and secondary outcomes. The results of these analyses are presented in Table S3 in Multimedia Appendix 1. We did not observe any notable relationships between the levels of chatbot use and the primary and secondary outcomes immediately after the intervention time frame and follow-up periods.

Discussion

Principal Findings

This 2-armed, fully remote RCT was the first to assess body image chatbot among Brazilian adolescents. These findings indicate that a chatbot containing microinterventions is an effective approach for eliciting small notable improvements in state- and trait-based outcomes for body image and associated well-being constructs. Girls and boys aged 13 to 18 years experienced small but substantial improvements in state body satisfaction and positive affect immediately following engagement with Topity techniques. Users also reported small notable improvements in trait-based body esteem, positive and negative affect, and body image self-efficacy relative to the assessment-only control condition. These group differences were observed at all 3 time points for the appearance positive and negative subscales of the Body Esteem Scale for Adolescents and Adults, and at 1-week and 1-month follow-ups for positive and negative affect and body image self-efficacy. Group differences in the weight subscale of the Body Esteem Scale for Adolescents and Adults were only observed at 1-month, in favor of the intervention group experiencing improvements. The intervention effects were comparable across girls and boys; therefore, they were not moderated by gender. However, the effects were moderated by baseline concerns, with those reporting lower baseline body esteem, positive affect, and self-efficacy experiencing greater intervention benefits than those with lower levels of concern. Finally, no dose effects were observed (eg, greater engagement was not associated with greater improvement).

Comparison With Previous Work

This is the third RCT to report small immediate and sustained improvements in young people’s state- and trait-based body image following engagement with a microintervention [22,23]. These small but notable effects across all 3 trials are likely owing to both the brevity of the intervention phases (ie, single sessions; 72 hours) and the use of universal samples (ie, varying degrees of body image concerns). Larger and more sustained effects have been observed in microintervention [39] and chatbot [27] studies with longer intervention phases (ie, 3 weeks [39]; 1 month [27]) and selected samples (eg, women with heightened weight and shape concerns), which is likely owing to the greater scope for symptom change. The current moderator analyses mirror these selected sample effects, with intervention benefits being the largest among young people with poor baseline levels of body image, affect, and self-efficacy. Notably, improvements in secondary outcomes (ie, positive and negative affect and body image self-efficacy) were not observed immediately after the intervention but emerged at 1-week and 1-month follow-ups. This pattern may be attributed to the specificity of the intervention content and mediating effect of improved body image on affect and self-efficacy, that is, body image has shown to be predictive of mood states [40], and participants may need to experience improved body image before thinking and feeling that they are self-efficacious in managing their body image concerns.

With respect to intervention adherence and user engagement, less than half (327/858, 44% of participants) of those randomized into the intervention group used the chatbot. Of these, the majority (258/327, 79% of participants) completed the minimum intervention dose of one microintervention technique, with an average of 5 techniques completed over the 72-hour intervention period. There was also a preference for the woman avatar, Dandara, with most girls and boys opting to receive guidance from her, relative to her counterpart, Gabriel. These engagement levels [27,39] and gender preferences [41] mirror previous body image research.
First, with respect to engagement levels, in 2 comparable microintervention [39] and chatbot [27] trials, women completed an average of 4 techniques over 21-day and 1-month periods, respectively. Although the number of techniques is comparable across the 3 trials, the current participants completed more techniques over a shorter period. More research is needed on the naturalistic and longitudinal use of microinterventions and chatbots to better understand how and when users engage with the content, particularly when an intervention time frame is not prescribed. Relatedly, this trial did not find support for dose response, with intervention effects unaffected by the number of techniques completed. To our knowledge, only one other microintervention study has considered dose response and found no support for this relationship [42].

Second, with respect to gender preferences of the avatar, a small body of research has examined the role of gender in body image interventions, particularly the gender of the intervention facilitator [41]. Specifically, adult women preferred when interventions were delivered by a woman, whereas men did not have a preference and were content with either a man or a woman. The current findings reflect this pattern among adolescents, with most girls (152/174, 87%) selecting Dandara and boys selecting a combination of Dandara (94/147, 64%) and Gabriel (53/147, 36%). Overall, there is limited research on adolescents’ chatbot intervention preferences, including avatar demographics (eg, age, gender, sexuality, and ethnicity), hosting platforms (eg, Facebook and WhatsApp), and chat functions (eg, predefined rules, machine learning, or artificial intelligence). These features require exploration with the end user during intervention development, to ensure an acceptable, feasible, and safe intervention is created.

The current attrition rates and patterns are also comparable with the abovementioned trials [27,39] and broader digital mental health research [43]. First, with respect to condition-specific dropouts, rates were higher in the current intervention condition relative to the control, a pattern that is likely owing to higher participant burden among this group. Second, with respect to overall attrition, rates were higher but still reflective of digital mental health interventions, including body- and eating-related interventions [44] and chatbots [45]. The current rates are likely explained by several methodological features known to exacerbate attrition in digital trials, including a burdensome recruitment and onboarding process, no contact or follow-up calls with a researcher, and the masking of the compensation amount [43]. These features are discussed in this section.

First, Brazil passed the General Data Protection Law in 2018, with policies coming into effect in February 2020. These laws require parents to read, sign, and upload information and consent forms to a secure portal for identity verification before their child’s participation. This process requires parents to have good literacy skills, and without literacy skills, they are unable to engage with and comprehend the research materials, thus restricting adolescents’ participation. The recruitment methods were adjusted based on stakeholder feedback, with an information video provided alongside the written content. However, parents were still required to sign and upload consent forms. Second, to streamline the recruitment and onboarding processes, communication with participants was conducted primarily through automated processes (eg, email), with little to no contact between participants and the researchers or a recruitment agency. Third, during the informed consent phase, participants were advised that they would receive compensation at study completion; however, according to Brazilian ethics, the amount was not disclosed until study completion (eg, at the 1-month follow-up). Collectively, these methodological features and the general nature of digital interventions likely explain the current attrition rates.

Overall, previous and present findings indicate that microinterventions are an effective intervention for young people; however, they may serve different purposes depending on the severity of a participant’s concern. From a stepped-care approach, microinterventions may serve as a stand-alone approach for young people with milder concerns (eg, offered to young people during a moment of body image distress) or as an adjunctive approach to those participating in longer traditional body image interventions (eg, offered to young people ahead of talking therapy to increase motivation and self-efficacy). Unfortunately, to date, a stepped-care model for the eHealth of body and eating concerns has not been formally conceptualized and warrants consideration. Finally, given the growing literature on microinterventions, a systematic review and meta-analysis of this intervention model are both timely and necessary. Specifically, the review should provide a comprehensive overview of extant mental health microinterventions and analyze different intervention and trial features to determine those associated with greater engagement, adherence, and effectiveness.

**Limitations, Strengths, and Future Impact**

This trial is not without limitations, most of which speak to the digital and remote nature of the trial, which were compounded by the global COVID-19 pandemic. As noted, this trial comprised several methodological features known to impact attrition (eg, a burdensome recruitment and onboarding process, no contact or follow-up calls with a researcher; the masking of the compensation amount). Furthermore, the trial was conducted during the peak of the COVID-19 pandemic in Brazil (ie, 92,625 cases per day) [46]. Notably, a high level of screen and social media fatigue was reported among adolescents during the pandemic [38], which is largely because of the exponential reliance on technology during this socially restrictive period (ie, web-based schooling and entertainment [eg, social media and streaming services] and video calls with friends and family). Moreover, numerous web-based mental health resources were developed, tested, or made available to young people during this time. Therefore, although body and eating concerns were equally problematic during the pandemic [8], it is possible that this intervention and research opportunity were dismissed because of the overwhelming digital demands of adolescents during this time. Finally, dropout was affected by participants’ age (those aged 18 years were the most likely to drop out), ethnicity (Indigenous participants were the most likely to drop out), and region (those from the central west region were the least likely to drop out). This suggests poor acceptance among these demographics and warrants further exploration.
Despite these limitations, the strengths and findings associated with this trial provide avenues for advancing this research field beyond those previously discussed. First, Topity has reached >40,000 young people since the RCT began in April 2021. Second, the digital infrastructure developed for this chatbot can be implemented and disseminated in other countries, with the content adapted for suitability in these contexts. This may include translating the content into different languages and incorporating intervention stimuli that are appropriate and salient to a particular country and culture. Next, this trial provides further support for the adaptation of traditional prevention and intervention techniques (eg, hard copy and in-person) for use in digital environments [47]. More broadly, mental health researchers are encouraged to examine existing evidence-based approaches and identify techniques that could be adapted for stand-alone use in digital environments. Isolating these techniques for self-guided use in digital settings that are already frequented by the consumer is likely to increase the accessibility, acceptability, and scalability of mental health resources and, in turn, lead to impactful and sustainable change.

**Conclusions**

This trial supports the use of chatbot technology to deliver mental health microinterventions within digital environments frequented by young people (eg, social media platforms and messaging apps). Microinterventions are proving to be an effective method for providing adolescents with immediate and short-term symptom relief and reducing imbalances in the ratio of harmful and helpful body image content on social media platforms. Although microinterventions are a promising intervention model, more research is needed to conceptualize how this model can be integrated into and enhance a stepped-care model for digital approaches targeting body and eating concerns.

**Acknowledgments**

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**Data Availability**

The body image chatbot, Topity, is freely available to those with access to Facebook Messenger. Anonymized survey data will be available on reasonable request for noncommercial purposes.

**Authors’ Contributions**

ELM, HGS, ACSA, JFFM, MCA, JL, MFT, and PCD were responsible for the formulation or evolution of overarching research goals and aims. ELM and PCD were responsible for the development and design of methodology. ELM and HGS were responsible for the provision of study materials. HGS, JL, and MFT accessed and verified underlying data. ELM was responsible for the preparation, creation, and presentation of the published work, specifically writing the initial draft, visualization, and data presentation. HGS, ACSA, JFFM, MCA, JL, MFT, and PCD were responsible for preparation, creation, and presentation of the published work by those from the original research group, specifically critical review, commentary, or revision including the pre- or postpublication stage. ELM and HGS were responsible for management and coordination responsibility for the research activity planning and execution. JL and MFT were responsible for application of statistical, mathematical, computational, or other formal techniques to analyze or synthesize study data. ELM and PCD were responsible for oversight and leadership responsibility for the research activity planning and execution, including mentorship external to the core team, and the acquisition of the financial support for the project leading to this publication.

**Conflicts of Interest**

JL was supported by the National Health and Medical Research Council Investigator Grant (APP1196948). PCD is an independent consultant to the mental health policy and programing team on Instagram (owned by Meta, the parent company of Facebook Messenger) and Dove (Unilever). All other authors declare no other conflicts of interest.

**Multimedia Appendix 1**
Supplementary tables pertaining to results of hypotheses 3 and 4.

**Multimedia Appendix 2**
CONSORT E-HEALTH Checklist (V 1.6.1).
References


29. Fitzsimmons-Craft EE. Developing an optimized conversational agent or 'chatbot' to facilitate mental health services use in individuals with eating disorders. National Institutes of Health. URL: https://grantome.com/grant/NIH/K08-MH120341-01 [accessed 2022-12-15]


Abbreviations

LMIC: low- and middle-income country
RCT: randomized controlled trial
Recommendations for the Quality Management of Patient-Generated Health Data in Remote Patient Monitoring: Mixed Methods Study

Robab Abdolkhani1,2, PhD; Kathleen Gray1, PhD; Ann Borda3, PhD; Ruth DeSouza4, PhD

1Centre for Digital Transformation of Health, The University of Melbourne, Melbourne, Australia
2Department of General Practice, Melbourne Medical School, The University of Melbourne, Melbourne, Australia
3Faculty of Medicine, Dentistry and Health Sciences, The University of Melbourne, Melbourne, Australia
4School of Art, Royal Melbourne Institute of Technology University, Melbourne, Australia

Corresponding Author:
Robab Abdolkhani, PhD
Centre for Digital Transformation of Health
The University of Melbourne
Level 13
305 Grattan Street
Melbourne, 3000
Australia
Phone: 61 90358703 ext 03
Email: Robab.abdolkhani@unimelb.edu.au

Abstract

Background: Patient-generated health data (PGHD) collected from innovative wearables are enabling health care to shift to outside clinical settings through remote patient monitoring (RPM) initiatives. However, PGHD are collected continuously under the patient’s responsibility in rapidly changing circumstances during the patient’s daily life. This poses risks to the quality of PGHD and, in turn, reduces their trustworthiness and fitness for use in clinical practice.

Objective: Using a sociotechnical health informatics lens, we developed a data quality management (DQM) guideline for PGHD captured from wearable devices used in RPM with the objective of investigating how DQM principles can be applied to ensure that PGHD can reliably inform clinical decision-making in RPM.

Methods: First, clinicians, health information specialists, and MedTech industry representatives with experience in RPM were interviewed to identify DQM challenges. Second, these stakeholder groups were joined by patient representatives in a workshop to co-design potential solutions to meet the expectations of all the stakeholders. Third, the findings, along with the literature and policy review results, were interpreted to construct a guideline. Finally, we validated the guideline through a Delphi survey of international health informatics and health information management experts.

Results: The guideline constructed in this study comprised 19 recommendations across 7 aspects of DQM. It explicitly addressed the needs of patients and clinicians but implied that there must be collaboration among all stakeholders to meet these needs.

Conclusions: The increasing proliferation of PGHD from wearables in RPM requires a systematic approach to DQM so that these data can be reliably used in clinical care. The developed guideline is an important next step toward safe RPM.

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KEYWORDS
data quality management; patient-generated health data; remote patient monitoring; wearable electronic devices; remote sensing technology; telemedicine; big data
Introduction

Remote Patient Monitoring

The use of remote patient monitoring (RPM) solutions and production of patient-generated health data (PGHD) to enable continuous monitoring of patients outside clinical settings are increasing with the growing availability of health wearable devices and the connected mobile apps and web portals [1]. The COVID-19 pandemic has accelerated the use of RPM to monitor mild cases of the disease remotely, given the limited capacity of acute care facilities [2].

As the pandemic is not yet over, RPM will likely contribute more to health care delivery owing to the availability of various affordable technologies and the need for remote treatment and monitoring. However, despite the urgent need and rapid implementation and use of RPM, investigation on how quality PGHD can best be collected and managed to lead to accurate decision-making is still lacking.

Ensuring the Quality of PGHD

Patients may collect some data as instructed by clinicians, mainly from medical wearables. Patients may also collect data, on their own accord or on advice from clinicians, from consumer wearables. There are fundamental similarities between the data collected upon patient initiation and those collected upon clinician initiation, whether from consumer or medical wearables, that erode the regulators’ distinctions: the data are generated outside the controlled environment of the clinic; the data collection is the responsibility of the individual wearer; and the data are shared electronically with parties who operate outside a controlled clinical setting, namely wearable companies. Thus, RPM data collected from wearables, whether upon patient initiation or upon clinician initiation, are covered by the broad concept of PGHD.

Outside the clinic, consumer and medical wearable technologies used in RPM capture a large amount of data continuously in rapidly changing circumstances during a patient’s daily life under the patient’s or caregiver’s supervision [3]. The wearable platform includes sensors that capture data automatically and a mobile app and web portal where the person enters data manually. Inside the clinic, RPM solutions are not integrated well into patient records or clinical workflows, and various digital health devices and platforms are used for different RPM purposes [4]. The quality of PGHD collected from disparate devices is compromised by various technical, behavioral, or operational issues that occur during data capture by the patient or caregiver, during the transmission of the data from the patient to the clinician, and during the clinician’s review of the data for decision-making [5].

Health data quality plays a vital role in health care systems. Clinicians need to trust the available data to make accurate decisions and provide efficient and timely care for their patients. Data are of good quality when they are fit for their intended use [6], that is, when they are accurate, accessible, consistent, complete, interpretable, timely, relevant, and compliant with the standards defined by health care organizations [7]. Any quality issue with data can affect patient safety, the reimbursement of health services, and the quality of clinical outcomes and other aspects of health care delivery [8].

Data quality management (DQM) refers to the processes of ensuring data quality when data are collected, stored, analyzed, reviewed, and used in clinical decision-making [9]. The core outcome of DQM is establishing the fitness of data for its intended use. National and international health care and health information–related organizations provide guidelines for the quality management of patient data that are generated within clinical settings [8-12]. However, in RPM, data are collected outside the clinical setting, and different stakeholders are involved at different stages of PGHD management both outside and inside the health care settings.

This paper describes the DQM recommendations provided to ensure that data from wearables are fit for use in clinical care.

Methods

Overview

Recommendations for the quality management of PGHD arose from a mixed methods study on the quality management of PGHD from wearables and were constructed following a guideline development convention in health care [13-18] through the stages listed in Textbox 1.

Most of the data collection in this research was done before the COVID-19 pandemic. However, the rapid deployment of RPM during the pandemic emphasizes the need for guidelines, such as the one constructed in this study, to improve the use of RPM initiatives and efficiently integrate them into the routine care.
Textbox 1. Stages involved the construction of the recommendations.

- Evidence reviews: a comprehensive literature review focused on original research within a 10-year time frame that discussed the barriers to and concerns of using patient-generated health data (PGHD) in clinical practice was conducted and published previously [19].

- Stakeholder involvement: in-depth interviews were conducted with PGHD stakeholders directly involved in the remote monitoring of patients with chronic diseases, including those with diabetes, those with cardiac arrhythmia, and those sleep disorders, in primary care, secondary care, and tertiary care settings to identify the challenges related to the quality management of PGHD. The interview participants were from Australia, the United Kingdom, and the United States. The interview results were published previously [5]. Then, a participatory workshop was held in Australia with stakeholders, including patients, clinicians, health information professionals, wearable developer companies, PGHD integration service providers and remote patient monitoring (RPM) consultants, to discuss the identified challenges and address potential solutions and stakeholders’ needs and expectations. The results of this study were published elsewhere [20].

- Documentation of recommendations: we used the approach of integrating multiple types of qualitative evidence to produce new knowledge [21], as shown in Figure 1, to construct a set of recommendations that cover all aspects of the quality management of PGHD during data flow from the patient to the clinician. We synthesized the findings of the aforementioned 2 stages along with supporting evidence from an updated review of scientific literature and new policies related to PGHD. The interpretation stage aimed to draw connections between the data points, themes, and findings. Then, the construction stage expressed new meaning and uncovered ways of understanding the realities regarding the research topic for the stakeholders. It acknowledged the importance of synthesized and interpreted elements in terms of stakeholders, context, and influencing issues. Moving from evidence to recommendations, the construction stage sought to examine how the synthesized findings related to the broader context in the past, present, and future. Details of the findings and the emerged themes applied in the construction of the guideline are provided in Multimedia Appendix 1. This step produced a guideline containing 19 separate recommendations. One of the researchers interpreted the findings and constructed the guideline, and then the guideline content was reviewed separately by 3 researchers and discussed in multiple meetings.

- Validation of recommendations: a 1-round Delphi method [22] using a web-based survey and 5-point Likert scale was adopted, 14 Australian international health informatics and health information management experts participated in the survey. The interview and workshop studies involved several groups of PGHD stakeholders, who shared their experience and perspectives related to the quality management of PGHD. However, except for health information professionals, the other stakeholders were experts in their own clinical or technical field but not in managing and governing patient health data. The data quality management (DQM) elements in the guideline still required validation by experts with a high-level understanding of and experience with health information management and health informatics principles and practices. These experts were purposefully selected based on their professional reputation and their known interest in PGHD. None of them had been involved in the previous studies of this project, so they could form an independent view of the resulting recommendations. The survey had 19 items in total, representing the 19 recommendations in the guideline. It used a 5-point Likert scale (not important, slightly important, moderately important, important, and very important) to capture the participants’ expert opinions about the extent to which each DQM recommendation is potentially important in contributing to the safety and the quality of RPM. Each survey item also included a free-text comment option so that the participants could further explain their response. Consensus on each recommendation for each DQM aspect of PGHD was deemed to be achieved by having 60% of votes fall within 2 adjacent categories of the 5-point scale. A method to group the responses for analysis was determined: if the participants reached at least an aggregated 60% agreement that a recommendation is “important” or “very important,” it was deemed to have been rated as essential; if the participants reached at least an aggregated 60% agreement that a recommendation is “slightly important” or “moderately important,” it was deemed to have been rated as desirable; and if the participants reached at least an aggregated 60% agreement that a recommendation is “not important,” it was deemed to have been rated as unnecessary.

Figure 1. Continuum of integrating multiple qualitative findings to create new evidence.

Ethics Approval
The stakeholder involvement studies received approval from the Human Ethics Advisory Group at the Department of General Practice at the University of Melbourne [5,20]. The ethics approval number for the validation study from the same group is 1955682.1.

Results

Recommendations and Key Themes
The ensuing guideline encompasses 19 recommendations. These recommendations were grouped according to 7 overarching DQM aspects. Table 1 lists these 7 aspects; their adapted definition for this research; and the key themes identified from the literature review, interviews, and workshop studies. The sociotechnical issues to be considered in relation to each DQM aspect have been discussed in the corresponding recommendations. Through this style of presentation, PGHD stakeholders can understand what actions they and others need to take to collect, manage, and use trustworthy PGHD in RPM.
Table 1. Data quality management (DQM) recommendations for patient-generated health data (PGHD) in remote patient monitoring.

<table>
<thead>
<tr>
<th>DQM aspects and key themes</th>
<th>Recommendations</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PGHD accessibility: authorized users of PGHD access them across all data management stages</strong></td>
<td></td>
</tr>
<tr>
<td>Patients’ and clinicians’ access to PGHD</td>
<td>Both raw and processed PGHD from wearables should be accessible to the patient and clinician.</td>
</tr>
<tr>
<td>Patients’ and clinicians’ awareness of PGHD access by others</td>
<td>A mechanism should be available to the patient and clinician to set up notice recurrence on where, when, how, and by whom PGHD from wearables are accessed.</td>
</tr>
<tr>
<td>Patients’ consent to PGHD access by different clinicians</td>
<td>A mechanism should be available to the patient to change permissions for clinicians to access PGHD from wearables.</td>
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<tr>
<td><strong>PGHD accuracy: error-free data</strong></td>
<td></td>
</tr>
<tr>
<td>Automatic and manual PGHD collection</td>
<td>PGHD should be collected automatically by the wearable device, with as little as possible manual intervention.</td>
</tr>
<tr>
<td>PGHD annotation</td>
<td>Annotation function for manually and automatically entered PGHD should be available to the patient and clinician in order to comment on inaccurate data.</td>
</tr>
<tr>
<td>Wearable calibration</td>
<td>The wearable should be calibrated automatically as required by the clinical standard of care of diseases.</td>
</tr>
<tr>
<td><strong>PGHD completeness: no PGHD are missing</strong></td>
<td></td>
</tr>
<tr>
<td>No active data collection</td>
<td>A protocol should be available to the patient and clinician that defines PGHD “downtime,” that is, the time range during which it is acceptable if the wearable is not collecting data.</td>
</tr>
<tr>
<td>Resuming PGHD collection after downtime</td>
<td>A protocol should be available to the patient and clinician for resuming PGHD collection when the acceptable downtime period is exceeded.</td>
</tr>
<tr>
<td>Context for incomplete PGHD</td>
<td>Annotation function should be available to the patient in order to provide context for any period of missing PGHD.</td>
</tr>
<tr>
<td><strong>PGHD consistency: data convey the same meaning no matter whether they are collected from one or different brands of wearables</strong></td>
<td></td>
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<tr>
<td>PGHD definitions and formats</td>
<td>PGHD from wearables should be collected based on clinically accepted and structured data definitions and standard formats.</td>
</tr>
<tr>
<td>PGHD integration with electronic medical records</td>
<td>PGHD from wearables should be integrated into the patient’s clinical care record.</td>
</tr>
<tr>
<td>PGHD exchange within and outside care settings</td>
<td>PGHD from wearables should be consistently exchanged inside and between clinical settings.</td>
</tr>
<tr>
<td><strong>PGHD interoperability: data presentation highlights the key message that is understood by PGHD stakeholders</strong></td>
<td></td>
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<tr>
<td>PGHD contextualization</td>
<td>PGHD from wearables should be accompanied by contextual data that are clinically important to patient management.</td>
</tr>
<tr>
<td>Dynamic and static PGHD visualization</td>
<td>Dynamic visual representation as well as a static snapshot (such as in PDF format) of PGHD from wearables should be available to the patient and clinician.</td>
</tr>
<tr>
<td>The patient’s understanding of PGHD</td>
<td>Alerts should be sent to the patient during PGHD collection by the wearable when data are outside the acceptable range, accompanied by clinical advice on action to take.</td>
</tr>
<tr>
<td><strong>PGHD relevancy: data are pertinent to the standard of care for the condition being monitored</strong></td>
<td></td>
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<tr>
<td>PGHD relevancy to the standards of care</td>
<td>There should be a shared understanding between the patient and clinician of relevant data for the disease based on the standards of care and make sure that all the relevant data are collected.</td>
</tr>
<tr>
<td><strong>PGHD timeliness: availability of up-to-date PGHD for patients and clinicians when needed</strong></td>
<td></td>
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<tr>
<td>PGHD availability to patients when needed</td>
<td>PGHD from wearables should be available to the patient within a timeframe (continuously to periodically) according to the standards of care of diseases.</td>
</tr>
<tr>
<td>PGHD availability to clinicians when needed</td>
<td>PGHD from wearables should be available to the clinician within a timeframe (continuously to periodically) according to the standards of care of diseases.</td>
</tr>
<tr>
<td>Time frame for PGHD sharing between patients and clinicians</td>
<td>A timeframe for sharing PGHD from wearables should be available to the patient and clinician.</td>
</tr>
</tbody>
</table>
PGHD Accessibility

PGHD accessibility was characterized by data access methods, privacy protection, and data ownership issues to be explored in RPM.

**Recommendation 1: Both Raw and Processed PGHD From Wearables Should Be Accessible to the Patient and Clinician**

The extent to which patients and clinicians currently have access to all the recorded PGHD is questionable. PGHD accessibility largely depends on who owns the data to have complete access to them. PGHD have not yet been fully incorporated into clinical workflows; therefore, these data are neither controlled nor owned by health care organizations. Rather, the raw and processed PGHD from each wearable platform are accessed and controlled by the device company outside the health care setting.

Access to raw and processed PGHD during data collection may increase patients’ awareness of their health status and whether they are required to take action or change their behavior and improve self-care. Now, the trend in wearable design is shifting toward data visibility to patients [23,24]. Nevertheless, clinicians may intentionally disable the access of raw data to patients during data collection, as it would lead to patient behavior change that might conflict with the purpose of the RPM program. The ability to access all raw and processed PGHD could also be limited by wearable companies. Medical device manufacturers should share comprehensive and contemporary health information with patients upon request [25]. Therefore, patients are within their rights to request health information that is captured, stored, and analyzed by and retrieved from a legally marketed medical device. Different policies suggest that wearable developers, regardless of the wearable type, should provide patients complimentary access to PGHD [26-28].

Considering these policies, PGHD ownership has not yet been defined clearly enough to determine who owns part or all of the data, affecting patients’ access to PGHD [29,30].

In terms of clinicians’ access to raw and processed PGHD, the necessity to access all the collected raw and processed data depends on which data are needed for decision-making. Our findings showed that it would be difficult for a clinician to find the log-in details of a patient’s wearable portal if the patient has changed their portal account information or the device without informing the clinician. Clinicians’ access to PGHD might also be prevented by patients, which might reveal that they have not followed their care plans [31].

Collecting various types of PGHD from different wearables outside the clinical environment means that data are stored across different platforms. Ideally, PGHD should be accessible to the people who collect them, and access methods should be transparent. The purpose of giving patients and clinicians access to PGHD is to enable them to have a clear picture of the former’s health status.

**Recommendation 2: A Mechanism Should Be Available to the Patient and Clinician to Set Up Notice Recurrence**

It is important that patients and clinicians be aware of who else has access to PGHD during data management from outside the health care setting to inside it. Patients and clinicians in this project had little understanding of how and by whom PGHD are accessed during data management stages in RPM [32].

Clinicians placed responsibility on the wearable developer for informing patients about who can access their data. Also, the installation terms and conditions of a large number of health wearables’ apps indicate that the wearable developers are the owners of PGHD and have authority to grant data access to others [26]. A review study of 4 known wearable products showed that the privacy policy of only 1 platform asserted PGHD as users’ sole and exclusive property [33]. However, these companies’ statements were not accompanied by strategies to support patients’ awareness of the accessibility of their data to others. Patients should be informed about what PGHD are collected and accessed, including possible lawful access by third parties; whether these data are identifiable or depersonalized; and how they are accessible for clinical decision-making [27,28,34,35]. Patients need transparency about PGHD access not only before data collection but also throughout all the PGHD management stages. Not knowing who has access to their data can deter or inhibit PGHD collection [23].

Initiatives such as the privacy notice checklist developed by the US Office of National Coordinator for Health Information Technology are to be used by wearable developer companies to disclose their privacy and security policies to patients and inform them about what happens to their PGHD once they purchase and use the device [36]. However, this notice appears to be more applicable to wearables for self-management than to those for RPM. In addition, one-off use of the privacy notice checklist cannot ensure the notification of all PGHD accesses during all data management stages. For example, PGHD might be transferred from the patient to the clinician through communication networks that might be hacked. Many RPM programs lack robust cybersecurity mechanisms [37].

Using PGHD in clinical practice means that clinicians might also need to be notified about PGHD flow to be able to track patient monitoring instructions from other clinicians if necessary. Patients and clinicians should be able to set up notification recurrence of PGHD access based on their preference.

**Recommendation 3: A Mechanism Should Be Available to the Patient to Change Permissions That Clinicians Have to Access PGHD From Wearables**

The patients’ and clinicians’ awareness of circumstances under which PGHD are accessed does not give patients the authority to consent to PGHD access by others.

It is unclear to PGHD stakeholders how patient’s consent to PGHD access should look [38]. Patients in the RPM of our 3 use cases, diabetes, cardiac arrhythmia, and sleep disorders, sign a consent form at the beginning of the program. However, the continuous nature of data collection and access in RPM might require constant PGHD access authorization when
different clinicians need to access the data for different purposes of patient care [29,39]. There are concerns that the clinicians may access PGHD at a stage where the data have not been granted access to by the patient. This might not be ethical even if done to benefit the patient [40].

Patients themselves may have little awareness of PGHD consent, and their attention may be confined to the terms and conditions statement before pressing the consent button for installing the wearable components. However, the wearable developers’ privacy policies and terms of service are often difficult to read and understand [41,42].

Appropriate consent management mechanisms enable patients to manage their consent preferences. Nevertheless, there is not yet a well-established consent mechanism for continuous data collection and use [28]. As various types of PGHD might be collected through different wearable platforms, sensitive data might be released when using one consent at the beginning of the RPM program. For example, patients might not want to provide details about their behaviors or lifestyles to clinicians in a certain time frame if it would lead to judgment or being shamed for perceived unhealthy choices during data collection. Thus, a process of dynamic consent might be more feasible to give patients control over the level of access to their data for different purposes and the choice of whether these data are anonymized or identifiable [43,44]. It could provide more personalized approaches and improve the continuous patient-clinician communication. Also, it gives patients the ability to understand and decide to what extent they are willing to share their data. Moreover, defining different levels of permission enables patients to review consent over a period to update or withdraw data at any time without affecting previously collected data [28].

**Validation Results**

Each of these 3 recommendations about PGHD accessibility was rated as “essential” to the to the safety and quality of care in RPM (reached an aggregated 60% agreement as being important to very important).

**PGHD Accuracy**

PGHD accuracy is compromised by a patient’s errors or other error sources during data management, as well as uncontrolled possibilities for data revision.

This aspect depends on the technical features of the wearable and its components and the behaviors of the patient or caregiver at the point of data collection. Clinicians’ trust of PGHD accuracy is significantly impacted by the differentiation between medical grade and consumer wearables. Clinicians trust the level of accuracy in PGHD captured by medical wearables owing to their preassessment and approval from regulatory bodies. Our findings showed that consumer wearables were not used in RPM because of not being regulated for clinical use. However, even a medical wearable may not work accurately in some instances, as identified in our interviews and workshop studies. Moreover, a study showed that the inaccuracy of continuous glucose monitoring (CGM) wearables was the most critical impediment (53%) to the use of these devices by diabetic adults [45]. Nevertheless, as the wearables collect data longitudinally, clinicians may trust the overall trends rather than doubting whether a single data point was captured correctly.

**Recommendation 4: PGHD Should Be Collected Automatically by the Wearable Device, With as Little as Possible Manual Intervention**

The way PGHD are collected can pose risks for data accuracy. Automated sensing via algorithms embedded into wearables can provide persistent collection and analysis, providing a comprehensive picture of a patient’s status over time. Automation can lower the tracking burden, improve PGHD accuracy, and accelerate data filtering for timely access [39]. For a patient with low digital health literacy, automated data collection can reduce the level of disengagement with the device.

In addition to automatic data collection, some wearables require types of PGHD such as meal, activity, and mood data to be entered manually in the wearable platform on a daily basis. This can place a burden on patients and result in inaccurate and inconsistent recordings [46]. Yet, there has been no innovation to change the manual collection of these types of PGHD into a seamless automatic process; however, the extent of engagement in manual PGHD collection and documentation might depend on the patients’ level of understanding of the data and the message that PGHD could convey to the patients [47]. From clinicians’ perspectives [48,49], automated data collection and transmission to the associated app is a more accurate mechanism to evaluate peak flow variability than a patient’s difficult and time-consuming manual calculations.

Some PGHD types that patients were required to record manually—such as activity data in the remote monitoring of patients with diabetes—could be automatically captured via consumer wearables. Synchronization shortages between different types of medical and consumer wearables and a lack of adoption of consumer wearables in RPM are barriers to increasing automation. Although it might not yet be possible for some data elements to be captured automatically, there could be strategies to limit free-text entries. For example, wearable developers can reduce the possibility of errors in manual data entry in the associated apps by requiring the user to choose from a list of options instead of entering free-text [50].

However, having all PGHD collected automatically may lead to less control by patients over their health status and reduce their engagement in their self-care [51]. In addition, behavioral factors such as improper application of a sensor on the body or changing the device settings can have adverse impacts on PGHD accuracy. Automation can provide more accurate data if it does not negatively impact patients’ engagement in self-care.

**Recommendation 5: Annotation Function for Manually and Automatically Entered PGHD Should Be Available to the Patient and Clinician in Order to Comment on Inaccurate Data**

Whether PGHD are collected automatically or manually, the ability to annotate them during data collection is a critical contribution to their accuracy [31]. In addition to the annotation of manual entries, the annotation of automatically collected data
can help patients prevent errors in them and mark questionable data to discuss with clinicians [52].

The rapidly changing environment surrounding the patients may contribute to inaccuracies in manual and automatic captures [53]. Sometimes, the wearable works inappropriately or the patient makes mistakes in wearing the device or entering data; however, the feature of annotating both data collected manually and those collected automatically is not designed in many wearable platforms and is often overlooked in the testing of wearables for use in RPM [47].

According to our findings, patients can add notes on inaccuracies only through their diaries to discuss with clinicians during the clinical consultations. However, the annotation feature could be embedded in the wearable design to reflect on data inaccuracy in real time instead of writing a diary note that might be forgotten. Patients could be notified of the incorrect values to annotate data or redo data collection instead of sending incorrect data to the clinician [30]. The wearable developers could also enable passive data annotation upon patients’ request [28]. Nonetheless, it is uncertain, if the patients themselves do not notice the errors, how they could annotate PGHD given that wearables often lack feedback mechanisms to alert the wearer about inaccuracies [54].

There is a concern that patients may use this functionality to override real actions. Therefore, the patients and caregivers need to be educated on PGHD annotation and build trust upon this functionality to enhance patient-clinician interaction and shared decision-making [46,55].

Clinicians should also be able to annotate the processed PGHD to understand data collection barriers and provide more efficient personalized care plans [29]. However, as the processed PGHD are usually represented as static snapshots to the clinician, it would be difficult for a clinician to annotate the reports and highlight the problematic areas of PGHD [56,57].

**Recommendation 6: The Wearable Should Be Calibrated Automatically as Required by the Clinical Standard of Care of Diseases**

Both medical and consumer wearables may collect inaccurate data. Therefore, it is important to ensure that wearables are calibrated to guarantee accurate sensing [30,39,58].

Some wearables need one-off calibration by the clinicians before initiating remote monitoring, whereas for other types such as CGM devices, the patient should frequently calibrate the device via a glucometer to ensure PGHD accuracy. Nonetheless, a patient’s responsibility in terms of how often and when they should calibrate the wearable device in RPM is often unclear [31]. The need to calibrate wearables not only is a burden on patients or their caregivers but also increases the likelihood of inaccuracies. Patients should be taught the importance of calibration and when it should be done. For example, from a clinician’s point of view, the 12-hour calibration for CGM wearables prescribed by most wearable developer companies [59] is not clinically acceptable; rather, calibration should be done 3 times a day when the blood glucose is not rapidly changing. Similarly, the best time to calibrate the device is when the glucose level is stable [60]. A study showed that nearly half of the participants reported calibrating CGM at more intervals than recommended by the wearable developer to ensure data accuracy [45].

Although regular calibration might be a burden, understanding its value would encourage patients to do it correctly [55]. However, considering the possibility for error to arise from the manual calibration of CGM devices with glucometers, an automatic calibration mechanism could be preferable.

Moreover, the wearable developers could conduct dynamic testing of the products. Clinicians want more collaboration with wearable developers to define strategies for continuous wearable assessment that can be achieved through various RPM interventions. Ideally, there should be a consensus among clinicians and wearable developers regarding guiding patients on the frequency of and providing instructions on calibration based on clinical principles.

**Validation Results**

Each of the 3 recommendations about PGHD accuracy was rated as “essential” (each one reached an aggregated 60% agreement as being important to very important).

**PGHD Completeness**

Incomplete PGHD may be a result of technical or behavioral issues. Battery failure, wearable dysfunction, lack of synchronization in different time zones, internet disconnection, or patient’s neglect are among the accidental causes of insufficient PGHD. This may compel clinicians to reorder data collection. Moreover, there might be deliberate data omissions for both manual and automatic entries because of demotivation, lack of digital literacy, body pain, or perception of having no changes owing to seeing similar trends over time [61].

Lack of continuous follow-up may also result in incomplete data. Different health care settings define data sharing time frames differently in the remote monitoring of the same health condition; this can create confusion in patient and clinician communication. Lack of continuous interaction with patients during remote monitoring could result in a lack of engagement in self-care and motivation to collect data [62]. None of the published RPM studies have reported an approach to identify the exact reason for data incompleteness.

**Recommendation 7: A Protocol Should Be Available to the Patient and Clinician That Defines PGHD Downtime, That Is, the Time Range During Which It Is Acceptable if the Wearable Is Not Collecting Data**

Given the constant automated sensing capabilities of wearables, it is unclear whether patients are required to wear the devices continuously in different RPM programs to provide sufficient data for their care planning. There was lack of awareness among PGHD stakeholders in our studies on standardizing “downtime” when patients can stop data collection in different RPM programs. From clinicians’ point of view, a CGM wearable should be worn for at least 80% of the RPM period so that it can provide complete data for interpretation and decision-making. However, it is thought to be burdensome for patients to have to wear the device day and night and calibrate.
it frequently [55]. New generations of wearables seem to address “downtime” by letting patients turn off the device. Alerts could be designed in wearables to help clinicians discuss the reasons for incomplete data with patients.

As mentioned in the PGHD Accuracy section, clinicians would prefer focusing on data trends over time rather than single data points; therefore, some degree of missing data is acceptable [51]. Some clinicians do not see PGHD completeness as fundamental for sound decision-making [63]. However, it is important to know the extent of the impact of incompleteness on data interpretation and decisions made for patient care in the remote monitoring of different diseases [51,64]. Having a predefined and transparent downtime protocol on which the patient and clinician agree could clarify the completeness of PGHD [65].

**Recommendation 8: A Protocol Should Be Available to the Patient and Clinician for Resuming PGHD Collection When the Acceptable Downtime Period Is Exceeded**

Applying the acceptable time frame in which patients can stop collecting PGHD cannot be thoroughly understood unless patients are aware of when to resume data collection.

However, this might not happen if patients forget to do so. Moreover, owing to a lack of technical infrastructure for the real-time transmission of data from outside to inside the health care setting, clinicians are not aware of the missing data during data collection and thus are unable to alert patients to resume data capture [66,67]. This could be considered in the wearable design; for instance, wearables can provide patients the ability to set an alarm based on the predefined acceptable downtime schedule.

**Recommendation 9: Annotation Function Should Be Available to the Patient in Order to Provide Context for Any Period of Missing PGHD**

Any missing data need to be supplemented by contextual information to help clinicians identify the causes and discuss them with patients [63]. Contextual information about the missing data can help clinicians understand whether the problem was technical, behavioral, or related to the process of data transmission. Incomplete data in themselves do not explain the circumstances that led to their incompleteness [51].

Although some wearables were reported to provide notification of missing data, they still lack contextual information. This could place a burden on patients to be constantly attentive to record the causes of incompleteness. Innovative mechanisms could be designed to increase the interaction between the device and the wearer to record contexts for the incomplete data in a real-time or on a daily basis. The annotation feature that was mentioned in the PGHD Accuracy section is equally important to enable patients to enter information regarding missing data [56].

**Validation Results**

Each of the 3 recommendations about PGHD completeness was rated as “essential” (all reached an aggregated 60% agreement as being important to very important).

**PGHD Consistency**

PGHD consistency is characterized by the ability to compare PGHD of one measurement from different devices as well as the ability to relate PGHD to the corresponding conventional clinical measurement.

Various wearables and associated mobile apps and web portals used in RPM programs may not represent data in a consistent manner. PGHD inconsistency can happen during data collection, transmission, and review, which immensely impacts data presentation that may have not been thoroughly recognized by PGHD stakeholders.

**Recommendation 10: PGHD From Wearables Should Be Collected Based on Clinically Accepted and Structured Data Definitions and Standard Formats**

Both consumer and medical wearable platforms may fail to represent data in clinically standardized formats [30,68,69]. Nonstandard presentation can result in confusion in data interpretation and inability to discern whether PGHD reports show normal or abnormal trends [51]. The standardization of health data elements is intended to define what data are to be collected, decide on how the collected data should be represented, and specify how the data should be encoded for transmission [70].

Collecting PGHD from different types and brands of wearables, each with its own data presentation format, could result in inconsistent reports [49,51]. Most of the recent PGHD-related policies advise developing standardized formats for PGHD collection that align with the clinical data standards, which are defined as protocols, terminologies, and specifications that are used during data management stages [23,50,54,71,72].

To ensure consistent definitions and formats for PGHD, 2 approaches should be considered: PGHD consistency at data collection and PGHD consistency at the data processing stage. Patients may need to be advised to collect PGHD from one type or brand of wearables for the remote monitoring of a particular health condition to provide consistent reports. Clinicians in our studies and others [62] preferred to give patients autonomy over device selection and stated that patients should have the right to select a convenient and easy-to-use wearable device. Nonetheless, because PGHD cannot be further filtered by information systems within a health care setting to fix the inconsistencies that emerge from collecting data in different formats, data that are presented for review might be difficult to interpret. Inconsistent reports at the data review stage are a consequence of collecting data from disparate wearable platforms. The second approach is to standardize PGHD at the data processing stage regardless of the wearable used in data collection. In this case, robust technical infrastructure needs to be in place to allow gathering PGHD from different wearables and their apps and portals in one database to filter and process data.
data and present standardized reports that are similar to clinical data presentation formats.

Universally accepted data definitions and data exchange formats are required to facilitate effectual data transfer. Data should be codified according to the known clinical standards. In addition, ontologies that could aggregate and enrich PGHD with definitions, synonyms, and term relationships can be developed to provide standardized formats and make data semantically exchangeable [73].

**Recommendation 11: PGHD From Wearables Should Be Integrated Into the Patient’s Clinical Care Record**

Lack of PGHD integration with electronic medical record (EMR) systems is another barrier to PGHD consistency [30,39,74-76]. Current RPM programs are project oriented and not embraced in routine clinical practices. Moreover, most current EMR systems are not designed to seamlessly gather various types of data from outside the clinical setting in a straightforward manner [77]. PGHD should be combined with the patient’s clinical record to identify potential correlation with past conditions and be used in future interventions [30,46,54].

Despite the clinicians’ preference for the patients to choose their own brand of wearable, PGHD integration with EMRs constrains the selection of wearable. Patients should only use wearables in RPM that follow the interoperability standards used in the health care setting.

Most policies addressed the necessity of integrating PGHD with EMRs [23,26,35,54], but few provided specific suggestions. For example, the American Medical Association’s best practices for digital health implementation recommend that standard communication templates be designed before implementing RPM intervention to ensure consistency in data documentation during the whole process [72]. Therefore, PGHD integration with EMRs might be facilitated by modifying the EMRs, developing external dashboards, or limiting the choices of the brand of wearable used for data collection.

**Recommendation 12: PGHD From Wearables Should Be Consistently Exchanged Inside and Between Clinical Settings**

In addition to the need for standardized formats and integration with EMRs, PGHD exchange inside and outside the health care setting needs to be consistent by following health data exchange protocols.

If >1 health care setting is actively represented in an RPM program for one disease cohort or different departments implement RPM in one health care setting, data should be exchanged consistently to be understandable by different clinicians. This requires standardized formats for various types of PGHD.

Interoperability initiatives developed by the Australian Digital Health Agency [78] defined standards to facilitate data and information exchange and provided compliance mechanisms in connected health programs. These standards are broad and cover both PGHD and clinical data collected from outside and within health care settings. More specific interoperability standards were introduced by the Personal Connected Health Alliance with its Continua guidelines for data interoperability in personal connected health devices [79]. These initiatives need to be tested in various RPM programs to assess the consistency in data exchange.

**Validation Results**

recommendations 10 and 11 about PGHD consistency were rated as “essential” (they reached an aggregated 60% agreement as being important to very important), whereas recommendation 12 was rated by 9 (90%) of the 10 participants and reached less than 60% agreement for inclusion in the defined categories.

**PGHD Interpretability**

Interpretability is affected by the way in which PGHD are presented as well as by the availability of contextual information regarding PGHD.

Not understanding the presented data can reduce patients’ and clinicians’ motivation for data collection and review [31,80,81]. Challenges of PGHD interpretation can occur at any stage of data management. This aspect was mentioned as the most challenging feature in our studies.

**Recommendation 13: PGHD From Wearables Should Be Accompanied by Contextual Data That Are Clinically Important to Patient Management**

The increasingly high volume and dynamically changing nature of PGHD make it difficult and time-consuming to gain a holistic view of a patient’s status from the data alone [31,74,82].

Most PGHD are not supplemented by contextual information about the circumstances in which the data were collected. Lack of context can lead to misunderstanding; misinterpretation; and, consequently, unsound decisions [80]. For example, when a clinician tries to discern a pattern in a processed PGHD report, it may be unclear whether a graph showing a lack of activity reflects the patient’s demotivation, a problem in the wearable’s function, or a medication interruption [56]. In this situation, relying on the patient’s verbal expression without recorded contextual information is not sufficient to draw an understanding of the patient’s situation per trend.

Similar to its application in PGHD completeness, context for PGHD is important for the data review stage so that clinicians can understand what the patient was doing at the point of data collection [31,52,74,83]. Among the wearables studied in this project, only CGM devices allowed the manual capture of limited contextual data—such as those about mood and exercise—in cases where the automatically captured data were reported to be erroneous or incomplete. PGHD from medical wearables can be contextualized by data that are automatically captured from consumer wearables [80,84]. However, no mechanism exists to integrate these 2 types of wearables in RPM, and there is uncertainty about which contextual data are more relevant to patient care. In addition, the ability to understand and interpret contextual information is still beyond clinicians’ expertise [85].

More collaboration between patients, clinicians, and wearable developers is needed to identify what contextual data need to be collected for each health condition and whether these data...
elements should be incorporated within the wearable design or require wearable integration.

**Recommendation 14: Dynamic Visual Representation as Well as a Static Snapshot (Such as in PDF Format) of PGHD From Wearables Should Be Available to the Patient and Clinician**

Clinicians review the processed PGHD reports either from the patient’s or clinician’s portal that the wearable developers design for them with static visualization of data that can be downloaded in a PDF format.

Having a snapshot of all the data collected over time provides a summary of the patient’s status, but as the amount of PGHD increases, such a report could be progressively more complex for their clinician to interpret [86]. Designing interactive visualization tools based on clinicians’ needs can result in easy PGHD interpretation [52,76,82,87].

Interactive visualizations could enable clinicians to highlight the most concerning areas and customize the reports based on different variables [87,88]. Interactive visualization supported by annotation capability can facilitate the counterinterpretation of PGHD report, such as the ability to add highlights in a graph to detect changes. It is beneficial to patients to have a saved version of points and notes of what they and their clinicians identified and discussed for use in the next consultations. Likewise, in the subsequent clinic visit, the clinician could readily recollect what the previous consultation was focused on, which helps recognize patterns and set efficient care plans [56]. A dynamic and interactive visualization could also layer PGHD displays based on clinicians’ preferences. Studies have shown that different layers of data presentation, such as a holistic summary, an individual data summary, and detailed individual data, support the comprehensive interpretation of PGHD [52,76,82].

Notwithstanding, it is a challenge for wearable developers to design data presentation formats that please all clinicians with varying levels of digital health literacy. Collaboration among PGHD stakeholders is needed to determine who should design interactive dashboards for PGHD presentation, whether the dashboards should be implemented within EMRs or somewhere else in the health care setting, and how the reports should be presented to the patient and clinician to inform shared understanding and decision-making.

**Recommendation 15: Alerts Should Be Sent to the Patient During PGHD Collection by the Wearable When Data Are Outside the Acceptable Range, Accompanied by Clinical Advice on Action to Take**

In addition to clinicians’ interpretation of PGHD, it is important to ensure that patients can also interpret the data correctly. Not understanding PGHD can reduce the motivation to continue data collection. Efforts toward changing the patients’ roles from passive participants to active players in RPM require patients to understand PGHD and make necessary changes during data collection [89].

However, wearables do not provide understandable contextual information on PGHD. Most wearables display PGHD without further explanations of their meaning, the normal range, what will happen to the patient’s health status if their measurements are out of range, or what actions the patient could take if their measurements are out of range. This is problematic if the patient cannot immediately communicate with their clinician when they see significant changes occur in their data trends and do not know what action to take.

There are alarms embedded in some types of consumer wearables that notify out of range measurements [85]. Although PGHD from these tools may not require urgent actions, such features could improve patients’ interpretations of the data and better inform and influence behavior change.

Some medical wearables are equipped with a feature that alarms when the raw data go outside the normal range. Devices without this feature could be dangerous to a patient’s health, as immediate medical action may not be undertaken when needed. Nevertheless, the questions of to what extent patients could interpret PGHD augmented with contextual information during RPM without a clinician's intervention and how sound a patient’s decision would be based on the interpretation are largely unexplored.

Counterinterpretation of PGHD improves the shared understanding of data reports and generates an additional layer of meaning for PGHD in patient care plans [90]. These strategies particularly depend on patients’ and clinicians’ training and collaboration with the wearable developers to improve PGHD presentation design and interpretation.

**Validation Results**

Each of the 3 recommendations about PGHD interpretability was rated as “essential” (reached an aggregated 60% agreement as being important to very important).

**PGHD Relevancy**

PGHD relevancy is characterized in various manners depending on the scope and coverage of data for each health condition. The values of conventional clinical data collected inside the health care setting are defined based on the standards of care. However, PGHD include a wide range of heterogeneous and new types of data whose relevancy to the monitored health condition might be unclear. Only 1 common theme was found in the previous studies of this project for PGHD relevancy, which resulted in the recommendation discussed next.

**Recommendation 16: There Should Be a Shared Understanding Between the Patient and Clinician of Relevant Data for the Disease Based on the Standards of Care, and Make Sure That All the Relevant Data Are Collected**

PGHD relevancy was perceived as the most distinguishing DQM factor in using PGHD from consumer wearables versus those from medical wearables in RPM, and its lack was perceived as the most predominant barrier to the adoption of PGHD in clinical practice [91]. Patients and clinicians might have different perspectives on which types of PGHD are relevant to patient care [31]. Patients’ enthusiasm to use a wide range of consumer wearables and collect new types of PGHD that have not been collected easily before (eg, heart rate, sleep quality, and activity...
level) increases their expectation from clinicians to review the data. By contrast, clinicians might not be convinced of the extent to which the data are relevant to the health condition and supplement the clinical data collected from medical wearables to provide a better picture of patients’ status.

Clinicians involved in this project along with other studies indicated that PGHD from consumer wearables have not yet been proven to correlate with most health conditions and that they are different from other clinical data in terms of clinical value [39,76,82].

Even if PGHD are collected from medical wearables, it would still be challenging to identify whether all the data are relevant to the specific health condition. Conversely, some wearables cannot capture all the relevant PGHD; therefore, important relevant data might be missed, which might lead to incorrect decisions about patient care [76,83]. The need for the collection and analysis of relevant data was addressed by recent PGHD-related policies [23,54,72]. Only 2 clinical guidelines developed to address the details and level of relevancy of PGHD collected from wearable devices for the remote monitoring of patients with diabetes and those with cardiac arrhythmia were identified [60,65]. More guidelines are needed to determine relevant PGHD for the remote monitoring of each health condition.

Validation Results

Half of the participants rated PGHD relevancy recommendation as very important (40%) to important (10%), whereas 40% addressed it as moderately (30%) to slightly important (10%).

PGHD Timeliness

PGHD timeliness is characterized by the timing and frequency of PGHD availability to patients and clinicians.

Recommendation 17: PGHD From Wearables Should Be Available to the Patient Within a Timeframe (Continuously to Periodically) According to the Standards of Care of Diseases

Our findings showed that the timing of PGHD availability to patients was overlooked. Although accessing data during data collection is critical when a decision needs to be made, some wearables do not provide real-time PGHD access to patients during data collection. As discussed in the PGHD Accessibility section, depending on the health condition and the purpose of RPM, PGHD presentation to patients in real time might be deliberately disabled by clinicians. However, studies have shown that accessing real-time data from the wearable increased patients’ awareness of the wearable’s function, further engaged them in self-care, and enhanced shared decision-making [92-94].

As PGHD collection in RPM are led by clinicians, patients may not be fully aware of their rights in accessing PGHD at data collection and how it might impact their safety. PGHD access in real-time or periodic mode needs to be defined according to the standards of care of the health condition [65]. RPM interventions could be designed based on patient-centered care models where time frames could be established so that patients can access their data during data collection to make a proper decision, change their behavior, or immediately contact the clinician.

Recommendation 18: PGHD From Wearables Should Be Available to the Clinician Within a Timeframe (Continuously to Periodically) According to the Standards of Care of Diseases

The most challenging issue reported about PGHD timeliness is the lack of clinicians’ access to data in real time [39,77,83]. As PGHD are not yet integrated with EMRs, it is difficult and time-consuming to frequently receive the data and follow-up with patients. PGHD integration with EMRs would provide possibilities for generating alerts on newly added PGHD in the EMR system in a real-time or near real-time basis so that clinicians can be updated on a patient’s status and provide prompt feedback [83]. Notwithstanding, the technical integration by itself is not the ultimate solution. PGHD need to be fully incorporated into clinical workflows such that clinicians could receive data based on predefined protocols and be able to provide timely advice to patients [95]. Timely access to PGHD without immediate feedback to patients would lead to patient demotivation on data sharing [96]. However, RPM interventions may have different protocols for PGHD availability to clinicians. In some cases of remote monitoring of patients with diabetes, clinicians remotely obtain PGHD reports from patients during data collection, whereas in others, they see the report after data collection during the clinic consultation. Having predefined protocols might facilitate clinicians’ access to PGHD within a specific time frame.

Recommendation 19: A Timeframe for Sharing PGHD From Wearables Should Be Available to the Patient and Clinician

As noted earlier, RPM programs apply disparate time frames for PGHD sharing. This way of accessing data can be challenging. Patients who access data in real time may also need to receive a clinical advice immediately, whereas data are not available to clinicians in the same time frame. Frequent data sharing during data collection could help recognize some behaviors that might not be identified when the collection period is finished.

PGHD need to be available when there is an urgent need for clinical advice so that the patient can change the way of data collection or their behavior accordingly [30,97]. However, findings showed that this depends on the health condition; for example, the guideline on using wearables in cardiac RPM emphasized that these services should not be mistaken with acute care; therefore, there is no urgent need for real-time feedback [65]. Hence, based on the health context, having transparent protocols on data sharing could help clinicians review PGHD and set patients’ expectations for data transmission and feedback [76].

As different RPM programs may need different approaches on data timeliness based on the standards of care, there should be a single time frame defined for the remote monitoring of each health condition to ensure consistency among the programs.
Validation Results
All of the recommendations about PGHD timeliness were rated as “essential” to the safety of and quality of care in RPM (reached an aggregated 60% agreement as being important to very important).

A Staged Model of Quality Management of PGHD in RPM
Figure 2 illustrates the recommendations according to the importance of their consideration at different stages of data management. This model can assist PGHD stakeholders in understanding what DQM actions need to be taken to efficiently collect, manage, and use PGHD in RPM.

As shown in Figure 2, all DQM aspects of PGHD require attention at the data collection stage. It indicates that the quality management of PGHD is critical when data are collected outside the clinical environment under patients’ or their caregivers’ supervision. Data access, consistency, and timeliness were the most critical DQM aspects to be considered during PGHD transmission from the patient to clinician. These 3 aspects along with PGHD interpretability require emphasis when clinicians review the data reports for shared decision-making and creating patient care plans.

As there are interconnections among DQM aspects, this model indicates that collaborative actions need to be undertaken by different PGHD stakeholders to practice DQM and ensure high-quality PGHD in RPM.

Figure 2. Recommendations for the quality management of patient-generated health data (PGHD) at the 3 stages of PGHD management. EMR: electronic medical record.


**Discussion**

**Principal Findings**

This paper presented the development of 19 recommendations for 7 DQM aspects of PGHD collected from wearable devices in RPM programs. The guideline aims to assure that high-quality data are collected, managed, and used in RPM programs to improve the safety and quality of these programs and enhance PGHD fitness for use in routine clinical practice.

The guideline was constructed by following 4 steps of guideline development process through 5 qualitative studies. The guideline was then conceptualized to address 3 main concepts: PGHD management process, DQM aspects of PGHD, and sociotechnical issues that influence the quality management of PGHD during the data management process.

The DQM guideline for PGHD is distinguished from conventional DQM guidelines for clinical data in several ways: (1) it emphasizes the need for action corresponding to each DQM aspect at each stage of PGHD management; (2) it considers both external sociotechnical factors and internal organizational factors that impact the quality management of PGHD in RPM; (3) it recognizes patients’ and clinicians’ needs for each DQM aspect of PGHD, as the key PGHD stakeholders in RPM. This guideline is intended mainly for using PGHD for patient care. It is anticipated that the guidelines can also be used alongside conventional DQM guidelines for clinical data to assure PGHD quality and when these data are integrated into EMR systems.

To effectively apply the guideline in the remote monitoring of various health conditions, wearable devices should not be considered as stand-alone tools that work in isolation. Instead, they should be looked at as one component of a bigger ecosystem where different stakeholders interact with each other, with the devices, data, technical infrastructure of the health care setting, and standards to ensure that high-quality PGHD are collected, managed, and used for patient care [3]. The guideline can be best applied when RPM is implemented for >1 health condition across the health care system and when PGHD are collected from >1 type of wearable device and system interconnections are facilitated [98]. Also, realizing the value of high-quality PGHD for patient care can potentially blur the reliability distinctions between the 2 types of wearables, consumer and medical wearables. Being approved by regulatory agencies as a medical grade wearable does not ensure that the PGHD from it achieve a satisfactory level of quality. PGHD from consumer wearables are rarely used in current RPM services, and the research findings mainly included PGHD from medical wearables, so unseen challenges might exist to the quality management of PGHD from consumer devices. Advances in the capabilities of consumer devices and patients’ and clinicians’ accessibility to them are likely to see greater crossover between medical and consumer wearables in the future.

The DQM guideline for PGHD in RPM cannot be successfully implemented and used if the health system does not address the factors listed in Textbox 2.

The implementation of PGHD quality management in RPM can benefit the health care system and those who are considered the stakeholders of PGHD and who might advantage from the incorporation of these data into clinical practice, including the groups listed in Textbox 3.

**Textbox 2.** Considerations for the implementation of the data quality management (DQM) guideline.

- Policies: clinical, technical, and organizational policies need to be in place in parallel with the guideline for the quality management of patient-generated health data (PGHD) to increase the likelihood that PGHD will be trustworthy for use in clinical care.
- Technical infrastructure: PGHD from wearables used in remote patient monitoring (RPM) programs are not yet integrated routinely into electronic medical record systems or able to flow securely across the health care system; both factors are key barriers to using PGHD in clinical care. The guideline can be best applied when a technical infrastructure is established to follow the recommendations for the systematic management, interactive and standardized presentation, and consistent exchange of PGHD and standardized and timely access of PGHD reports to patients and clinicians.
- Digital health literacy: understanding the quality management of PGHD requires sufficient digital health literacy among all PGHD stakeholders. The conceptual model shows that all DQM aspects need action in the stage when patients collect PGHD, emphasizing patients’ need for literacy to understand DQM. Training delivered to patients and caregivers could enhance their engagement in the collection and management of high-quality data. Moreover, RPM teams could be expanded to include professionals who could provide DQM advice and support to clinical stakeholders.
- Collaboration: without collaboration among all PGHD stakeholder groups, the guideline recommendations cannot be implemented effectively in RPM. In addition to the stakeholders that were involved in this project, other stakeholders such as payers, policy makers, and health care administrative need to collaborate with the RPM team to understand the implementation requirements of the DQM guideline of PGHD. Continuous collaborative efforts to evaluate wearable devices, PGHD, and the data management processes could provide the health system with high-quality data that are fit for clinical care, population health management, and secondary uses.
Patients and carers: patients will be able to collect high-quality data to manage their conditions. They will learn to correctly use digital health devices and collect high-quality PGHD that could be clinically valuable and used optimally in clinical care. Moreover, by collecting relevant and quality-assured PGHD and sharing them with a single RPM system, patients’ role in RPM could be changed from passive to active participants, strengthening their interactions with clinicians, improving shared decision-making, and better engaging them in their health self-management.

Clinicians: the pandemic has increased clinicians’ awareness of the potential uses of RPM and PGHD. However, they need a reliable and convenient way to determine the utility of PGHD from patients, based on how and when these data are collected and reported and how and when they and others can access and interact with the data. The use of PGHD quality management recommendations enable clinicians to assess the quality of available data to support a patient consultation and how these data can form a valuable basis for efficient shared decision-making. Through this, they could optimize their focus on PGHD during and between patient visits.

Health information professionals: health information professionals are nonclinical staff, including health informaticians, health information managers, and other experts who monitor data and information management within the health care system. The implementation of the guideline could bring new responsibilities and roles for these professionals. For example, these experts can play a critical role in defining new approaches to manage PGHD and use their skills to work collaboratively on data integration and management. In addition, they could act as gatekeepers before PGHD become available to clinicians and filter and analyze the data to provide the most meaningful information for clinicians.

Health care organizations: for maintaining RPM after the pandemic, health care organizations need to be sure that PGHD from different digital health tools will support safer, higher-quality, and faster decision-making, based on more persuasive patient-clinician communication, leading to more effective and efficient health outcomes. The implementation of the RPM system driven by the PGHD quality management guideline could assist health care organizations in taking a standard approach to data integration, quality assurance, and risk management of these data to increase their trustworthiness for use in patient care. It may also provide health care organizations with strategies to think about the required infrastructure, policies, human resources, and potential collaborations with other parties to enhance the use of PGHD in clinical practice.

Digital health technology companies: medical device companies may be alerted to the existing unrecognized problems in ensuring the quality of data from their proprietary devices and offer solutions to overcome these. This may address the need for better synergies with the existing health data standards and health information system architectures to enable data sharing from various devices. Consumer device companies may also realize the gaps in ensuring the quality of data from their devices. This could assist in developing higher-quality devices with user-friendly and validated data handling solutions that are capable of being integrated more readily into the existing clinical information systems.

Other beneficiaries: findings from this research may also have indirect benefits, including providing insights into PGHD features and functions to the developers of electronic clinical information systems, such as patient records and point-of-care decision-support. These insights may inform the development of health policies and regulation of PGHD, including their use in research and public health, and could also provide more research opportunities in this area considering other kinds of PGHD and solutions for the further use of such data in broader contexts.

Limitations
PGHD collection for self-management purposes without clinical use was out of the scope of this research. Moreover, this study did not concentrate on the concept of data quality as used in the biomedical engineering domain, such as the accuracy of the formula or algorithms embedded in wearables. We also limited the exploration of PGHD to their use in direct patient care, engaging with the stakeholders in this kind of use, and excluded the secondary uses of data, such as in outcomes research, surveillance, reimbursement strategies, and purposes other than patient care.

The recommendations of the DQM guideline of PGHD were defined at a high level. They would benefit from the addition of details that specify the roles and responsibilities of different stakeholder groups. This would require the guideline to be investigated more deeply with participation from different stakeholder groups to identify further considerations in different contexts.

The guideline might be questioned as not being specific to one health condition when it is known that RPM initiatives are management of all the health conditions that a patient might have [72]. Nevertheless, for further exploration, the guideline can be implemented in each disease-based RPM to provide more specific recommendations based on particular needs. Understanding what makes PGHD more reliable for shared decision-making can motivate PGHD stakeholders to have a shared understanding of the value of these data and use them more efficiently to achieve better health outcomes.

Comparison With Prior Work
Research on the adoption, integration, and evaluation of RPM, wearables, and PGHD in clinical practice is rapidly growing [99-106], particularly during the COVID-19 pandemic, when many RPM initiatives were implemented around the world.

However, a few studies focused on PGHD quality [51,62,69,107] had aims and scopes that were different from those of our research. This is the first study of its kind that adapted 7 common aspects of DQM and investigated them in PGHD context during PGHD management stages. It also involved various groups of international PGHD stakeholders to share their experiences, concerns, and expectations regarding the quality management of PGHD and constructed and validated a set of recommendations as a novel guideline. This process helped reach a consensus among the participants on the recommendations they could follow to effectively collaborate for better patient care.

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Conclusions

Although the quality of PGHD is addressed as a vital factor in increasing their reliability in clinical decision-making, this research is the first of its kind to explore the quality management of PGHD through 7 aspects during data management stages. The guideline developed in this research provides a major step forward in this regard. It gives PGHD stakeholders a framework for improving the quality management of PGHD collected and used in RPM underpinned by collaboration.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

The synthesis of the findings of this project’s previous studies and the resulting themes that constructed the recommendations. [DOCX File, 42 KB - mhealth_v11i1e35917_app1.docx ]

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Abbreviations

CGM: continuous glucose monitoring
DQM: data quality management
EMR: electronic medical record
PGHD: patient-generated health data
RPM: remote patient monitoring

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Interventions Aimed at Enhancing Health Care Providers’ Behavior Toward the Prescription of Mobile Health Apps: Systematic Review

Ohoud Alkhaldi1,2, BSc, MSc; Brian McMillan3, BSSc, MBChB, PhD; Noha Maddah1,4, BSc, MSc; John Ainsworth1, MSc, PhD

1Division of Informatics, Imaging and Data Sciences, School of Health Sciences, Faculty of Biology, Medicine and Health, The University of Manchester, Manchester, United Kingdom
2Health Information Management and Technology Department, College of Public Health, Imam Abdulrahman Bin Faisal University, Dammam, Saudi Arabia
3Centre for Primary Care and Health Services Research, The University of Manchester, Manchester, United Kingdom
4Department of Health Services and Hospitals Administration, Faculty of Economics and Administration, King Abdulaziz University, Jeddah, Saudi Arabia

Corresponding Author:
Ohoud Alkhaldi, BSc, MSc
Division of Informatics, Imaging and Data Sciences, School of Health Sciences
Faculty of Biology, Medicine and Health
The University of Manchester
Vaughan House
Portsmouth St
Manchester, M13 9GB
United Kingdom
Phone: 44 7415085174
Email: ohoud.alkhaldi@postgrad.manchester.ac.uk

Abstract

Background: Mobile health (mHealth) apps have great potential to support the management of chronic conditions. Despite widespread acceptance of mHealth apps by the public, health care providers (HCPs) are reluctant to prescribe or recommend such apps to their patients.

Objective: This study aimed to classify and evaluate interventions aimed at encouraging HCPs to prescribe mHealth apps.

Methods: A systematic literature search was conducted to identify studies published from January 1, 2008, to August 5, 2022, using 4 electronic databases: MEDLINE, Scopus, CINAHL, and PsycINFO. We included studies that evaluated interventions encouraging HCPs to prescribe mHealth apps. Two review authors independently assessed the eligibility of the studies. The “National Institute of Health’s quality assessment tool for before-and-after (pretest-posttest design) studies with no control group” and “the mixed methods appraisal tool (MMAT)” were used to assess the methodological quality. Owing to high levels of heterogeneity between interventions, measures of practice change, specialties of HCPs, and modes of delivery, we conducted a qualitative analysis. We adopted the behavior change wheel as a framework for classifying the included interventions according to intervention functions.

Results: In total, 11 studies were included in this review. Most of the studies reported positive findings, with improvements in a number of outcomes, including increased knowledge of mHealth apps among clinicians, improved self-efficacy or confidence in prescribing, and an increased number of mHealth app prescriptions. On the basis of the behavior change wheel, 9 studies reported elements of environmental restructuring such as providing HCPs with lists of apps, technological systems, time, and resources. Furthermore, 9 studies included elements of education, particularly workshops, class lectures, individual sessions with HCPs, videos, or toolkits. Furthermore, training was incorporated in 8 studies using case studies or scenarios or app appraisal tools. Coercion and restriction were not reported in any of the interventions included. The quality of the studies was high in relation to the clarity of aims, interventions, and outcomes but weaker in terms of sample size, power calculations, and duration of follow-up.

Conclusions: This study identified interventions to encourage app prescriptions by HCPs. Recommendations for future research should consider previously unexplored intervention functions such as restrictions and coercion. The findings of this review can
help inform mHealth providers and policy makers regarding the key intervention strategies impacting mHealth prescriptions and assist them in making informed decisions to encourage this adoption.

**KEYWORDS**
mHealth; mobile apps; prescription; behavioral change; mobile phone

**Introduction**

**Background**
The number of patients living with chronic conditions continues to increase worldwide [1], and empowering these patients to manage their diseases is vital. Mobile health (mHealth) provides digital solutions to patients to help them track and manage their diseases. With the increased number of available mHealth apps to download and use [2], it is expected that the number of consumers, whether they are members of the general public, patients, or health care providers (HCPs), will continue to grow. The purpose of different types of mHealth apps vary from well-being, prevention, management, and monitoring to follow up with HCPs. Some of these apps may be potentially suitable to be prescribed to patients for the diagnosis or treatment of medical conditions. The concept of “prescribable” health apps is recently introduced to refer to health apps that are currently available and have demonstrated effectiveness [3].

Studies evaluating the effectiveness of mobile apps on health outcomes are increasing in number. Several systematic reviews have concluded that mobile apps have the potential to improve patients’ health conditions, such as diabetes [4], mental health [5], and cardiovascular diseases [6]. Governments in several countries have acknowledged the benefits of mHealth and have endeavored to meet the urgent need to accelerate the adoption of mHealth apps. Germany became the first country in the world to prescribe mobile apps. HCPs can prescribe mHealth apps, which can be reimbursed by health insurance companies [7]. In the United Kingdom, the National Institute for Health and Care Excellence has published guidance about “Sleepio,” a digital therapeutic to treat insomnia, and has recommended the use of Sleepio as a cost-saving option in comparison with sleep hygiene or sleeping pills [8]. On the basis of the results of 28 studies, it has been concluded that Sleepio is more effective than the usual treatment in reducing symptoms of insomnia in adults [9].

In a survey study, HCPs from the United Kingdom were more likely to prescribe apps if they were tagged with National Health Service approval or recommended by work colleagues [10]. The same study reported that National Health Service–approved mHealth apps were more influential than evidence-based research. In Germany, a study of physicians’ attitudes toward prescribable mHealth apps found that only one-third of the physicians intended to prescribe apps, and the rate of HCPs who had already prescribed them was lower than expected, despite the existence of regulations and facilitators from the government accelerating the mHealth app adoption among HCPs [11]. The study authors suggested that a range of factors influenced app prescribing, including gender, age, the lack of intention to prescribe, and limited apps for some specialties.

These studies shed light on various barriers to mHealth app adoption in clinical care and provide opportunities to design future behavior change interventions to improve HCPs’ evidence-based app prescription behaviors. To date, there have been no systematic or comprehensive literature reviews that compile evidence of interventions for enhancing HCPs’ app prescription behaviors. Bringing together the findings from such interventions could potentially provide policy makers and stakeholders with a better understanding of valuable strategies that can be implemented to enhance HCPs’ uptake of mHealth apps. In this review, we address this gap by identifying interventions that aim to redirect HCPs’ behavior toward prescribing or recommending apps to patients.

**Behavior Change Framework**
Several approaches are available to guide behavior change intervention designs. Among these approaches are the person-based approach [12], the British Medical Research Council’s framework on the development and evaluation of complex interventions [13], and intervention mapping [14]. Although each of these approaches offers considerable value to researchers, each concentrates on a different component of intervention development or has been criticized for lacking comprehensiveness and coherence [15].

The behavior change wheel (BCW) is used to characterize and evaluate behavior change interventions [15]. This framework provides a comprehensive approach to identifying sources of behavior and classifying them into the capability, opportunity, motivation, and behavior (COM-B) model, which represents the wheel’s hub (Figure 1). These components interact with each other to produce a change in behavior. Surrounding this is a layer of 9 intervention functions that can be selected depending on the behavioral analysis reached with the COM-B. The final layer contains 7 types of policies that one can use to deliver these intervention functions. The intervention functions are connected to behavior change techniques, which are the smallest active elements of an intervention (eg, self-monitoring, goal setting, action planning etc) [16]. Behavior change techniques used in interventions can be categorized using a taxonomy comprising 93 different techniques.

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Understanding the target behavior is essential before designing an intervention. However, the BCW can also be applied retrospectively to intervention studies to identify and describe the behavior change strategies that have been used. It can also be used to improve current interventions or to introduce and evaluate an intervention that looks promising. Therefore, the interventions included in this review are classified into intervention functions of the BCW.

**Objectives**

The study objectives were (1) to summarize and evaluate interventions aimed at encouraging HCPs to prescribe mHealth apps to patients and (2) to classify and map intervention strategies with the intervention functions of the BCW.

**Methods**

**Research Question**

This study was based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analyses) guidelines [18]. The research question was created based on the PICO framework (population, intervention, comparator, and outcome) and was defined as follows: “How do interventions designed to encourage mobile health app prescription change the practices, knowledge or self-confidence of healthcare providers?”

**Eligibility Criteria**

The population of interest was HCPs or trainees (eg, health personnel, general practitioners [GPs], physicians, clinicians, dietitians, and students of health specialties). Intervention studies to encourage mHealth app prescriptions, regardless of the design, were considered eligible. The primary outcome of interest reflected any measures of practice or behavior changes such as number of app prescriptions or self-reported or objectively measured changes in knowledge or confidence. The included studies had to be conducted in primary care settings. Studies were excluded if they were about patients’ adoption of mHealth apps or interventions to improve patients’ health outcomes. Other mHealth technologies such as wearables, mobile phone messaging, video consultations, or electronic health records (EHRs) were excluded. Studies of apps for HCPs’ medical education and training or decision support systems via mobile devices were also excluded.

**Sources of Information and Search**

A search of 4 electronic databases (MEDLINE, Scopus, CINAHL, and PsycINFO) was conducted to identify studies published between January 1, 2008, and August 5, 2022. The official start of mobile apps was chosen as 2008, as the iPhone App Store was launched that year [19]. Studies published in English and peer-reviewed papers were included. A manual search of the reference lists of eligible studies was conducted. Medical Subject Headings terms were used wherever possible to locate the relevant studies. The Boolean operators AND and OR were used to enhance the search strategy. The search string used in 2 databases is shown in Multimedia Appendix 1.

**Study Selection**

The search results were exported to the EndNote Web software (Clarivate Analytics) for screening and removing duplicates. After eliminating duplicates, screening of all titles and abstracts
was independently conducted by 2 reviewers (OA and NM). The same 2 researchers reviewed the full texts of the papers identified as relevant to the objectives. In cases of disagreement, the research team discussed them and made the final decision.

**Risk of Bias Assessment**

The risk of bias was assessed using 2 quality appraisal tools based on the study design. The National Institute of Health’s quality assessment tool for before-and-after (pretest-posttest design) studies with no control group was used for uncontrolled before-and-after studies [20]. This tool is composed of 12 items with response options “yes,” “no,” “not reported,” and “not applicable,” and the overall quality of each study can be classified as “good,” “fair,” or “poor.” The grading was decided by the total score: 0 to 4 (poor), 5 to 9 (fair), and 10 to 12 (good).

The mixed methods appraisal tool (MMAT) was used to assess the quality of the remaining studies. The MMAT is a comprehensive tool for assessing the quality of quantitative, qualitative, and mixed methods study designs [21]. This tool begins with 2 screening questions to determine whether a research objective is clear and whether the collected data allow a research question to be answered. The remaining 5 questions assess the methodologies. A score of 0-2 was considered low; a score of 3-4 was considered moderate; and a score of 5 was considered high.

**Data Collection and Synthesis**

**Data Extraction**

After the study selection, data were extracted from eligible studies. The following data were extracted: study characteristics (author, year of publication, country, aim, types of mHealth apps used, mode of delivery, length of study/number of sessions, study design, and sample size); outcomes of each study; and main findings related to the research question of this systematic review. One reviewer (OA) performed the data extraction, and the research team checked the accuracy of the extracted data.

**Data Synthesis**

The diversity of measures and outcomes identified in the eligible studies did not allow for quantitative data synthesis; therefore, a narrative synthesis was conducted. The 9 intervention functions of the BCW [15] were used to classify intervention strategies to help inform future attempts to design interventions. Each intervention was categorized as performing one or more of the 9 functions [22]. Definitions of the intervention functions are listed in Textbox 1.

Textbox 1. Definitions of intervention functions in the behavior change wheel.

<table>
<thead>
<tr>
<th>Function</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education</td>
<td>Increasing knowledge or understanding</td>
</tr>
<tr>
<td>Persuasion</td>
<td>Using communication to induce positive or negative feelings or stimulate action</td>
</tr>
<tr>
<td>Incentivization</td>
<td>Creating an expectation of reward</td>
</tr>
<tr>
<td>Coercion</td>
<td>Creating an expectation of punishment or cost</td>
</tr>
<tr>
<td>Training</td>
<td>Imparting skills</td>
</tr>
<tr>
<td>Restriction</td>
<td>Using rules to reduce the opportunity to engage in the target behavior (or to increase the target behavior by reducing the opportunity to engage in competing behaviors)</td>
</tr>
<tr>
<td>Environmental restructuring</td>
<td>Changing the physical or social context</td>
</tr>
<tr>
<td>Modeling</td>
<td>Providing an example for people to aspire to or imitate</td>
</tr>
<tr>
<td>Enablement</td>
<td>Increasing means or reducing barriers to increase capability or opportunity beyond environmental restructuring</td>
</tr>
</tbody>
</table>
Results

Study Selection

The search strategy retrieved 3464 records. Of these, 466 (13.6%) studies were duplicates and were removed, leaving 2998 (86.5%) studies for screening. The screening of titles and abstracts excluded 2959 (98.7%) studies. Therefore, 39 (1.3%) studies were eligible for full-text screening. Another 10 records were identified through citation searching, and 6 (60%) of these were included for full-text screening. Full-text screening of the 45 studies yielded a total of 11 (24%) studies in the final review. The study selection process and the reasons for exclusion are shown in Figure 2.

Figure 2. Study selection flow diagram based on the PRISMA (Preferred Reporting Item for Systematic Reviews and Meta-Analyses) guidelines. HCP: health care professional; mHealth: mobile health.

Characteristics of the Included Studies

The studies were published between 2015 and 2020 and were performed in the United States (6/11, 54%), Australia (2/11, 18%), the Netherlands (1/11, 9%), Catalonia (1/11, 9%), and the United Kingdom (1/11, 9%). All the included studies contained an interventional component. Of the total 11 studies, 6 (54%) were pretest-posttest design studies with no control group; 3 (27%) were mixed methods studies; 1 (9%) was a usability study; and 1 (9%) was a qualitative description study.

The studies varied regarding study participants; some were focused on HCPs in primary care settings [23-25], whereas others targeted specific specialties, such as dietitians [26,27], behavioral health providers [28,29], providers in weight management clinics [30], clinical nutrition and physician assistant students [31], or interdisciplinary groups [32,33]. Most studies (8/11, 73%) had a sample size ranging from 5 to 40 HCPs, apart from 3 (27.3%) studies that reported the results of interventions conducted over multiple years or many training sessions in which the sample size ranged from 78 to 760 [28,29,31]. The functions of the mHealth apps used in these studies included weight management [27,30] or diet and activity tracking [26,31]. A total of 45% (5/11) of the studies used a list of approved apps for a range of health conditions [23,25,28,29,32], and 9% (1/11) used an app for chronic obstructive pulmonary disease (COPD) [33]. An overview of the characteristics of the individual studies included in the systematic review is provided in Multimedia Appendix 2 [23-33].

The most common changes resulting from the intervention were self-reported changes in knowledge, confidence, or self-efficacy [28,30-33]. Only 1 (1/11, 9%) study reported HCPs’ intention...
to use or recommend the app [33], and 1 (1/11, 9%) study evaluated app acceptance and use in dietetic care [27]. However, the outcomes were objectively estimated using the change in the number of apps prescribed in 36% (4/11) studies [23-25,32].

Quality of the Evidence and Risk of Bias in the Included Studies

Using the National Institute of Health quality assessment tool, the studies by Armstrong et al [28,29], Byambasuren et al [25], Chen et al [26], and Rodder et al [31] were assessed as having a moderate risk of bias. The study by Al-Lami et al [30] was assessed as having a high risk of bias owing to a lack of clarity around several categories that were not reported, particularly regarding the selection and eligibility of participants. In all studies (6/11, 54%), it was difficult to determine whether the researchers were blinded to the intervention. An additional limitation of many of the included studies was their small sample size. Of the 11 studies, this was particularly the case for 2 studies (18%): one with 5 participants [26] and the other with 6 [30]. Most studies (5/6, 83%) lacked power calculations to accommodate the consequences of participants dropping out, thus resulting in missing values in the postintervention measurements, with the exception of Byambasuren et al [25]. The studies by Armstrong et al [28,29] and Byambasuren et al [25] did not present P values to compare outcome measures at pretest and posttest. The details of the quality assessment are presented in Multimedia Appendix 3 [23-33].

Using the MMAT, the qualitative description study was deemed high quality [27]. Out of the 3 mixed methods studies, 1 (33%) was judged to be of low quality [27] and 2 (67%) were of moderate quality [24,33]. The independent assessment of their quantitative and qualitative components lowered the methodological quality of all mixed methods studies. The quantitative study was deemed to be of low quality [32] owing to concerns regarding the poor description of patient selection and the high nonresponse rate. However, all studies clearly stated the objectives, interventions, and outcomes. The follow-up periods were generally short (immediately after the intervention up to 4 months after the intervention). More details on the quality assessments for each study are shown in Multimedia Appendix 3.

Effectiveness of Interventions

The results reported by the interventions included were generally positive, with improvements being seen in several outcomes such as changes in current practices, increased knowledge, or improved self-efficacy. Although the levels of significance for the included outcomes varied, only 1 (9.1%) study found that the interventions had nonsignificant results [27].

Changes in Practice

A total of 54% (6/11) of studies reported changes in HCP practice following the intervention. Byambasuren et al [25] reported effective changes in GPs’ prescriptions of mHealth apps. Although the study did not report a P value for the number of prescriptions at pretest and posttest, the number of apps recommended per GP per fortnight increased from 1.7 to 4.1. The use of videos had no significant impact on the number of app prescriptions. Similarly, Makhni et al [32] reported the results of an 8-week trial; users at the 5 clinical sites prescribed more than 2000 apps; this exceeded the adoption targets, which was set at 100 health apps. In the study by Segui et al [23], the use of the AppSault platform to prescribe apps was reported. A total of 32 doctors made 79 app recommendations to patients, which represented 79% of the recommendations compared with what was expected during the pilot design [23]. This increase in the percentage of platform use was seen as a successful change in current practice. The staff use of apps was reported in the study by Hoffman et al [24], but it was self-reported through questionnaires. Clinical staff were receptive to apps, with 83% (19/23) incorporating behavioral health apps into their clinical work, and 25% (5/20) introducing apps to patients up to 50% of the time.

In total, 2 (18%) studies measured changes in practice using qualitative methods. First, the intervention by Korpershoek et al [33] measured the feasibility of using the Copilot app and reported HCPs’ high satisfaction and high levels of interest in the app. They also believed that the app was user-friendly and relevant to daily practice and that it fit well within the organizational culture. Second, Barnett et al [27] reported the myPace app’s acceptance among HCPs who were positive about the app. However, the uptake and recommendation of the myPace app were lower than expected.

Change in Knowledge

Of the 11 studies, 3 (27%) studies reported changes in the knowledge of HCPs about mHealth apps. The core competency training designed and delivered by Armstrong et al [28,29] was successful in transferring the knowledge of the enrolled clinicians. One of these studies reported the results of 3 years of the training program [28]. There was a 28.96% increase in HCPs’ self-reported knowledge of the use of mHealth in clinical care when comparing pretraining measurements (mean 2.97, SD 1.07; n=537) with posttraining measurements (mean 4.31, SD 0.76; n=537). The other study reported the results of 1 year of training and showed that the number of HCPs who rated their overall knowledge of the use of mHealth in clinical care as good or excellent before training increased from 34% (67/199) to 93% (185/199) after the training [29]. The intervention of Al-Lami et al [30] consisted of providing HCPs with a list of evaluated apps to make recommendations from, educating them about the efficacy of using mHealth apps in weight management and training them in the use of apps’ critical appraisal tools. A significant knowledge increase was reported (P=.02).

Changes in Confidence and Self-efficacy

In the remaining 2 studies, the curriculum expansion to enable physician assistant (PA) and clinical nutrition (CN) students to use mHealth apps in clinical care yielded increased self-reported confidence in their skills from pretest to posttest (P≤.001) [31]. The findings were supported by students’ Objective Structured Clinical Examination (OSCE) scores, which showed that both PA and CN students effectively taught standardized patients to use mobile apps for disease management. In the intervention by Chen et al [26], dietitians rated their self-efficacy before and after completing an educational and skill-training session on apps and after receiving 12 weeks of real-world experience using mHealth apps in their practice. A significant improvement
in dietitians’ overall self-efficacy with mHealth apps was reported (ANOVA $F_{2, 12}=7.0; P=.01$).

**Intervention Functions**

The included studies were analyzed using the BCW framework. By doing so, the framework allowed an examination of which intervention functions are most commonly applied in the context of mHealth app prescriptions. Given that some strategies can be classified as falling into >1 category, that is, multiple intervention functions, it was difficult to link outcomes to a single intervention function. Therefore, the following sections report how the intervention strategies fit within the BCW’s 9 intervention functions. The intervention functions, outcomes, and main findings are reported separately in Table 1.
Table 1. Intervention functions adopted in each of the reviewed studies and main findings.

<table>
<thead>
<tr>
<th>Author and year</th>
<th>Education</th>
<th>Persuasion</th>
<th>Incen- tivization</th>
<th>Coerc- tion</th>
<th>Training</th>
<th>Re- stric- tion</th>
<th>Environmental restructuring</th>
<th>Modeling</th>
<th>Enable- ment</th>
<th>Main findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Armstrong et al [28], 2018 and Armstrong et al [29], 2019a</td>
<td>7-hour CEb workshop</td>
<td>Interactive material to allow learners to engage with the material</td>
<td>N/A</td>
<td>N/A</td>
<td>1. mHealth apps used as examples for hands-on experience Interpersonal skills on how to discuss mobile apps with patients</td>
<td>N/A</td>
<td>Site champion to offer additional training</td>
<td>Site champion to offer support</td>
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<td></td>
<td>• In total, 93.7% reported that the information and skills learned from the training would be used in their clinical care [28].</td>
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<td></td>
<td></td>
<td>• In total, 95.8% reported that the information and skills learned from the training would be used in their clinical care [29].</td>
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<td>Byambasuren et al [25], 2020</td>
<td>A letter with a brief description of each app and the study time frames and procedures was mailed.</td>
<td>1. Having prescription pads worked as a visual reminder or cue to prescribe apps Videos after 2 months demonstrating the content, features, and function of each app</td>
<td>N/A</td>
<td>N/A</td>
<td>Prescription pads were developed and given to GPs with apps that are relevant in general practice.</td>
<td>N/A</td>
<td>N/A</td>
<td>1324 app prescriptions were dispensed over 4 months</td>
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<td></td>
<td>• The GPs’ confidence in prescribing apps doubled from a mean of 2 (not so confident) before the study to 4 (very confident) at the end of the study</td>
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</tr>
<tr>
<td>Author and year</td>
<td>Education</td>
<td>Persuasion</td>
<td>Incitivization</td>
<td>Coercion</td>
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<td>Main findings</td>
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<tr>
<td>Chen et al [26], 2019</td>
<td>Workshop to educate dietitians about a range of mHealth apps</td>
<td>Verbal persuasion about capabilities to master app use even in difficult situations</td>
<td>N/A</td>
<td>N/A</td>
<td>1. Case studies Dietitians were trained to appraise the quality of these apps</td>
<td>Easy Diet Diary Connect platform</td>
<td>N/A</td>
<td>1. Workshop facilitator is a dietitian modeling and working with apps 2. Working with colleagues enabled social comparisons to be made</td>
<td>Ongoing support during 12 weeks of the intervention</td>
<td>• A significant improvement in overall self-efficacy with using mHealth apps (ANOVA F2, 12=7.0; P=.01)</td>
</tr>
<tr>
<td>Rodder et al [31], 2018</td>
<td>Curriculum expansion to educate students on the use of mHealth</td>
<td>Pass the OSCE assessment</td>
<td>N/A</td>
<td>N/A</td>
<td>1. Students trained in how to evaluate apps using the SAAT® appraisal tool 2. Students trained in interpersonal skills, such as how to educate patients 3. Students trained to download and use recommended apps using case studies</td>
<td>MyNetDiary and Withings Health Mate apps</td>
<td>N/A</td>
<td>Peer comparison</td>
<td>N/A</td>
<td>• Confidence levels improved significantly for all survey measures, for both PA and CN students (P&lt;.001)  • OSCE results showed that both PA and CN students were able to download MyNetDiary (96.4%), enter food into the app (98.4%), and discuss the advantages of using the app for food tracking with patients (90.3%).</td>
</tr>
<tr>
<td>Al-Laemi et al [30], 2019</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>Training in how to use the Ped-WHAT App appraisal tool before making app recommendations</td>
<td>Providing HCPs with a list of evaluated apps from which to make recommendations</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Author and year</td>
<td>Education</td>
<td>Persuasion</td>
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<tr>
<td>Makhni et al [32], 2017</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>Personal training in the use of the RxUniverse platform</td>
<td>N/A</td>
<td>RXUniverse app-prescribing system</td>
<td>Demonstrating a trial process for prescribing an app</td>
<td>Considerations of the workflow to minimize disruption and time burdens of participants</td>
<td></td>
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<tr>
<td>Hoffman et al [24], 2019</td>
<td>Series of staff meetings on best practices for using mental health apps within clinical care</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>During an 8-week trial, over 2000 apps were prescribed to all users in the 5 clinical sites. Users felt that RxUniverse performed well. The group mean for the overall SUS² score was 84.2, an “excellent” rating.</td>
</tr>
</tbody>
</table>

- Provider knowledge of the use of apps significantly increased after the training (mean 1.00, SD 1.00 vs mean 1.67, SD 0.52; t=3.16; P=.025).
- Provider confidence in recommending apps to patients increased significantly after the training (mean 1.00, SD 0 vs mean 1.67, SD 0.52; t=3.16; P=.025).
<table>
<thead>
<tr>
<th>Author and year</th>
<th>Education</th>
<th>Persuasion</th>
<th>Incen-tivization</th>
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<th>Enablement</th>
<th>Main findings</th>
</tr>
</thead>
</table>
| Korper-shoek et al [33], 2020 | HCPs were introduced to the Copilot app and the scenario for use of the app in daily practice, and the intended role of both HCPs and patients | N/A | N/A | N/A | N/A | A fictional patient scenario was given to HCPs, who were asked to conduct several tasks | Copilot app for COPD self-management | N/A | N/A | - Main themes: high satisfaction, user-friendly, relevant for daily practice, app fit well within the organizational culture, high level of interest  
- An average score of 83.8 (SD 15.1) on the SUS, indicating good usability of the app |
| Barnett et al [27], 2015 | N/A | N/A | N/A | N/A | Personal training in the use of myPace software and how to make app recommendations to patients | MyPace app for weight loss designed to fit daily dietetic practice | N/A | N/A | - The dietitians were positive and enthusiastic about the app; however, their enthusiasm did not translate into actual uptake, use, and recommendation |
| Segui et al [23], 2018 | Follow-up and monitoring | N/A | N/A | N/A | N/A | AppSalut platform to prescribe apps | | N/A | | |

- In total, 82.6% incorporated BH apps into their clinical work; 25% introduced apps to patients 25% to 50% of the time In total, 42% expressed a need for more practice and training in using each tool within the CHA's mobile app toolkit.
Main findings

Enablement

Modeling

Environmental restructuring

Restric- tion

Training

Support by periodic follow-ups accompanied by training for doctors and solving any technical problems

Persuasion

Coercion

Incen- tivization

Re- stric-

Incitivization

Virtually no doctors made recommendations to patients, representing 160% of doctors and 79% of recommendations compared with what was expected.

Main findings

In total, of the 11, 9 (81.8%) studies included elements of education. Education came in the form of workshops in 4 studies [26,28-30]. The workshops covered the best practices for using mHealth apps in patient care and considerations of privacy, security, and ethical and cultural issues of using mHealth apps with patients [28,29]. The workshop in the study by Chen et al [26] educated dietitians about the range of commercially available apps. Similarly, the workshop in the study by Al-Lami et al [30] provided background information on mobile apps’ efficacy and validity in weight management therapy. It introduced a list of apps to use when making recommendations to patients. However, Hoffman et al [24] used a series of staff meetings as the mode of delivery to educate behavioral health staff about the best practices for using mHealth apps with patients. One study, which was conducted in an academic health center, also involved education through curriculum expansion and focused on mHealth apps [31].

In the study by Byambasuren et al [25], education was part of the intervention in 2 ways. A letter was mailed to each participant describing the study and containing instructions and guides on prescribing the app. The second education element was also delivered via videos showing the app’s content, features, and functions. In this study, the authors aimed to assess the impact of videos on the number of app prescriptions.

Creating guides or providing HCPs with instructions on when to introduce and discuss apps with patients were carried out in 2 studies as an educational form [23,24]. Another study used education; however, the content was tailored to the platform under testing. Koreospek et al [33] introduced the Copilot app to study participants and explained the intended use of the app for the self-monitoring of symptoms by patients with COPD. Moreover, a tutorial was given on how to use the app and perform essential functions, such as registering patients and customizing an action plan.

These educational elements of the interventions aimed to improve HCPs’ knowledge. In addition, of the 11 studies, 3 (27%) captured and reported changes in self-reported knowledge before and after the intervention [28-30]. The remaining studies measured different outcomes, such as a change in self-confidence [25,31], self-efficacy [26], or an increased number of prescriptions [25]. However, these measures were reported as the results of the intervention as a whole and were not specific to education.

Persuasion

A total of 45% (5/11) of the studies reported elements of persuasion. Periodic follow-ups with study participants served as a method of reminding and motivating HCPs to modify their prescribing habits [23]. Visual reminders were used in another study in 2 forms. First, videos were sent to study participants after month 2 of the intervention [25]. These videos not only...
were educational but also worked as a tool to remind study participants of the study. Second, the design and dissemination of prescription pads involved reminders or cues to prescribe apps.

Persuasion was reflected in both studies by Armstrong et al [28,29]. The development of educational materials involved adopting evidence-based interactive educational experiences to allow learners to engage in the material and ensure promising results regarding behavior change. In a study by Chen et al [26], persuasion was sought verbally to convince dietitians of their capabilities to prescribe mHealth apps, even in difficult situations such as short consultations.

**Incentivization**

Incentivization can be social, such as a promotion in status, or fiscal. Students’ desires to pass the OSCE exam by demonstrating their capabilities to recommend and use mHealth apps in nutrition care worked as a social incentive [31]. According to the OSCE results, PA and CN students successfully taught patients how to use mobile apps to track food intake and test blood pressure. None of the remaining interventions used strategies that fall into the incentivization category.

**Training**

A total of 8 (72.7%) interventions reported elements of training to improve HCPs’ skills when using apps. The focus and range of skills offered to HCPs varied in each study. Three interventions used case studies or scenarios to help HCPs develop and master the basic skills of using and recommending apps [26,31,33]. Training on how to use Ped-WHAT, an app appraisal tool, when making recommendations to patients and their families was critical in the intervention by Al-Lami et al [30]. Similarly, Rodder et al [31] trained students to evaluate mobile apps using a smartphone app appraisal tool.

Participants received personal training in using myPace software and were allowed to practice with it [27]. They were also allowed to provide feedback on their first impression of the software during these training sessions and were encouraged to use or recommend the app to make it a standard tool to support everyday practice. The training in the intervention by Makhni et al [32] intervention was also individualized. HCPs were instructed on how to use the RxUniverse system to make app prescriptions and were then observed to ensure successful app prescription.

The term “hands-on experience” was used in the study by Armstrong et al [28] to refer to practical experience; however, if training was involved, it was not detailed enough. Interpersonal skills were targeted in 2 interventions [28,29]. Competencies in discussing mobile apps with patients and showing an understanding of patients’ concerns about privacy and security were at the core of these interventions. Rodder et al [31] also mentioned measuring students’ communication skills in OSCE examinations. Students were asked to demonstrate skills in discussing the benefits of using apps for food tracking and blood pressure measurement.

**Environmental Restructuring**

To promote app prescription behavior among HCPs, 9 interventions contained methods of environmental restructuring. Most included studies offered technical resources to facilitate app prescriptions, such as developing an electronic platform. The study by Segui et al [23] tested the feasibility of using an app catalog named AppSault for recommending apps to patients. The apps were free to download and passed the quality control process, guaranteeing a safe and reliable environment for their use. Makhni et al [32] used RxUniverse, a digital medicine-focused care delivery platform with a library of apps chosen based on published evidence-based reviews of their efficacy and usability. Some studies provided HCPs with specialized apps and measured how they fit daily practice. The MyNetDiary and Withings Health Mate apps were provided for PA and CN students in a study by Rodder et al [31], myPace for dietitians in a study by Barnett et al [27], and Copilot for COPD self-management in a study by Korpershoek et al [33]. The Easy Diet Diary Connect platform was used to allow dietitians to track patients in a study by Chen et al [26]. Other studies have used lists of apps given to HCPs to make recommendations [24,25,30]. Environmental restructuring came in the form of EHRs’ standardized “smart phrases” to facilitate the prescription process [24].

**Modeling**

A total of 5 (45.5%) studies reported on methods of modeling [26,28,29,31,32]. The intervention by Armstrong et al [28,29] used “site champions” as onsite facilitators who offered additional training to local staff. Modeling was presented in different forms in the intervention by Chen et al [26]. First, the workshop moderator, who was also a dietitian, like the other study participants, modeled and used the app. Second, during the intervention, working with colleagues who had participated in the study and were successful in using the app enabled a social comparison to be made. Another study used modeling by comparison and competition among students or peers of each class [31]. Makhni et al [32] used a similar modeling method by demonstrating the functionality of the platform to participants who were thereafter asked to prescribe an mHealth app.

**Enablement**

Enablement was used in 5 (45.5%) studies. In 1 study, enablement came in the form of ongoing support throughout the study to reduce barriers associated with prescribing mHealth apps [26]. Support was also provided to study participants by consulting office managers and study participants about the specific operational workflows of each clinical site and the optimal implementation plan for RxUniverse at each pilot site to minimize the time burden [32]. The periodic follow-ups in the study by Segui et al [23] were accompanied by solving any technical problems, which enabled the implementation of corrective actions and extra training [23]. Recognizing site champions in Armstrong et al [28,29] offered support to sustain behavior change after the training.
None of the interventions included in this review used the intervention functions of coercion or restriction.

**Linking Interventions With the COM-B Model**

We looked at the most often used intervention functions in the studies with successful outcomes to gain a better understanding of why the included intervention functions provided substantial changes. As seen in Table 1, successful interventions used a variety of intervention functions (environmental restructuring, education, and training). These intervention functions cover most components of the COM-B model, which suggests that interventions are more likely to produce effective results and make changes in current behavior if they target a wide spectrum of the COM-B model’s components. For example, the study by Chen et al [26] used all COM-B components to increase dietitians’ app use behaviors through dietitians’ education and skill training as well as environmental restructuring by providing physical app-based infrastructure. Modeling, coaching, and improving self-efficacy were also addressed. Therefore, the reported change in ratings of dietitians’ self-efficacy when using mHealth apps was significant (P=.01). The Tukey post hoc test revealed significantly higher post–workshop mHealth app self-efficacy ratings compared with the baseline (P=.02), and the ratings were sustained at 12 weeks (P=.01).

In addition, the intervention functions used in the ineffective study were linked to only 2 COM-B model components (physical capability and physical opportunity), suggesting a need to understand the target behavior by collecting data from multiple sources to ensure successful behavior change.

**Discussion**

**Principal Findings**

This review included 11 studies investigating the effects of interventions aimed at encouraging app prescription behavior among HCPs. Most studies demonstrated positive findings for outcomes such as self-confidence, knowledge of mHealth apps, and number of app prescriptions. The studies included differed widely in terms of interventions, measures of practice change, types of mHealth apps used, modes of delivery, and study settings.

A broad range of interventions, all related to methods for enhancing mHealth app adoption, specifically mHealth prescribing, was covered in this review, including education (workshops, class lectures, individual sessions with a dietitian or research team, videos, or toolkits), persuasion (reminders or verbally about capabilities), incentivization (expectation to pass the course), training (case studies or scenarios or app appraisal tools), modeling (site champions or observing peers), enablement (support), and environmental restructuring (lists of apps, technological systems, time, and resources).

**Comparisons With Other Works**

More than half of the interventions included in this review had training (8/11, 72.7%) or educational (9/11, 81.8%) functions that targeted HCPs’ capabilities (physical or psychological). A lack of knowledge and awareness of available apps are major barriers reported in the literature [34-36]. A study reported that HCPs consider the lack of knowledge of available apps that have proven their effectiveness in improving patient health outcomes an important barrier to prescribing [35]. This confirms the urgent need to provide training programs or educational sessions regarding the available mHealth apps that support patient self-management of long-term conditions.

However, the terms training and education are often used interchangeably. Some studies reported training as part of the intervention, but these studies included only elements of imparting knowledge and understanding, not skill development [24,28]. One possible explanation is the lack of attention to different types of training in behavior change interventions. Hence, there is difficulty in perceiving what training might entail. Therefore, it is vital to distinguish between the 2 terms. This overlap has also been reported between other intervention functions. Another study reported the existence of some overlap when providing education to participants because it serves a persuasion function at the same time [37]. This is mainly because education may induce positive feelings toward app prescription.

The lack of coercion (defined as “creating expectation of punishment or cost”) may be because it was not deemed a suitable approach for improving self-efficacy or confidence in app prescriptions or it may have been deemed counterproductive when trying to create positive attitudes or encourage app prescriptions. Furthermore, it is impractical to penalize HCPs for not prescribing mHealth apps.

None of the interventions adopted restrictions such as rules to increase HCP app prescriptions or decrease any competing behavior. The absence of regulations that ensure apps’ highest quality and accuracy and the lack of data validity and reliability of existing apps keep HCPs from prescribing apps to their patients [38,39]. To compensate, some interventions have provided study participants with a list of trustworthy apps to use when making app recommendations to patients. Other interventions adopted digital solutions such as building software or electronic systems containing approved apps. Removing such barriers by providing practical resources is a form of environmental restructuring.

Minimizing the disruption of HCPs’ time is a form of enablement reported in only one intervention [32]. HCPs’ concerns about time to discuss and instruct patients on how to use apps were reported as barriers to app prescription. In a pilot study, participants were concerned that recommending apps to patients would lengthen the duration of consultations [23]. In France, a qualitative study presented a theme after interviews with GPs about “Doctor Protection,” which mainly introduced concerns about increased workload and prescriptions of apps as an additional task [40]. One significant distinction between apps and medications is that many drugs can be prescribed with simple directions, whereas an app may require more specific instructions.

One way to minimize physicians’ workloads is to integrate and synchronize health information produced from mHealth apps to patients’ EHRs. By doing this, the physician’s ability to access patient data is centralized. In an acceptability and
feasibility study that examined integrating patient data generated from smartphones into EHRs [41], clinicians reported that by using the graph feature, they could evaluate longitudinal data during consultations, which was quick and easy. When compared with retrieving information by recording histories, this was thought to be a possible time saver. Furthermore, this approach provided an accurate reflection of disease changes and treatment responses.

**Strengths and Limitations of the Study**

This review has several strengths and limitations. This is the first review that addresses interventions to improve HCPs' confidence and capabilities to prescribe or recommend mHealth apps to patients. We consider the included studies to be a complete set of studies from 2008 to 2022. The studies were sourced from a variety of electronic databases, with the reference lists of the included papers checked for potentially relevant studies. This systematic review used a robust methodology that included screening all the studies for relevance by 2 independent reviewers.

However, the number of studies included in this review was limited, and the findings depended on the quality of the included studies. Of the 11 studies, 3 (27.3%) studies were found to be at high risk of bias, 7 (63.6%) at moderate risk of bias, and only 1 (9.1%) at low risk of bias (see Appendix 3). A total of 6 (54.5%) studies were pretest-posttest design interventions; these are known for their methodological issues such as selection bias and short durations, which do not make it possible to determine whether the intervention is effective and sustainable [42]. Furthermore, 7 (63.6%) studies used self-reported data to reflect possible changes in behaviors. With self-reported outcomes, it is impossible to tell whether the reported change in knowledge or practice is owing to response-shift bias or an actual adoption of the targeted behaviors. This emphasizes the importance of using objective measures instead. Objective measures such as the number of app prescriptions and OSCE scores were reported in 4 (36.4%) studies. However, the assessment of behavior changes or intentions to change app prescription behaviors cannot always be performed using objective measures. This is the case, in particular with interventions that lack technical systems to track the changes in the number of prescriptions before and after the intervention. Combining objective and self-reported measures could bring more insight and different perspectives to the study findings.

**Unanswered Questions and Future Research**

Several gaps in the research were identified in this review. Coercion and restriction were not reported in any of the interventions included; however, this may be because they were not deemed appropriate approaches for changing app prescription behaviors in this population. The impact of other forms of intervention functions not used in any of the interventions reviewed could be explored, such as the use of incentives (financial or nonfinancial) that, if appropriately applied and supported with other intervention functions, could potentially make an impact and encourage HCPs to prescribe apps [43]. Evidence on the acceptability and impact of such programs in the context of mHealth is lacking. This can be answered with future studies.

High-quality studies with adequate sample sizes and longer study periods are now essential for detecting differences in app prescription behaviors. Future interventions could adopt theoretical frameworks and behavior change frameworks to systematically understand HCPs' behavior toward the prescription of mHealth apps.

The COM-B model, as part of the BCW, is a useful tool to make behavioral diagnoses and identify what needs to change [22]. Evidence from successful interventions, interviews, or surveys with HCPs about what motivates or limits their mHealth app prescription behaviors can provide sufficient information to understand the sources of those behaviors. Therefore, future interventions can address the target behavior (app prescriptions) and its influencing factors.

**Conclusions**

This study identified interventions aimed at improving HCPs’ app-prescribing behaviors. On the basis of the BCW, environmental restructuring and education were the most frequently used intervention functions in the included studies, followed by training. The findings of this study provide evidence that combining elements of training, education, and environmental restructuring is more likely to produce effective changes in HCPs’ behavior toward app prescribing.

**Acknowledgments**

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**Conflicts of Interest**

None declared.

**Multimedia Appendix 1**

Results of the search strategies used in the MEDLINE and CINAHL databases.

[DOCX File - mhealth_v11i1e43561_app1.docx]

**Multimedia Appendix 2**

Characteristics of individual studies included in the systematic review.

[DOCX File - mhealth_v11i1e43561_app2.docx]
Multimedia Appendix 3
Risk of bias assessment of included studies.
[DOCX File, 16 KB - mhealth_v11i1e43561_app3.docx]

References


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Abbreviations

BCW: behavior change wheel
CN: clinical nutrition
COM-B: capability, opportunity, motivation, and behavior
COPD: Chronic Obstructive Pulmonary Disease
EHRs: electronic health records
GPs: general practitioners
MMAT: mixed methods appraisal tool
OSCE: Objective Structured Clinical Examination
PA: physician assistant
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-analyses
Effectiveness of a Mindfulness Meditation App Based on an Electroencephalography-Based Brain-Computer Interface in Radiofrequency Catheter Ablation for Patients With Atrial Fibrillation: Pilot Randomized Controlled Trial

Ying He¹*, BSc; Zhijie Tang²*, MSc; Guozhen Sun¹, MSc; Cheng Cai¹, MD; Yao Wang¹, MD; Gang Yang¹, MD; ZhiPeng Bao¹, MSc

¹Department of Cardiology, The First Affiliated Hospital of Nanjing Medical University, Nanjing, China
²School of Nursing, Nanjing Medical University, Nanjing, China
*these authors contributed equally

Corresponding Author:
ZhiPeng Bao, MSc
Department of Cardiology
The First Affiliated Hospital of Nanjing Medical University
300 Guangzhou Road, Gulou District
Nanjing, 210029
China
Phone: 86 15895903958
Fax: 86 025 68303041
Email: baozhipeng1219@163.com

Abstract

Background: Radiofrequency catheter ablation (RFCA) for patients with atrial fibrillation (AF) can generate considerable physical and psychological discomfort under conscious sedation. App-based mindfulness meditation combined with an electroencephalography (EEG)-based brain-computer interface (BCI) shows promise as effective and accessible adjuncts in medical practice.

Objective: This study aimed to investigate the effectiveness of a BCI-based mindfulness meditation app in improving the experience of patients with AF during RFCA.

Methods: This single-center pilot randomized controlled trial involved 84 eligible patients with AF scheduled for RFCA, who were randomized 1:1 to the intervention and control groups. Both groups received a standardized RFCA procedure and a conscious sedative regimen. Patients in the control group were administered conventional care, while those in the intervention group received BCI-based app–delivered mindfulness meditation from a research nurse. The primary outcomes were the changes in the numeric rating scale, State Anxiety Inventory, and Brief Fatigue Inventory scores. Secondary outcomes were the differences in hemodynamic parameters (heart rate, blood pressure, and peripheral oxygen saturation), adverse events, patient-reported pain, and the doses of sedative drugs used in ablation.

Results: BCI-based app–delivered mindfulness meditation, compared to conventional care, resulted in a significantly lower mean numeric rating scale (mean 4.6, SD 1.7 [app-based mindfulness meditation] vs mean 5.7, SD 2.1 [conventional care]; P=.008), State Anxiety Inventory (mean 36.7, SD 5.5 vs mean 42.3, SD 7.2; P<.001), and Brief Fatigue Inventory (mean 3.4, SD 2.3 vs mean 4.7, SD 2.2; P=.01) scores. No significant differences were observed in hemodynamic parameters or the amounts of parecoxib and dexmedetomidine used in RFCA between the 2 groups. The intervention group exhibited a significant decrease in fentanyl use compared to the control group, with a mean dose of 3.96 (SD 1.37) mcg/kg versus 4.85 (SD 1.25) mcg/kg in the control group (P=.003). The incidence of adverse events was lower in the intervention group (5/40) than in the control group (10/40), though this difference was not significant (P=.15).

Conclusions: BCI-based app–delivered mindfulness meditation effectively relieved physical and psychological discomfort and may reduce the doses of sedative drugs used in RFCA for patients with AF.

Trial Registration: ClinicalTrials.gov NCT05306015; https://clinicaltrials.gov/ct2/show/NCT05306015
Introduction

Atrial fibrillation (AF) is recognized as the most common cardiac arrhythmia worldwide, with an estimated prevalence of 2%-4% in adults [1]. Epidemiological studies indicate that AF increases the risk of stroke by 5-fold and the risk of overall mortality by 3.5-fold [2,3]. AF is becoming an increasingly extensive public health problem and causes substantial health economic burden [4-6]. Radiofrequency catheter ablation (RFCA) has become a first-line therapy for AF to improve symptoms, cardiac function, and quality of life, and has been shown to be cost-effective [7-9]. In China, the number of patients with AF is estimated to be approximately 20 million, and the number of RFCA procedures for AF exceeds 30,000 every year [10,11].

Considering the longer general anesthesia preparation time, higher economic costs, and potential complications, conscious sedation is used for RFCA at most centers in China [12-14]. However, even under well-tolerated doses of sedative drugs, sedation-related side effects such as nausea, vomiting, and oversedation are common [15]. Furthermore, patients are required to remain motionless and endure radiofrequency energy burning their myocardia for hours during the complex RFCA procedure. Consequently, even under deep sedation, patients may still experience considerable pain, anxiety, fatigue, and other discomforts, which may be associated with poor outcomes [16-18]. Several studies have indicated that nonpharmacological interventions could be ideal adjuncts to sedative drugs, effectively reducing patients’ physical or psychological discomfort and the required doses of sedative drugs during medical invasive procedures [19,20].

Mindfulness meditation originates from Buddhist teachings and refers to a category of techniques used to pay attention to the present moment and accept all that arises without judgment [21]. Numerous studies suggest that mindfulness meditation may hold potential for alleviating pain, fatigue, and negative emotions [22,23]. However, the effects of mindfulness meditation during AF ablation remain uncertain. In recent years, with the rapid development of digital medicine, app-based mindfulness interventions have been preliminarily shown to be effective and accessible [24].

A brain-computer interface (BCI) is defined as a technology for establishing external information communication and control pathways between the human brain and computers or other electronic devices [25]. Electroencephalography (EEG) is a conventional form of brain signal acquisition, which can be recognized and reflected (usually through visual or auditory signals) by BCI [26]. Studies have shown that EEG-based BCI devices can sense and classify human psychological states, which may facilitate mindfulness meditation practice [27,28].

This study aimed to determine the effects of a BCI-based mindfulness meditation app on RFCA for patients with AF. The primary hypothesis was that the intervention group would experience significant improvements in perceived pain, anxiety, and fatigue compared to the control group. We also hypothesized that the intervention might decrease the use of sedative drugs and the incidence of adverse events.

Methods

Study Design

This was a single-center, 2-arm, parallel-group, prospective, pilot randomized controlled trial. Patients were randomized 1:1 to the intervention and control groups using a computer-generated randomization list. Due to the nature of the study design, neither program implementers nor patients could be blinded to the intervention. However, the investigators performing the outcome assessments and data analysis were blinded to the group allocation.

Participants

Overview

Patients were eligible for the study if they were (1) diagnosed with AF, (2) at least 18 years old, (3) undergoing their initial RFCA procedure, and (4) willing to participate in the study. Patients were excluded if they had (1) severe systemic diseases such as malignant tumors, (2) a history of mental illness and cognitive complaints, and (3) difficulty understanding the questionnaire and the study aims. They were also excluded if they experienced drastic changes in their condition during RFCA.

Sample size calculations were conducted using PASS 2021 (NCSS LLC) software and based on previous studies [29,30]. Power analysis showed that a sample size of 70 participants was sufficient to have 90% statistical power at a 2-sided α of .05 for significance. To account for a 20% loss rate, the planned sample size was 84 participants.

All patients underwent a standardized RFCA procedure for AF with a 3D mapping system (CARTO 3, Biosense Webster) and were provided with standardized information about the study and the potential benefits and risks of the interventions. Both groups received the same sedative regimen during RFCA, which was adjusted by the interventional physician based on the patient’s response to the medication and reported pain levels. The regimen included a single dose of parecoxib (40 mg), fentanyl (1 mcg/kg/hour), and dexmedetomidine as necessary, with dosing adjustments made in accordance with standard pain management procedures at our institution. The fentanyl maintenance infusion rate ranged from 0 to 2 mcg/kg/hour, while the dexmedetomidine maintenance infusion rate ranged from 0 to 1 mcg/kg/hour.
**Intervention Group**

Patients in the intervention group received mindfulness meditation guidance delivered through a Chinese-language interface and voice app (Focus Zen, version 2.1.1) along with a BCI-based headband. A mobile phone and a Samsung tablet device with the preinstalled app were prepared in the cardiac catheterization laboratory. Before ablation, study staff briefly introduced the method and meaning of mindfulness meditation to help patients understand the intervention content. Mindfulness meditation represents a practice of awareness in which the person gradually and purposely focuses on the present without judgement to achieve a state of deep relaxation [31]. The app’s developers designed a 35-minute mindfulness meditation course specifically for patients with AF to help them relax during ablation without affecting the ablation procedure (eg, the course instructed patients to breathe evenly rather than deeply). We provided patients with Bluetooth earphones and set the background sound within the app in accordance with the patients’ preferences, such as forest, beach, or rain sounds. During the mindfulness meditation practice, patients were guided by a female voice through the app to relax muscles, regulate breathing, and practice visualization and body scanning. Simultaneously, the app collected EEG information using a headband device that was synchronized with the app through Bluetooth technology (Figure 1). An artificial intelligence algorithm included in the app was used to analyze the EEG data and classify the patient’s brain state as active, calm, relaxed, or meditative. The app interface and headband light color were adjusted in accordance with the patients’ state. Additionally, the app prompted the patients’ current brain state through background sound effects and guided the patient to maintain the state or make adjustments through the app voice.

*Figure 1.* Screenshots of the study app. (A) Device connection, (B) background sound setting, and (C) mindfulness meditation course.

**Control Group**

The control group received routine care for their ablation procedure and was informed about the procedure of ablation and characteristics of impending pain in ablation, as in the intervention group. Psychological and supportive care were provided in accordance with the patients’ needs. However, patients in the control group wore the headband device without using the earphones and did not receive mindfulness meditation guidance provided by the app.

**Outcome Measurements**

Both the intervention and control groups were administered 2 surveys, one 30 minutes before ablation and one within 30 minutes after ablation, to assess pain intensity, fatigue, and anxiety using specific paper questionnaires. Demographic information and characteristics of participants were collected at baseline. The study staff recorded patients’ hemodynamic parameters (heart rate, blood pressure, and peripheral oxygen saturation [SpO₂]), spontaneously reported pain, the doses of sedative drugs used, and adverse events during ablation.

The primary outcomes were pain and anxiety levels during ablation and fatigue severity after ablation. The intensity of pain was measured using the numeric rating scale, with scores that ranged from 0 (no pain) to 10 (the worst possible pain) [32,33]. The State Anxiety Inventory (A-State) is a subscale of the State-Trait Anxiety Inventory [34], which is mainly used to assess the anxiety state in a specific situation. The A-State score was used in this study to explore the anxiety level of patients.
during ablation. We evaluated the patients’ fatigue after ablation using the Brief Fatigue Inventory (BFI) [35], a 10-item validated scale. A higher score indicates a greater level of fatigue.

Secondary outcomes included mean heart rate, blood pressure, and SpO₂ during ablation. Adverse events were defined as excessive fluctuations in blood pressure (fluctuations of >50 mm Hg in systolic blood pressure), nausea and vomiting, and vasovagal reaction. The study staff also recorded the number of times of spontaneously reported pain and the doses of sedative drugs used during ablation.

**Statistical Analysis**

Statistical analysis was performed using SPSS (version 22.0; IBM Corp) and based on the intention-to-treat principle with a 2-sided significance level of .05. Data were analyzed using descriptive statistics and checked for the normality of their distribution. Descriptive continuous variables are presented as mean (SD) values and categorical variables as frequency and percentage values. Differences between study groups were analyzed using an independent 2-sample t test for numerical variables and the Mann-Whitney U test, chi-square test, or the Fisher exact test for categorical variables.

**Ethical Considerations**

This study was conducted at the cardiac catheterization laboratory of the First Affiliated Hospital of Nanjing Medical University, Nanjing, China, from April to September 2022. All study patients provided oral or written informed consent. This study was approved by the ethics committee of the First Affiliated Hospital of Nanjing Medical University (2022-SR-086) and registered at ClinicalTrials.gov (NCT05306015). Procedures were conducted in accordance with the tenets of the Declaration of Helsinki.

**Results**

**Baseline Characteristics**

A total of 84 patients (42 patients each in the intervention and control groups) were enrolled and completed baseline measures in this study. A total of 4 patients (2 each from the intervention and control groups) were excluded from the study. Figure 2 shows the CONSORT (Consolidated Standards of Reporting Trials) diagram for this clinical trial.

No significant differences were found between the intervention group and the control group in baseline characteristics (Table 1). Neither group had previous experience with practicing mindfulness meditation.
Table 1. Baseline characteristics of the study participants (N=80).

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<td>CHDd, n (%)</td>
<td>3 (8)</td>
<td>9 (23)</td>
<td>.06</td>
</tr>
<tr>
<td>Type of AFe, n (%)</td>
<td></td>
<td></td>
<td>.37</td>
</tr>
<tr>
<td>Paroxysmal</td>
<td>24 (60)</td>
<td>20 (50)</td>
<td></td>
</tr>
<tr>
<td>Persistent</td>
<td>16 (40)</td>
<td>20 (50)</td>
<td></td>
</tr>
<tr>
<td>NYHAF class, n (%)</td>
<td></td>
<td></td>
<td>.59</td>
</tr>
<tr>
<td>Class I</td>
<td>32 (80)</td>
<td>30 (75)</td>
<td></td>
</tr>
<tr>
<td>Class II</td>
<td>8 (20)</td>
<td>10 (25)</td>
<td></td>
</tr>
<tr>
<td>RFCAg time (minutes), mean (SD)</td>
<td>40.1 (14.3)</td>
<td>42.6 (15.0)</td>
<td>.44</td>
</tr>
<tr>
<td>RFCA energy (Watts), mean (SD)</td>
<td>42.2 (3.8)</td>
<td>42.1 (3.6)</td>
<td>.81</td>
</tr>
<tr>
<td>RFCA temperature (℃), mean (SD)</td>
<td>28.8 (3.3)</td>
<td>29.5 (4.3)</td>
<td>.39</td>
</tr>
</tbody>
</table>

aLAD: left atrium diameter.
bLVEF: left ventricular ejection fraction.
cDM: diabetes mellitus.
dCHD: coronary heart disease.
eAF: atrial fibrillation.
gRFCA: radiofrequency catheter ablation.

Primary Outcomes

We found no significant difference in the baseline pain, anxiety, and fatigue scores between the intervention and control groups (Table 2). After the intervention, compared to the control group, there were significant differences in numeric rating scale (mean 4.6, SD 1.7 [intervention group] vs mean 5.7, SD 2.1 [control group]; P=.008) and A-State (mean 36.7, SD 5.5 vs mean 42.3, SD 7.2; P<.001) scores after ablation. The BFI score after ablation was significantly lower in the intervention group than in the control group (mean 3.4, SD 2.3 vs mean 4.7, SD 2.2; P=.01).

Table 2. NRSa, A-Stateb, and BFIC scores of the intervention and control groups.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Baseline</th>
<th></th>
<th>Post intervention</th>
<th></th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Intervention group, mean (SD)</td>
<td>Control group, mean (SD)</td>
<td>P value</td>
<td>Intervention group, mean (SD)</td>
<td>Control group, mean (SD)</td>
</tr>
<tr>
<td>NRS score</td>
<td>0.3 (0.5)</td>
<td>0.4 (0.5)</td>
<td>.66</td>
<td>4.6 (1.7)</td>
<td>5.7 (2.1)</td>
</tr>
<tr>
<td>A-State score</td>
<td>30.7 (4.4)</td>
<td>31.8 (6.2)</td>
<td>.39</td>
<td>36.7 (5.5)</td>
<td>42.3 (7.2)</td>
</tr>
<tr>
<td>BFI score</td>
<td>1.4 (1.7)</td>
<td>1.2 (1.5)</td>
<td>.49</td>
<td>3.4 (2.3)</td>
<td>4.7 (2.2)</td>
</tr>
</tbody>
</table>

aNRS: numerical rating scale.
bA-State: State Anxiety Inventory.
cBFI: Brief Fatigue Inventory.
Secondary Outcomes

Between the intervention and control groups in ablation, there were no significant differences in the mean heart rate (mean 87.4, SD 15.7 [intervention group] vs mean 91.1, SD 16.4 [control group] beats per minute; *P*=.31), systolic blood pressure (mean 127.2, SD 15.7 vs mean 131.9, SD 17.4 mm Hg; *P*=.21), diastolic blood pressure (mean 81.1, SD 10.5 vs mean 82.7, SD 9.6 mm Hg; *P*=.49), and SpO\(_2\) (mean 98.4%, SD 1.3% vs mean 98.5%, SD 1.2%; *P*=.71; Figure 3).

There were no significant differences in parecoxib and dexmedetomidine use between the intervention and control groups during ablation. The intervention group had significantly decreased fentanyl use compared to the control group (*P*=.003; Table 3). Additionally, patients in the intervention group reported significantly fewer times of pain than those in the control group (*P*<.001). The incidence of adverse events in the intervention group was lower than that in the control group, but the difference did not reach statistical significance (*P*=.15).

Figure 3. Hemodynamic parameters of the 2 groups. bpm: beats per minute; DBP: diastolic blood pressure; HR: heart rate; RFCA: radiofrequency catheter ablation; SBP: systolic blood pressure; SpO\(_2\): peripheral oxygen saturation.

<table>
<thead>
<tr>
<th>Medications and outcomes</th>
<th>Intervention group (n=40)</th>
<th>Control group (n=40)</th>
<th><em>P</em> value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parecoxib (mg), mean (SD)</td>
<td>29.0 (18.1)</td>
<td>27.0 (19.0)</td>
<td>.63</td>
</tr>
<tr>
<td>Fentanyl (mcg/kg), mean (SD)</td>
<td>3.96 (1.37)</td>
<td>4.85 (1.25)</td>
<td>.003</td>
</tr>
<tr>
<td>Dexmedetomidine (mcg/kg), mean (SD)</td>
<td>1.49 (0.82)</td>
<td>1.85 (1.00)</td>
<td>.57</td>
</tr>
<tr>
<td>Patient reports of pain (times), mean (SD)</td>
<td>1.5 (1.4)</td>
<td>2.8 (1.7)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Adverse events, n (%)</td>
<td>5 (13)</td>
<td>10 (25)</td>
<td>.15</td>
</tr>
</tbody>
</table>

Discussion

Principal Findings

The purpose of this study was to evaluate the effectiveness of a novel BCI-based mindfulness meditation app for patients with AF to improve their physical and psychological status in RFCA. The selected app provides EEG feedback for mindfulness meditation, which may help patients relax and reduce unpleasant experiences without interfering with the ablation process. The key findings showed significantly lower pain, anxiety, and fatigue scores in the intervention group than among those receiving conventional care. No significant differences were found in the mean heart rate, blood pressure, or SpO\(_2\) between groups during RFCA. Additionally, the intervention group had a significant decrease in fentanyl use, while the differences in other sedative drugs were not significant. Although the incidence of adverse events was lower in the intervention group, the difference was not significant.

Mobile health, via wireless technologies such as smartphone apps and wearable devices, is currently used for patients with AF mostly for screening, management, and rehabilitation [36-39]. Numerous studies have investigated the impact of meditation on cardiac disease and suggest that it may offer potential benefits for cardiovascular health, including reducing...
blood pressure, improving psychological and physiological responses to stress, and possibly mitigating AF progression by modulating the autonomic nervous system [21,40]. Mobile app–based mindfulness meditation has the potential to serve as an adjunct to the RFCA procedure for patients with AF owing to its low risks, potential benefits, and relatively low cost. Nevertheless, it is essential to acknowledge the costs associated with using a commercialized app and headband device, along with the requirement for labor and its cost to monitor the app. Additionally, caution should be exercised in making claims about the low risk of this intervention, as it is based solely on the findings of this small pilot study. Further research is needed to explore the relationship between meditation and AF ablation.

To our knowledge, this is the first study to assess the effectiveness of a mindfulness meditation app together with a BCI-based wearable device for patients with AF during RFCA. This study achieved promising results and indicated that this type of intervention could be easily integrated into the standard RFCA workflow.

It is well known that RFCA for AF can be accompanied by considerable pain and anxiety when conscious sedation is used, which, however, has potential side effects [15]. Anxiety is common in patients with AF [41]. Patients may experience pain and uncertainty for several hours during RFCA, which could amplify negative emotions such as anxiety and make them feel exhausted. Therefore, it is necessary to monitor and intervene in patients with AF’s anxiety during ablation procedures [16].

Previous studies have indicated that apps based on nonpharmacological interventions could effectively reduce the fatigue, anxiety, pain, and the use of sedative drugs in invasive medical treatment [42–44]. Nørgaard et al [45] examined the effects of visualization together with usual pain medication in comparison with conventional care among patients with AF undergoing RFCA, and found significant reductions in the perception of pain and anxiety, as well as the doses of analgesics used in the intervention group [46]. Wearable devices are drastically changing medical practices nowadays. Roxburgh et al [47] implemented a virtual reality headset for patients with AF undergoing cryoballoon ablation under conscious sedation and found that the virtual reality group had a significantly lower perceived pain score and higher comfort score. In recent years, there has been a growing body of literature examining the effects of mindfulness training supported by EEG feedback. Crivelli et al [48] investigated the potential benefits of EEG-based brain-sensing device–supported mindfulness practices in individuals with mild stress levels and found a significant reduction in stress and anxiety. Similarly, Balconi et al [49] used mindfulness exercises in combination with wearable EEG information sensor devices to explore the effect of reducing overall stress levels in healthy individuals and found significant improvements in physiological (heart rate and variability) and subjective markers of stress (perceived stress, anxiety, and mood states). These findings are in line with those of this study, suggesting that EEG feedback may facilitate meditation by providing real-time information to aid users in achieving a mindfulness state. In our study, we assessed the effectiveness of an intervention based on a mindfulness meditation app combined with a BCI-based wearable device, which provides meditation guidance with synchronous EEG feedback to patients. This intervention has a minimal learning curve without requiring specialist training and provides personalized feedback, which may enhance patient engagement and adherence [50]. The potential mechanisms underlying pain, anxiety, and fatigue relief through mindfulness meditation are likely linked with the ability of meditation to change the activity of the insula, somatosensory cortex, anterior cingulate cortex, and prefrontal cortex. These changes may reduce patients’ attention, memory, and perception of physical and psychological discomfort [51,52]. When patients experience physical and mental discomfort in RFCA, the levels of catecholamines, adrenocorticotrophic hormone, prolactin, cortisol, and prostaglandins in their blood may increase [53], which could result in unstable hemodynamic parameters (heart rate, blood pressure, and SpO₂) [54] and, thereby, affect the performance of procedures and patient safety. Previous studies have indicated that nonpharmacological interventions could effectively stabilize hemodynamic parameters in invasive operative procedures [42,55]. In this study, however, the between-group differences in mean heart rate, blood pressure, or SpO₂ during RFCA did not reach statistical significance. The observed discrepancy between objective and subjective outcomes may be attributed to various factors. One possible explanation is that blood pressure changes induced by meditation through the autonomic nervous system may be a long-term process [21]. Furthermore, the timing of data collection may have influenced the findings, as objective measures were collected during the intervention, whereas subjective data were gathered through self-reports post intervention. It is worth noting that patients with AF frequently experience AF episodes during RFCA procedures, which may lead to variations in heart rate and blood pressure levels and contribute to the lack of significant differences between the groups. Additional research with larger sample sizes may help elucidate the potential impact of the intervention on these objective parameters. Although there was no significant difference, the incidence of adverse events was lower in the intervention group. This indicates a possibility for the potential protective effects of our intervention during RFCA, which merit further investigations.

**Strengths and Limitations**

A strength of this study is that it is the first randomized controlled trial, to our knowledge, to explore the effectiveness of a mindfulness meditation app together with a BCI-based wearable device among patients with AF during RFCA, which adds to the evidence base in the areas of meditation and mobile health. This study was designed rigorously. We provided the same care protocol and implemented the use of wearable devices for both groups, and recorded the time, energy, and temperature of ablation to ensure comparable conditions. In addition, this study was performed in a pragmatic setting and no maximum age for participation was stated, which adds to the generalizability of our findings.

This study also has some limitations. First, it was not a double-blind trial. Neither study staff nor patients were blinded to the intervention due to the nature of the study design. However, the data analysts were masked to group allocation. Additionally, meditation practice is a long-term process. Even
with the help of apps and wearable devices, it takes time to master meditation techniques to reach a meditative state faster. At least one preoperative practice session could be added to the protocol for the intervention group; however, this might affect the comparability of the baseline measures. Lastly, this is a single-center study, thus limiting the generalizability of our findings.

Conclusions
In conclusion, this study shows that BCI-based app–delivered mindfulness meditation significantly relieved pain, anxiety, fatigue, and may reduce the doses of sedative medication used during RFCA for AF. Although no significant differences in hemodynamic parameters and the incidence of adverse events were observed, there was a decrease in the incidence of adverse events in the intervention group. Smartphone apps and wearable devices could serve as feasible and promising adjuncts to improve patients with AF’s experience in RFCA.

Acknowledgments
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Authors' Contributions
YH and ZB contributed to the development and administration of the project. YH, ZB, ZT, CC, and GY assisted with implementing the protocol, collecting data, performing statistical analyses, and writing the manuscript. ZB and GS contributed to the conceptualization, methodology, supervision, and funding acquisition. All authors provided edits to the manuscript.

Conflicts of Interest
None declared.

Multimedia Appendix 1
CONSORT-eHEALTH checklist (V 1.6.1).
[PDF File (Adobe PDF File), 1295 KB - mhealth_v11i1e44855_app1.pdf ]

References


Abbreviations

AF: atrial fibrillation
A-State: State Anxiety Inventory
BCI: brain-computer interface
BFI: Brief Fatigue Inventory
CONSORT: Consolidated Standards of Reporting Trials
EEG: electroencephalography
RFCA: radiofrequency catheter ablation
SpO₂: peripheral oxygen saturation

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The Treatment Outcome of Smart Device–Based Tinnitus Retraining Therapy: Prospective Cohort Study

Myung-Whan Suh1,2*, MD, PhD; Moo Kyun Park1,2*, MD, PhD; Yoonjoong Kim3,4, MD; Young Ho Kim2,3, MD, PhD

1Department of Otorhinolaryngology, Seoul National University Hospital, Seoul, Republic of Korea
2Sensory Organ Research Institute, Seoul National University Medical Research Center, Seoul, Republic of Korea
3Department of Otorhinolaryngology-Head and Neck Surgery, Seoul Metropolitan Government-Seoul National University Boramae Medical Center, Seoul, Republic of Korea
4Department of Otorhinolaryngology-Head and Neck Surgery, Chungbuk National University Hospital, Cheongju-si, Republic of Korea

*these authors contributed equally

Corresponding Author:
Young Ho Kim, MD, PhD
Department of Otorhinolaryngology-Head and Neck Surgery
Seoul Metropolitan Government-Seoul National University Boramae Medical Center
20 Boramae-ro 5-gil
Dongjak-gu
Seoul, 07061
Republic of Korea
Phone: 82 28702442
Fax: 82 28703863
Email: yhkiment@gmail.com

Abstract

Background: Tinnitus retraining therapy (TRT) is a standard treatment for tinnitus that consists of directive counseling and sound therapy. However, it is based on face-to-face education and a time-consuming protocol. Smart device–based TRT (smart-TRT) seems to have many advantages, but the efficacy of this new treatment has been questioned.

Objective: The aim of this study was to compare the efficacy between smart-TRT and conventional TRT (conv-TRT).

Methods: We recruited 84 patients with tinnitus. Results were compared between 42 patients who received smart-TRT and 42 control participants who received conv-TRT. An interactive smart pad application was used for directive counseling in the smart-TRT group. The smart pad application included detailed education on ear anatomy, the neurophysiological model of tinnitus, concept of habituation, and sound therapy. The smart-TRT was bidirectional: There were 17 multiple choice questions between each lesson as an interim check. The conv-TRT group underwent traditional person-to-person counseling. The primary outcome measure was the Tinnitus Handicap Inventory (THI), and the secondary outcome measure was assessed using a visual analogue scale (VAS).

Results: Both treatments had a significant treatment effect, which comparably improved during the first 2 months. The best improvements in THI were −23.3 (95% CI −33.1 to −13.4) points at 3 months and −16.8 (95% CI −30.8 to −2.8) points at 2 months in the smart-TRT group and conv-TRT group, respectively. The improvements on the VAS were also comparable: smart-TRT group: −1.2 to −3.3; conv-TRT: −0.7 to −1.7.

Conclusions: TRT based on smart devices can be an effective alternative for tinnitus patients. Considering the amount of time needed for person-to-person counseling, smart-TRT can be a cost-effective solution with similar treatment outcomes as conv-TRT.

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KEYWORDS

tinnitus; tinnitus retraining therapy; smart device; sound therapy; rehabilitation; therapy; tablet application; app-based; therapy; digital therapy; device-based therapy
Introduction

Tinnitus retraining therapy (TRT) is a habituation therapy that can alleviate tinnitus-induced distress by means of directive counseling and sound therapy [1,2]. Despite the various attempts to cure tinnitus, currently there is no treatment that can completely eliminate tinnitus. Psychological and behavioral interventions such as cognitive behavioral therapy and TRT have been applied as alternatives. According to the 2014 guideline from the American Academy of Otolaryngology–Head and Neck Surgery, clinicians should “educate” patients with persistent, bothersome tinnitus about management strategies [3]. Also, clinicians may recommend “sound therapy” to patients with persistent, bothersome tinnitus [3]. These 2 strategies constitute the basis of TRT. Although high-quality randomized clinical trials are still lacking, it has been proposed in a Cochrane Database systematic review that TRT is more effective than sound masking [4].

One problem with TRT is that it is very time-consuming. With classic TRT, patients undergo at least 3 or 4 sessions of extensive, one-on-one, 60-minute, directive counseling that includes education about the auditory system, brain function, and Jastreboff’s neurophysiological model [2,5]. Due to the long and extensive counseling, it takes a lot of manpower and time. This problem is also associated with the high cost of TRT. In order to overcome this problem, group counseling [6] and simplified TRT [7] have been proposed by several researchers. Simplified TRT is efficient in that the counseling is short (30 minutes) and it omits the lengthy explanation about the anatomy and physiology of hearing. According to previous results, it seems that the treatment effect of simplified TRT is similar to that of classic TRT [7].

To further save manpower and time, we have come up with a TRT using interactive applications and smart devices (smart pad and smartphone). Instead of the classic one-on-one, 60-minute counseling, patients may engage with an application that delivers all the directive counseling content. A tablet computer or smart pad such as an iPad can be used for the bidirectional and intuitive operation. Traditional audiovisual devices such as a television are unidirectional: They can provide information to the user but cannot give any feedback. With the help of recent technology, we can now build applications that are bidirectional: The system can ask questions and assess progress, mimicking one-on-one counseling [8]. This system may also be beneficial for patients, since the cost of TRT can be reduced and there are fewer constraints around time and space [9,10]. Sound therapy can also be provided using an application or mp3 file installed on the patient’s smartphone.

Smart device–based TRT (smart-TRT) seems to have many advantages, but the efficacy of this new treatment has been questioned. Especially, the low level of human contact during TRT may lead to insufficient engagement with the educational intervention [11]. If this new technology is to be recommended to patients, the treatment outcome should be similar or better than conventional TRT (conv-TRT). The aim of this study was to compare the efficacy between smart-TRT and conv-TRT.

Methods

Participants

This study was a prospective trial with 2 arms. Both groups were recruited from the same institute during the same period, but group allocation was not randomized. The participants freely selected between the newly developed intervention or the conventional treatment. Of the 94 participants assessed for eligibility, 1 participant was excluded because the person refused to participate. Of the remaining 93 participants, 51 participants were allocated to the smart-TRT group, and 42 participants were allocated to the conv-TRT group (Figure 1). All participants underwent the intervention, and no one dropped out. We excluded 9 participants from the final analysis in order to match the 2 groups in terms of age, sex, and severity of tinnitus. The inclusion criteria were patients who were older than 20 years and had experienced chronic essential tinnitus for more than 6 months. Patients with vascular tinnitus, posttraumatic tinnitus, psychological disorders, severe hearing loss, sleep disorders, dementia, organic brain disorders, substance abuse, chronic renal failure, or uncontrolled malignancy were excluded from the study. Normal middle ear status was confirmed via audiogram and otoscopy, and we screened for abnormal psychological conditions such as depression, anxiety, and insomnia using the validated version of the Beck Depression Inventory (BDI) for depression [12,13], the State-Trait Anxiety Inventory (STAI) for anxiety [14], and the Pittsburgh Sleep Quality Index (PSQI) for sleep quality [15].
Ethics Approval
This study was approved by the Seoul National University Hospital Institutional Review Board (IRB no. 1207-112-419) and was conducted according to the tenets of the Declaration of Helsinki. All participants provided written informed consent.

Directive Education
For the smart-TRT group, 3 different interactive smart pad applications were prepared for the 3 directive education sessions. Each application was a composite of numerous video clips. Two screens were displayed on the smart pad: a big screen that showed illustrations or cartoons and a small screen that showed the face of the speaker (1st session, MWS; 2nd session, MKP; 3rd session, YHK). The 3 smart pad applications were presented to the patients with a 1-month interval between each at the clinic. We did not allow the participants to use these applications at home by themselves, to allow a fair comparison with the control group.

The smart pad applications included detailed education on the anatomy and physiology of the ear and auditory pathways, the perception of sound in the auditory cortex, “selective” listening, why tinnitus becomes a problem, the misconception that tinnitus causing hearing difficulties, an explanation of habituation as a goal, subconscious processing of auditory stimuli, “filtering” and “blocking” auditory stimuli from reaching consciousness, how to apply “sound therapy,” the neurophysiological model, and homework for the patient. Although the first session explained every aspect of these points, the second and third sessions reviewed the first session and added some new points with further examples. The smart-TRT was bidirectional: There were 17 multiple choice questions between each lesson for an interim check. The questions were mandatory, and the education session did not proceed if the patient did not respond. After the patient’s response, the correct answer was provided with further explanation why the answer was correct or incorrect. Since the patient’s response to each question was quite variable, the duration of the directive education differed between participants. It took at least 45 minutes for a patient to complete the first education session if the patient answered all the questions correctly and quickly. It took at least 25 minutes for a patient to complete the second and third education sessions. For some patients who had difficulty understanding the directive education, it could take more than 1 hour to complete 1 session.

For the conv-TRT group, simplified group (1-4 patients/session) counseling was provided by a single clinician (MWS). The counselor in the conv-TRT group was identical to the first speaker in the smart-TRT group (MWS). The contents and teaching materials for the directive counseling were also identical between the 2 groups. It took about 45 minutes to 60 minutes for a patient to complete the first session. It took about 10 minutes to 20 minutes for a patient to complete the second and third education sessions. The second and third sessions were rather short in the conv-TRT group, because most of the essential information and strategies were already well-covered. It took less time to review the last session and add new knowledge and encourage higher levels of motivation. Other than these points, all the other treatment and follow-up conditions were the same in the 2 groups.

Sound Therapy
The same sound source file (white noise) was provided to the patients in both groups. The patients used their own smartphone or a portable mp3 player to play the sound. If the patient was familiar with using smartphone applications, a sound therapy application that had been built by our group was installed on their smartphone. We instructed the patients in both groups to use the sound therapy device at the level of the mixing point for at least 6 hours a day.

Outcomes and Statistical Analysis
To calculate the sample size, the study was powered at 80% with a type I error of 5%. We assumed that a 5.9 difference in the Tinnitus Handicap Inventory (THI) score with an SD of 8
between the treatment groups was significant based on the study by Kaldo et al [16]. Assuming a loss of 30%, the number of patients needed for each group was 42 (84 patients total).

The primary outcome measure was the THI score. The change in the THI score was defined as ΔTHI = postTHI score − preTHI score. The secondary outcome measure was a visual analogue scale (VAS) score to quantify awareness of tinnitus, loudness of tinnitus, annoyance caused by tinnitus, and the effects of tinnitus on daily life [17-20]. The change in the VAS score was defined as ΔVAS = postVAS score − preVAS score. The effects of TRT were assessed based on changes in the THI and VAS scores at 0, 1, 2, and 3 months after the TRT. Continuous variables are expressed as mean (SD), and all statistical analyses were performed using SPSS version 16.0 (SPSS Inc, Chicago, IL). A repeated measure analysis of variance was used to evaluate the effect of time, group, and interaction between time and group. We used t tests to compare continuous variables and chi-square tests to compare categorical variables. P values <.05 were considered to indicate statistical significance.

Results

Demographics

Among the 84 participants (mean age 57.9, SD 11.1 years; 40 men and 44 women), the mean baseline THI was 48.7 (SD 20.9). The baseline clinical characteristics of the smart-TRT group and conv-TRT group are summarized in Table 1. There were no differences in age, gender, affected ear, baseline THI, baseline VAS, baseline STAI, baseline BDI, baseline PSQI, loss to follow-up rate, and pure tone audiometry threshold.

Table 1. Baseline characteristics.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Smart TRTa (n=42)</th>
<th>Conventional TRT (n=42)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years), mean (SD)</td>
<td>55.8 (12.0)</td>
<td>59.9 (9.9)</td>
<td>.09</td>
</tr>
<tr>
<td>Gender, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>22 (52)</td>
<td>18 (43)</td>
<td>.38</td>
</tr>
<tr>
<td>Female</td>
<td>20 (48)</td>
<td>24 (57)</td>
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<tr>
<td>Side, n (%)</td>
<td></td>
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<td>.72</td>
</tr>
<tr>
<td>Right</td>
<td>9 (21)</td>
<td>10 (24)</td>
<td></td>
</tr>
<tr>
<td>Left</td>
<td>12 (29)</td>
<td>16 (38)</td>
<td></td>
</tr>
<tr>
<td>Both</td>
<td>15 (36)</td>
<td>12 (29)</td>
<td></td>
</tr>
<tr>
<td>Head or unclear</td>
<td>6 (14)</td>
<td>4 (10)</td>
<td></td>
</tr>
<tr>
<td>Baseline Tinnitus Handicap Inventory, mean (SD)</td>
<td>46.9 (20.7)</td>
<td>50.5 (21.1)</td>
<td>.43</td>
</tr>
<tr>
<td>Baseline VASb (awareness), mean (SD)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Awareness</td>
<td>7.1 (3.4)</td>
<td>7.2 (2.9)</td>
<td>.92</td>
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<td>Annoyance</td>
<td>5.9 (2.7)</td>
<td>6.6 (2.8)</td>
<td>.22</td>
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<td>Loudness</td>
<td>5.8 (2.4)</td>
<td>6.8 (2.3)</td>
<td>.06</td>
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<td>Effect on daily life</td>
<td>4.4 (2.3)</td>
<td>4.9 (2.9)</td>
<td>.41</td>
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<td>State-Trait Anxiety Inventory, mean (SD)</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>X1</td>
<td>44.1 (9.1)</td>
<td>46.0 (10.9)</td>
<td>.39</td>
</tr>
<tr>
<td>X2</td>
<td>43.0 (7.2)</td>
<td>45.7 (12.0)</td>
<td>.24</td>
</tr>
<tr>
<td>Beck Depression Inventory, mean (SD)</td>
<td>13.4 (9.6)</td>
<td>15.1 (10.0)</td>
<td>.43</td>
</tr>
<tr>
<td>Pittsburgh Sleep Quality Index, mean (SD)</td>
<td>7.8 (3.9)</td>
<td>8.9 (5.8)</td>
<td>.35</td>
</tr>
<tr>
<td>Loss to follow-up at 3 months, n (%)</td>
<td>19 (55)</td>
<td>19 (55)</td>
<td>.99</td>
</tr>
<tr>
<td>PTAc threshold (dB HLd, mean (SD))</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Right</td>
<td>23.2 (14.6)</td>
<td>25.6 (16.8)</td>
<td>.49</td>
</tr>
<tr>
<td>Left</td>
<td>24.0 (15.4)</td>
<td>28.9 (20.6)</td>
<td>.22</td>
</tr>
</tbody>
</table>

aTRT: tinnitus retraining therapy.
bVAS: visual analogue scale.
cPTA: pure-tone audiometry; mean 6-tone average = (500 Hz + 2*1000 Hz + 2*2000 Hz + 4000 Hz)/6.
dHL: hearing loss.
Primary Outcome Measure: THI

Figure 2 shows the mean ΔTHI as a function of time. The best ΔTHI score was –23.3 points (95% CI –33.1 to –13.4) at 3 months and –16.8 points (95% CI –30.8 to –2.8) at 2 months in the smart-TRT group and conv-TRT group, respectively. In both groups, the THI score significantly improved over time (within-participant effect: $F_{1.8,42.1} = 10.741, P < .001$), but there was no difference in the treatment outcome between the 2 groups (between-participant effect: $F_{1,24} = 0.094, P = .76$). Also, there was no interaction between time and group (time x group effect: $F_{1.8,42.1} = 0.773, P = .45$). That is, the pattern of gradual improvement as well as the outcome were similar between smart-TRT and conv-TRT.

When each time point was evaluated, a significant reduction in the THI score was found in the smart-TRT group at 1 month ($t_{27} = –3.312, P = .003$), 2 months ($t_{23} = –5.040, P < .001$), and 3 months ($t_{18} = –4.947, P < .001$). A significant reduction was also found in the conv-TRT group at 1 month ($t_{30} = 2.183, P = .04$) and 2 months ($t_{16} = –2.549, P = .02$). The treatment effect was marginal ($t_{18} = –2.037, P = .057$) after 3 months of conv-TRT (Table 2).

Figure 2. Mean (SD: error bars) change in the Tinnitus Handicap Inventory (THI) score (ΔTHI) as a function of time. Conv-TRT: conventional tinnitus retraining therapy; Smart-TRT: smart device tinnitus retraining therapy. *$P < .05$.

Table 2. Treatment outcome at 3 months.

<table>
<thead>
<tr>
<th>Outcomes</th>
<th>Smart TRT&lt;sup&gt;a&lt;/sup&gt; group</th>
<th>Conventional TRT group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Results, mean (95% CI)</td>
<td>$P$ value&lt;sup&gt;b&lt;/sup&gt;</td>
<td>Results, mean (95% CI)</td>
</tr>
<tr>
<td>Primary outcome measure: change in the Tinnitus Handicap Inventory</td>
<td>–23.3 (–33.1 to –13.4)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Secondary outcome measure: change in the visual analogue scale</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Awareness of tinnitus</td>
<td>–3.28 (–4.99 to –1.57)</td>
<td>.001</td>
</tr>
<tr>
<td>Annoyance due to tinnitus</td>
<td>–2.89 (–4.24 to –1.54)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Loudness of tinnitus</td>
<td>–1.22 (–2.41 to –0.03)</td>
<td>.045</td>
</tr>
<tr>
<td>Effect on daily life by tinnitus</td>
<td>–2.67 (–3.93 to –1.40)</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

<sup>a</sup>TRT: tinnitus retraining therapy.
<sup>b</sup>1-sample t test compared with 0.

Secondary Outcome Measure: VAS

Figure 3 shows the mean ΔVAS as a function of time. In both groups, the VAS significantly improved over time (within-participant effect) in 3 VAS categories: awareness of tinnitus ($F_{2,4,4} = 6.667, P = .002$), annoyance caused by tinnitus ($F_{3,66} = 4.358, P = .007$), and effect of tinnitus on daily life ($F_{3,66} = 4.288, P = .008$). There was no significant change in the loudness of tinnitus over time ($F_{2,4,51.9} = 0.795, P = .48$).

There were no differences in the treatment outcome between the 2 groups (between-participant effect) in all 4 VAS categories: awareness of tinnitus ($F_{1,22} = 1.196, P = .29$), annoyance caused by tinnitus ($F_{1,22} = 2.507, P = .13$), loudness of
tinnitus ($F_{1,22}=0.163, P=.96$), and effect of tinnitus on daily life ($F_{1,22}=2.518, P=.13$). Also, there were no significant interactions between time and group (time x group effect): awareness of tinnitus ($F_{2.47.7}=0.790, P=.47$), annoyance caused by tinnitus ($F_{3,66}=1.371, P=.26$), loudness of tinnitus ($F_{2.451.9}=0.568, P=.60$), and effect of tinnitus on daily life ($F_{3,66}=1.606, P=.20$).

When the ΔVAS was evaluated within each time point, a significant treatment effect was found in the smart-TRT group within 1 month to 2 months. The maximum treatment effect was found at the last follow-up time point (3 months; Table 2). That is, ΔVAS for awareness of tinnitus ($t_{17}=-4.038, P=.001$), annoyance caused by tinnitus ($t_{17}=-4.506, P=.045$), loudness of tinnitus ($t_{17}=-2.170, P<.001$), and effect of tinnitus on daily life ($t_{17}=-4.038, P=.001$) were significantly different from 0 (1-sample t test) at 3 months. A similar pattern was found in the conv-TRT group, but the significant improvements were only found in ΔVAS for annoyance caused by tinnitus ($t_{10}=-2.511, P=.02$) and effect of tinnitus on daily life ($t_{18}=-2.191, P=.04$) after 3 months (Figure 3).

**Discussion**

**Principal Findings**

From this study, we were able to show that the treatment outcome of smart-TRT is similar to that of conv-TRT. That is, both treatments had a significant treatment effect that comparably improved over time. For the primary outcome measure (ΔTHI), the improvement was –23.3 in the smart-TRT group and –16.8 in the conv-TRT group (significant improvement over time within both groups, but no difference between groups). These improvements are not only statistically significant but also clinically significant, given that a change in THI score of 7 or greater is clinically meaningful [21]. The secondary outcome (ΔVAS) was also similar between the 2 groups, with a slight advantage in the smart-TRT group (between –1.2 and –3.3) compared with the conv-TRT group (between –0.7 and –1.7). At 3 months, the THI score slightly deteriorated in the conv-TRT group, while the effect lasted in the smart-TRT group. Although the P value was marginal, the ΔTHI score at 3 months was not different from baseline. This finding may imply a deterioration of the treatment result after 3 months. Meanwhile, the secondary outcome measure (VAS scores for annoyance and effect on daily life) showed a steady decrease at 3 months in both groups. It seems that TRT delivered...
via smart devices can be an alternative treatment for tinnitus patients with similar treatment effects.

The attempt to use smart devices [22] and internet-based audiovisual media [8] for educational interventions for patients with chronic health conditions is a common trend. For example, video-based education and interactive games have been used for patients with type 2 diabetes mellitus [23,24]. Multimedia-based animations and quizzes have helped patients with obesity [25]. Osteoarthritis has also been managed with educational modules consisting of text and video [26]. The use of information and communication technology (ICT) for health-related purposes was able to help disease management by facilitating access to health information and helping to increase understanding of the disease [8,27]. Directive counseling in TRT is more complicated than these examples because it is bidirectional. The counselor must understand the individual condition of each patient and tailor the instructions and counseling content depending on the patient’s response. However, recent studies postulated that ICT-based interaction can provide not only 1-way educational interventions but also 2-way, interactive counseling via electronic counseling or e-counseling [8]. We agree that smart-TRT can be limited in this bidirectional interactive communication. Also, the low level of human contact may decrease the efficacy and motivation [11]. However, there seems to be other advantages that can balance these limitations.

The biggest advantage of smart-TRT is that it is cost-effective. Since the directive counseling is performed by an application installed on a smart pad, the health provider does not have to spend much time with each patient. Delivering the main idea of TRT and checking whether the patient is making good progress can be done via the smart pad. During this study, the health provider only had to answer questions after each smart-TRT course. The high cost-effectiveness of ICT-based management has been proven for other interventions such as lifestyle modification [9], weight gain prevention [10], and smoking cessation [28]. There is no cost-effectiveness analysis for smart-TRT yet. However, we think it will at least reduce medical personnel expenses for each counseling session. Moreover, by using multiple smart pad devices, many patients can simultaneously undergo directive counseling under the supervision of 1 health provider. Another advantage of smart-TRT is that it can be used for contactless health care and telemedicine. W Beukes et al [29] reported that Internet-based cognitive behavioral therapy for tinnitus could overcome accessibility barriers. The COVID-19 outbreak has greatly changed our way of living as well as how we obtain medical information [30]. We think smart-TRT can be a contactless solution for tinnitus during such difficult times.

The smart pad interface and interactive nature of the multimedia content seem to be critical to the outcome of smart-TRT. The high efficacy of ICT-based education is now generally accepted [31]. As a result, ICT-based courses in college and university have increased by 440% during the past decade [32]. However, there are 2 differences between patients with tinnitus and higher education students. First, the input method and device interface can be a barrier to some patients with tinnitus. Most patients with tinnitus are old and not completely comfortable with a computer, mouse, trackpad, and keyboard. Smart devices using a touch screen interface may play an important role in such situations. That is, given the simplicity and self-explanatory nature, most patients can easily learn how to operate and interact with a smart pad. During our study, it took less than 2 minutes to explain how to use the device, despite some patients having no experience with smart pads. Second, the desire to adopt new information, attitudes, and ideas is much lower in patients with tinnitus. Simply delivering information via a single medium (especially text) does not sustain attention nor positively influence patients with tinnitus. Thanks to the flexibility and expandability of smart pad applications, we can now mix graphic, audio, video, and text content to maximize treatment effect even in less motivated or elderly patients.

Interestingly, the smart-TRT group had a slightly better treatment outcome (3-month \( \Delta \text{THI} \) of \(-23.3\) points) than the conv-TRT group and in former publications on conv-TRT. Other studies reported a \( \Delta \text{THI} \) of \(-8.3\) or \(-14.5\) points at 3 months [33,34]. This is very similar to our results in the conv-TRT group (\( \Delta \text{THI} \) of \(-16.8\) points). The interpretation of why smart-TRT is slightly better can be controversial. The most probable explanation is that this difference is not statistically nor clinically significant. Another explanation can be that smart-TRT is better because the educational interventions were delivered by 3 different specialists. For conv-TRT, a single health provider was in charge and provided a continued series of directive counseling. This can ensure a good patient-doctor relationship, but the counseling technique and content can become monotonous after several visits. In contrast, 3 different specialists can provide different insights and opportunities for motivation, despite delivering the content through a smart pad. The basic idea and general approach in treating tinnitus were the same, but details on how to deliver the idea were different between specialists. Also, the patients might have felt more confident about their treatment program because 3 different specialists spoke with one voice and repeated the main idea every time.

**Limitations**

There are several limitations in this study. First, this was not a randomized trial. Although this was a prospective study and the smart-TRT group was enrolled according to the predetermined plan, the conv-TRT group had pre-existing data that were closely matched to the smart-TRT group. However, we believe this point did not undermine the main idea of this study. This is because (1) all the baseline demographics were very similar between the 2 groups and (2) the patients were recruited from the same institute during a similar period, managed by the same medical personnel, and evaluated using identical questionnaires at identical time points. Second, the follow-up duration was not long enough. Since tinnitus is a chronic disorder, the treatment effect should be followed for several months to years. Unfortunately, we were only able to follow the patients up to 3 months. There is a possibility that the results could be different in the long term. However, according to our previous studies, the short-term effect of TRT can also provide clinically important information [1,35]. Third, both smart-TRT and conv-TRT were not able to decrease the perceived sound itself. That is, there was no treatment effect in the VAS category of...
tinnitus loudness. TRT may only be effective in controlling the distress caused by tinnitus. This is different from recently introduced treatments that can also control the loudness of tinnitus [17,36].

Conclusions

TRT could be effectively delivered to patients with tinnitus using smart devices. TRT-based smart devices could save the time and cost associated with conventional in-person therapy. These methods have gained attention during the COVID-19 era for the potential to decrease the chance of viral spread.

Acknowledgments

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Conflicts of Interest

None declared.

References


Abbreviations

BDI: Beck Depression Inventory
conv-TNT: conventional TRT
ICT: information and communication technology
KHIDI: Korea Health Industry Development Institute
NRF: National Research Foundation
PSQI: Pittsburgh Sleep Quality Index
smart-TNT: smart device–based TRT
SMG-SNU: Seoul Metropolitan Government-Seoul National University
STAI: State-Trait Anxiety Inventory
THI: Tinnitus Handicap Inventory
TRT: tinnitus retraining therapy
VAS: visual analogue scale

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Impact of an eHealth Smartphone App on Quality of Life and Clinical Outcome of Patients With Hand and Foot Eczema: Prospective Randomized Controlled Intervention Study

Wanja Alexander Weigandt, MD; Yannic Schardt, MD; Aimee Bruch, MD; Raphael Herr, PhD; Matthias Goebeler, MD; Johannes Benecke, MD; Astrid Schmieder, MD

1Department of Dermatology, University Medical Center Mannheim, Heidelberg University, Mannheim, Germany
2Center for Preventive Medicine and Digital Health Baden-Württemberg (CPD-BW), Medical Faculty Mannheim, Heidelberg University, Mannheim, Germany
3Department of Dermatology, Venereology and Allergology, University Hospital Würzburg, Würzburg, Germany

Corresponding Author:
Astrid Schmieder, MD
Department of Dermatology
Venereology and Allergology
University Hospital Würzburg
Josef-Schneider Strasse 2
Würzburg, 97080
Germany
Phone: 49 931 201 26234
Fax: 49 931 201 26700
Email: schmieder_a@ukw.de

Abstract

Background: Chronic hand and foot eczema is a polyetiological dermatological condition. Patients experience pain, itching, and sleep disturbances and have a reduced quality of life. Skin care programs and patient education can improve the clinical outcome. eHealth devices offer a new opportunity to better inform and monitor patients.

Objective: This study aimed to systematically analyze the effect of a monitoring smartphone app combined with patient education on the quality of life and clinical outcome of patients with hand and foot eczema.

Methods: Patients in the intervention group received an educational program; attended study visits on weeks 0, 12, and 24; and had access to the study app. Patients in the control group attended the study visits only. The primary end point was a statistically significant reduction in Dermatology Life Quality Index, pruritus, and pain at weeks 12 and 24. The secondary end point was a statistically significant reduction in the modified Hand Eczema Severity Index (HECSI) score at weeks 12 and 24. This is an interim analysis at week 24 of the 60-week randomized controlled study.

Results: In total, 87 patients were included in the study and randomized to the intervention group (n=43, 49%) or control group (n=44, 51%). Of the 87 patients, 59 (68%) completed the study visit at week 24. There were no significant differences between the intervention and control groups regarding quality of life, pain, itch, activity, and clinical outcome at weeks 12 and 24. Subgroup analysis revealed that, compared with the control group, the intervention group with an app use frequency of fewer than once every 5 weeks had a significant improvement in the Dermatology Life Quality Index at weeks 12 (P=.001) and 24 (P=.05), in pain measured on a numeric rating scale at weeks 12 (P=.02) and 24 (P=.02), and in the HECSI score at week 12 (P=.02). In addition, the HECSI scores assessed on the basis of pictures taken by the patients of their hands and feet correlated strongly with the HECSI scores recorded by physicians during regular personal visits (r=.898; P=.002) even when the quality of the images was not that good.

Conclusions: An educational program combined with a monitoring app that connects patients with their treating dermatologists can improve quality of life if the app is not used too frequently. In addition, telemedical care can at least partially replace personal care in patients with hand and foot eczema because the analysis of the pictures taken by the patients correlates strongly with that of the in vivo images. A monitoring app such as the one presented in this study has the potential to improve patient care and should be implemented in daily practice.

Trial Registration: Deutsches Register Klinischer Studien DRKS00020963; https://drks.de/search/de/trial/DRKS00020963

https://mhealth.jmir.org/2023/1/e38506
Introduction

Background

The prevalence of combined chronic hand and foot eczema in industrialized cities is 5.4% [1]. Women are more frequently affected than men, with an incidence of 9.6 per 1000 compared with 4.0 per 1000 [2].

Hand and foot eczema is considered to be chronic if it persists for >3 months despite adequate therapy or recurs with a frequency of more than twice a year [3]. It does not represent a homogeneous disease entity. The clinical picture, morphology, localization, and etiology can be very different. In general, 4 different etiologies of hand and foot eczema exist: allergic contact, acute-toxic, cumulative-toxic, and atopic hand and foot eczema [4]. Allergic contact hand and foot eczema is typically a type IV sensitization to diverse allergens such as nickel, cobalt, chromates, and fragrances [5]. Cumulative-toxic hand and foot eczema occurs after repeated exposure to substances that only mildly irritate the skin. Over time, the regenerative capacity of the skin is exceeded, and the eczematous reaction becomes visible. Atopic hand and foot eczema develops on the basis of a genetic predisposition called atopic diathesis. It is therefore a localized variant of atopic eczema with a corresponding etiology [3,6].

The severity of eczema ranges from very mild to very severe, with therapy-refractory courses associated with intense pain and itching [7]. In addition, patients with eczema often have to face social stigmatization and struggle with feelings of shame [8]. These physical and psychological circumstances often lead to a radical reduction in quality of life and may even result in depression [9].

More often than not, patients with eczema have limited knowledge of the pathogenesis of their skin condition and the correct disease management [10]. In many other diseases such as type 2 diabetes mellitus, patient education has proven to be an effective method to increase knowledge of the disease, thereby improving the clinical outcome. Coppola et al [11] have shown that patient education is usually associated with an improvement in clinical knowledge, lifestyle, and psychosocial outcomes in comparison with usual care. In Germany, there are skin protection seminars run by employers’ liability insurance associations, but these are reserved for people whose eczema is caused or exacerbated by their professional activity.

In our department of dermatology, patient education alone for patients with psoriasis had no significant effect on the clinical outcome [12]. We therefore assume that one-time education of patients with chronic inflammatory skin conditions may not suffice to ameliorate the disease in the long term.

eHealth-based supporting systems for patients are becoming popular and are incorporated more frequently into patient care. Germany recently set up the German acronym for Digital Health Applications (DiGA) directory, which lists Conformité Européenne–marked medical devices that aim to detect, monitor, treat, or alleviate diseases or to detect, treat, alleviate, or compensate for injuries or disabilities [13]. Physicians (MDs) in Germany can prescribe eHealth devices listed in the DiGA directory. There are currently no DiGA directory–listed eHealth devices for patients experiencing hand and foot eczema in Germany, and scientific data on the beneficial effect of eHealth applications for these patients are missing.

Objectives

The aim of this prospective randomized controlled intervention study was to analyze whether a monitoring smartphone app combined with patient education would improve the quality of life and clinical outcome of patients with hand and foot eczema. The study app was developed specifically for this study. With the app, our patients were able to periodically measure Dermatology Life Quality Index (DLQI) and Hand Eczema Severity Index (HECSI; modified version for foot eczema) scores, as well as the impact on activity and pain (both measured on a numeric rating scale [NRS]), and document the progression of their disease through photographs [14-16]. In addition, the app allowed patients to directly contact their own treating physicians through a chat function.

Furthermore, the DLQI, HECSI, and NRS (for activity and pain) scores were assessed by the treating physicians during personal visits at weeks 0 (before the intervention), 12, and 24.

The final aim behind the development of the app was to reduce waiting time for a physician’s appointment in case of an emergency by expanding teledermatological services for patients with hand and foot eczema and to allow precise self-monitoring by the patients.

Methods

Study Design

The aim of this 60-week randomized controlled intervention study was to investigate the effect of patient education in combination with a monitoring smartphone app on patients experiencing chronic hand and foot eczema. This is an interim analysis of the data from study weeks 0, 12, and 24.

The study was carried out at the department of dermatology, venereology, and allergology at the University Medical Center Mannheim in Mannheim, Germany, from August 13, 2018, to August 30, 2021. The inclusion criteria included a physician-confirmed diagnosis of chronic hand and foot eczema, ability to give informed consent, access to a smartphone, and patient age between 18 and 75 years. During the first study visit (week 0 [V1]), the study participants were randomly assigned to the control or intervention group in a ratio of 1:1.
To assign patients to a group, we created 50 lots for the intervention group and 50 lots for the control group. These were sealed in an urn, and the patients were asked to draw lots.

In total, 90 participants were included in the study, but 3 (3%) dropped out of the study before they were assigned to a group. Of the 87 remaining participants, 43 (49%) were assigned to the intervention group and 44 (51%) to the control group.

The control group started the first study visit at week 0. Information on sociodemographic data, preexisting conditions, and previous and current therapies were collected, and standardized questionnaires such as the DLQI administered. In addition, patients’ current level of knowledge about their disease, severity of the disease measured using the HECSI or a modified form of the HECSI for foot eczema, and the intensity of the pain and itch measured using an NRS ranging from 0 to 10 were recorded. Furthermore, the negative impact on the activity measured using the NRS of patients was assessed. In-person follow-up visits were carried out at V2 and V3. The same parameters were recorded for the intervention group. In addition, these patients received a 2-hour detailed training session on pathogenesis, classification, therapeutic options, and behavioral recommendations from 2 dermatological specialists at our clinic. Each patient also received a personal access code to our app, DermaScope Mobile. Using this app, patients were able to take pictures of their hands and feet, use a chat function to ask questions that were answered by their treating dermatologists, and complete questionnaires on quality of life (DLQI) and current symptoms (NRS for itch and pain). Screenshots of the app can be found in the paper by Domogalla et al [17]. The highest possible app use frequency was once a week.

The quality of each image uploaded in the app by the patients was categorized by the rater (YS) as good or bad based on the following criteria: well-illuminated picture, sharp and focused image, and complete presentation of the hands and feet. All 3 criteria had to be met for the image to be rated as good. Each image was assigned to the rater (YS), who checked its quality based on these 3 criteria. If all criteria were met, the image was rated as of good quality. We then calculated an electronic HECSI (eHECSI) score based on these images and statistically examined the extent to which this score correlated with the HECSI score collected in person.

The primary end point of the study was to determine the effect of extensive patient training, physician-patient contact on demand, and our app on quality of life as well as itching and pain at weeks 12 and 24. The secondary end points were the effect on the disease outcome assessed with the HECSI at weeks 12 and 24. Modulating effects of sex, age, and disease duration were evaluated for each end point.

**Ethics Approval**

The medical ethics committee of the Medical Faculty Mannheim, Heidelberg University, approved the study (2017-655N-MA), and the implementation complied with the Declaration of Helsinki. All participants were instructed in detail regarding the study design and gave their informed consent before participating in the study.

**Statistical Analysis**

Linear panel data regression analyses estimated the trajectories in the outcomes. Random effect regressions determined the main and interaction effects of group membership (intervention vs control group) and visit time point (V1, V2, and V3) on DLQI, pain, daily activity, and HECSI scores. Two models of adjustment were calculated. The first model was unadjusted, whereas the second model was adjusted for sex, age, and disease duration. In additional analyses, the effects of app use frequency over 24 weeks were included (group membership: control vs <20% app use frequency vs ≥20% app use frequency). Therefore, the intervention group was divided into 2 groups: one comprised patients with app use frequency <20%, and the other was made up of patients with app use frequency ≥20% during the observation period of 24 weeks. The chosen cutoff of 20% equals app use frequency of once every 5 weeks. Variables were tested for normal distribution, and where relevant, they were transformed to approach normal distribution (power transform square root of DLQI and log_{10} of HECSI). All statistical analyses were performed using STATA Special Edition (version 14.0; StataCorp LLC).

To determine the extent to which the eHECSI score correlated with the HECSI score assessed at the face-to-face visit, we calculated Spearman correlation coefficients. We also examined within the intervention group the socioeconomic factors that influenced the course of HECSI and DLQI.

Table 1 shows mean values of the scales, Figure 1 shows the flowchart of the study, and Figures 2-4 show predictive margins (delta method).
Table 1. Patient characteristics.

<table>
<thead>
<tr>
<th></th>
<th>Week 0 (V1)</th>
<th>Week 24 (V3)</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Overall (n=87)</td>
<td>Control group (n=44)</td>
</tr>
<tr>
<td><strong>Sex, n (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>51 (59)</td>
<td>25 (57)</td>
</tr>
<tr>
<td>Male</td>
<td>36 (41)</td>
<td>19 (43)</td>
</tr>
<tr>
<td><strong>Age (years)</strong></td>
<td>Mean (SD)</td>
<td>47.07 (15.42)</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>50</td>
</tr>
<tr>
<td><strong>BMI (kg/m²)</strong></td>
<td>Mean (SD)</td>
<td>27.62 (7.53)</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>25.78</td>
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<td>Smoker, n (%)</td>
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<tr>
<td><strong>Duration of eczema (years)</strong></td>
<td>Mean (SD)</td>
<td>6.9 (8.23)</td>
</tr>
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<td><strong>Antieczema therapy, n (%)</strong></td>
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</tr>
<tr>
<td>Topical urea</td>
<td>78 (90)</td>
<td>41 (93)</td>
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<tr>
<td>Topical glucocorticoids</td>
<td>57 (66)</td>
<td>30 (68)</td>
</tr>
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<td>Topical calcineurin inhibitor</td>
<td>14 (16)</td>
<td>9 (21)</td>
</tr>
<tr>
<td>Systemic therapy</td>
<td>10 (12)</td>
<td>3 (7)</td>
</tr>
<tr>
<td><strong>DLQI</strong> (scores range from 0 to 30)</td>
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<td>7.97 (6.38)</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>6</td>
</tr>
<tr>
<td><strong>Pain</strong> (scores range from range 0 to 10)</td>
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<tr>
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<td><strong>HECSI</strong> (scores range from 0 to 360)</td>
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<td>22.53 (21.29)</td>
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<td>&lt;20%</td>
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<td>N/A</td>
</tr>
<tr>
<td>≥20%</td>
<td>N/A</td>
<td>N/A</td>
</tr>
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*a* V: visit time point.

*b* Data for BMI, smoking, and eczema duration were collected at the first visit only.

*c* DLQI: Dermatology Life Quality Index.

*d* HECSI: Hand Eczema Severity Index.

*e* Data for app use frequency were calculated over the whole 24 weeks.

*f* N/A: not applicable.
Figure 1. Flow chart of the study cohort and subcohorts.
Figure 2. Progression of Dermatology Life Quality Index (DLQI), pain, activity, and Hand Eczema Severity Index (HECSI) in the control group (n=36) versus that in the intervention group (n=23). (A) Progression of DLQI over 24 weeks in the intervention group compared with that in the control group. Changes in both groups from baseline were significant (week 12: $P=.006$; week 24: $P<.001$). There were no significant differences between the groups (week 12: $P=.09$; week 24: $P=.11$). (B) Progression of pain scores over 24 weeks in the intervention group compared with that in the control group. Changes in both groups from baseline were not significant (week 12: $P=.48$; week 24: $P=.28$). There were no differences between the groups (week 12: $P=.90$; week 24: $P=.27$). (C) Progression of activity scores over 24 weeks in the intervention group compared with that in the control group. Changes in both groups from baseline were significant (week 12: $P=.04$; week 24: $P=.001$). There were no significant differences between the groups (week 12: $P=.21$; week 24: $P=.26$). (D) Progression of HECSI over 24 weeks in the intervention group compared with that in the control group. Changes in both groups from baseline were significant (week 12: $P=.03$; week 24: $P=.002$). There were no significant differences between the groups (week 12: $P=.26$; week 24: $P=.14$). Significance at $P<.05$. NRS: numeric rating scale.
Figure 3. Progression of Dermatology Life Quality Index (DLQI), pain, activity, and Hand Eczema Severity Index (HECSI) in the control group (n=36) versus that in the intervention group with <20% app use frequency (n=8) versus that in the intervention group with ≥20% app use frequency (n=15).

(A) Progression of DLQI over 24 weeks in the intervention group with <20% app use frequency compared with that in the intervention group with ≥20% app use frequency compared with that in the control group. Changes were significant in the <20% app use frequency group (week 12: \(P=0.001\); week 24: \(P=0.049\)) but not in the ≥20% app use frequency group (week 12: \(P=0.91\); week 24: \(P=0.39\)) compared with controls. (B) Development of pain scores over 24 weeks in the intervention group with <20% app use frequency compared with that in the intervention group with ≥20% app use frequency compared with that in the control group. Changes were significant in the <20% app use frequency group (week 12: \(P=0.02\); week 24: \(P=0.02\)) but not in the ≥20% app use frequency group (week 12: \(P=0.91\); week 24: \(P=0.91\)). (C) Development of activity scores over 24 weeks in the intervention group with <20% app use frequency compared with that in the intervention group with ≥20% app use frequency compared with that in the control group. Changes in the <20% app use frequency group were significant at week 12 but not at week 24 (week 12: \(P=0.01\); week 24: \(P=0.17\)), whereas in the ≥20% app use frequency group (week 12: \(P=0.98\); week 24: \(P=0.56\)), there were no significant differences. (D) Progression of HECSI over 24 weeks in the intervention group with <20% app use frequency compared with that in the intervention group with ≥20% app use frequency compared with that in the control group. Changes in the <20% app use frequency group were significant at week 12 but not at week 24 (week 12: \(P=0.94\); week 24: \(P=0.35\)). Significance at \(P<0.05\). NRS: numeric rating scale.
Figure 4. Sex-specific progression of the Hand Eczema Severity Index in the intervention group over 24 weeks. Female participants in the intervention group were compared with male participants. Changes were significant only for the male participants (week 12: \( P=.008 \); week 24: \( P=.003 \)). Significance at \( P<.05 \).

Results

Patient Demographics

In total, 90 patients were included in the study. The main reasons for declining participation were lack of time, amelioration of hand and foot eczema, or distance to our outpatient clinic.

Of the 90 patients who signed the informed consent form, 87 (97%) took part in the baseline visit and were randomized 1:1 to the intervention (n=43, 49%) or control (n=44, 51%) groups. Of the 90 patients initially included in the study, 3 (3%) dropped out of the study before the baseline visit. Of the 87 remaining patients, 23 (26%) discontinued the study after the baseline visit or the educational program (intervention group: 17/43, 40%, and control group: 6/44, 14%). Leading up to week 24, of the 64 remaining patients, 5 (8%) discontinued the study, resulting in 59 (92%) patients completing the week 24 visit (Figure 1).

Effects of the Intervention on Quality of Life, Pain, Activity, and Clinical Outcome

Patients in both the intervention and control groups showed an improvement in quality of life (DLQI) at weeks 12 (V2) and 24 (V3; week 12 [V2]: \( r=-0.56; P=.006 \); week 24 [V3]: \( r=-0.86; P<.001 \); Figure 2; Table 2) compared with the baseline visits. No significant differences were observed between the control and intervention groups (\( r=-0.23; P=.42 \)) and their progress (week 12 [V2]: \( r=0.45; P=.09 \); week 24 [V3]: \( r=0.42; P=.11 \); Table 2), although the intervention group showed a greater improvement than the control group.

Regarding pain, patients in both groups showed no significant amelioration over time compared with the baseline visits (V2: \( r=0.48; P=.48 \); V3: \( r=-0.74; P=.28 \); Figure 2; Table 2). There were no significant differences between the intervention and control groups (\( r=0.46; P=.53 \)) and their trajectories (V2: \( r=0.11; P=.90 \); V3: \( r=0.96; P=.27 \); Table 2).

A significant improvement was observed in the activity score from V1 until V3 (V2: \( r=-1.39; P=.04 \); V3: \( r=-2.35; P=.001 \); Figure 2; Table 2). There was no difference between the 2 groups (\( r=0.08; P=.92 \)) and their progress (V2: \( r=1.09; P=.21 \); V3: \( r=0.99; P=.26 \); Table 2).

There was also a significant improvement in the severity of eczema as assessed by the HECSI in both groups compared with the baseline visits (V2: \( r=-0.51; P=.02 \); V3: \( r=-0.72; P=.002 \); Figure 2; Table 2). There was no difference between the groups (\( r=-0.16; P=.56 \)) or their trajectories (V2: \( r=0.33; P=.26 \); V3: \( r=0.43; P=.14 \); Table 2). All results were independent of sex, age, or disease duration (model 1; Table 2). Table 1 shows mean values of the scales, whereas Figure 2 shows predictive margins (delta method).
<table>
<thead>
<tr>
<th>Assessment</th>
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<th>Model 1</th>
</tr>
</thead>
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<td>$P$ value</td>
</tr>
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<td></td>
<td></td>
</tr>
<tr>
<td>Week 0</td>
<td>Refb</td>
<td>Ref</td>
</tr>
<tr>
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<td>-0.561 (0.205)</td>
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</tr>
<tr>
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<tr>
<td>Intervention group</td>
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<td>Ref</td>
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<tr>
<td>Control group</td>
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<td>.11</td>
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<td>N/A</td>
</tr>
<tr>
<td>$R^2$: between</td>
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</tr>
<tr>
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</tr>
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<td>Pain</td>
<td></td>
<td></td>
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<tr>
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<td>Ref</td>
<td>Ref</td>
</tr>
<tr>
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<td>Ref</td>
<td>Ref</td>
</tr>
<tr>
<td>Control group</td>
<td>0.459 (0.723)</td>
<td>.53</td>
</tr>
<tr>
<td>Week 0 x control group</td>
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<td>Ref</td>
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<td>Week 12 x control group</td>
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</tr>
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</tr>
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<tr>
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<tr>
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<td>Ref</td>
<td>Ref</td>
</tr>
<tr>
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<td>-1.390 (0.677)</td>
<td>.04</td>
</tr>
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<td>Week 24</td>
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<td>.001</td>
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<td>Ref</td>
<td>Ref</td>
</tr>
<tr>
<td>Control group</td>
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<td>Week 0 x control group</td>
<td>Ref</td>
<td>Ref</td>
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<td>Week 12 x control group</td>
<td>1.090 (0.867)</td>
<td>.21</td>
</tr>
<tr>
<td>Week 24 x control group</td>
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<td>.26</td>
</tr>
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<td>$R^2$: within</td>
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<td>$R^2$: overall</td>
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<td>HECSI</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Week 0</td>
<td>Ref</td>
<td>Ref</td>
</tr>
</tbody>
</table>

* DLQI: Dermatology Life Quality Index
* $R^2$: Coefficient of determination

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Table 2. Random effect regression models over 24 weeks. Model 0 unadjusted, and model 1 adjusted for age, sex, and disease duration (n=59; observations=177).
<table>
<thead>
<tr>
<th>Assessment</th>
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<th>Model 1</th>
<th></th>
</tr>
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<td>P value</td>
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<td>.03</td>
<td>-0.513 (0.229)</td>
<td>.03</td>
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<tr>
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<td>.002</td>
<td>-0.715 (0.229)</td>
<td>.002</td>
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<tr>
<td>Intervention group</td>
<td>Ref</td>
<td>Ref</td>
<td>Ref</td>
<td>Ref</td>
</tr>
<tr>
<td>Control group</td>
<td>-0.158 (0.273)</td>
<td>.56</td>
<td>-0.062 (0.254)</td>
<td>.81</td>
</tr>
<tr>
<td>Week 0 × control group</td>
<td>Ref</td>
<td>Ref</td>
<td>Ref</td>
<td>Ref</td>
</tr>
<tr>
<td>Week 12 × control group</td>
<td>0.327 (0.293)</td>
<td>.26</td>
<td>0.327 (0.293)</td>
<td>.26</td>
</tr>
<tr>
<td>Week 24 × control group</td>
<td>0.429 (0.293)</td>
<td>.14</td>
<td>0.429 (0.293)</td>
<td>.14</td>
</tr>
<tr>
<td>$R^2$: within</td>
<td>0.102 (N/A)</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
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<td>$R^2$: between</td>
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<td>N/A</td>
<td>0.286 (N/A)</td>
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<tr>
<td>$R^2$: overall</td>
<td>0.044 (N/A)</td>
<td>N/A</td>
<td>0.211 (N/A)</td>
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</tbody>
</table>

*aDLQI: Dermatology Life Quality Index.*

*bRef: reference value.*

*cN/A: not applicable.*

*dHECSI: Hand Eczema Severity Index.*

An App Use Frequency of Fewer Than Once Every 5 Weeks Leads to a Significant Amelioration of Quality of Life, Pain, Activity, andExtent of Eczema

When analyzing the outcomes in regard to app use frequency, the subgroup with an app use frequency of <20% showed a highly significant improvement in quality of life (DLQI) compared with the control group (V2: $r=-1.23; P=.001$; V3: $r=-0.73; P=.05$; Figure 3; Table 3). Overall, <20% app use means an app use frequency of <5 times over the study period. For the subgroup with ≥20% app use, there was no significant difference in the DLQI score compared with the control group (V2: $r=-0.03; P=.91$; V3: $r=0.25; P=.39$; Figure 3; Table 3).

The pain also improved significantly in the subgroup with <20% app use frequency compared with the control group (V2: $r=-2.96; P=.02$; V3: $r=-2.97; P=.02$; Figure 3; Table 3). In the subgroup with ≥20% app use frequency, there was again no significant effect (V2: $r=1.41; P=.14$; V3: $r=-0.11; P=.91$; Figure 3; Table 3).

In regard to the activity score of the patients, a significant improvement in the subgroup with <20% app use frequency in comparison with the control group was noted for V2, but not for V3 (V2: $r=-3.07; P=.01$; V3: $r=-1.76; P=.17$; Figure 3; Table 3). There were no significant differences in the subgroup with ≥20% app use frequency (V2: $r=-0.03; P=.98$; V3: $r=-0.57; P=.56$; Figure 3; Table 3).

The HECSI showed a significant improvement in the subgroup with <20% app use frequency in comparison with the control group at V2 but again not at V3 (V2: $r=-0.99; P=.02$; V3: $r=-0.65; P=.12$; Figure 3; Table 3). There were again no significant differences in the subgroup with ≥20% app use frequency in comparison with the control group (V2: $r=0.03; P=.94$; V3: $r=-0.31; P=.35$; Figure 3; Table 3). Again, all results were independent of sex, age, or disease duration (model 1; Table 3).
Table 3. Random effect regression models of the app use frequency subgroups <20% and ≥20% over 24 weeks. Model 0 unadjusted, and model 1 adjusted for age, sex, and disease duration (n=59; observations=177).

<table>
<thead>
<tr>
<th>Assessment</th>
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<th>Model 1</th>
<th>P value</th>
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<td>Ref</td>
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<td>.49</td>
<td>−0.110 (0.159)</td>
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<td>−0.440 (0.159)</td>
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<td>Ref</td>
<td>Ref</td>
</tr>
<tr>
<td>Intervention group with &lt;20% app use frequency</td>
<td>0.524 (0.421)</td>
<td>.21</td>
<td>0.531 (0.419)</td>
<td>.21</td>
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<td>Intervention group with ≥20% app use frequency</td>
<td>0.079 (0.331)</td>
<td>.81</td>
<td>−0.089 (0.337)</td>
<td>.79</td>
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<td>Ref</td>
<td>Ref</td>
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</tr>
<tr>
<td>Week 12 × intervention group with &lt;20% app use frequency</td>
<td>−1.230 (0.373)</td>
<td>.001</td>
<td>−1.230 (0.373)</td>
<td>.001</td>
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<td>Week 12 × intervention group with ≥20% app use frequency</td>
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<td>.91</td>
<td>−0.032 (0.292)</td>
<td>.91</td>
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<td>Week 24 × intervention group with &lt;20% app use frequency</td>
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<td>.049</td>
<td>−0.733 (0.373)</td>
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<td>−0.253 (0.292)</td>
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<td>Ref</td>
</tr>
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<td>Week 12</td>
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<td>0.222 (0.521)</td>
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<td>Control group</td>
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</tr>
<tr>
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<td>Ref</td>
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<td>Week 12 × intervention group with &lt;20% app use frequency</td>
<td>−3.070 (1.250)</td>
<td>.01</td>
<td>−3.070 (1.250)</td>
<td>.01</td>
</tr>
<tr>
<td>Week 12 × intervention group with ≥20% app use frequency</td>
<td>−0.028 (0.986)</td>
<td>.98</td>
<td>−0.028 (0.986)</td>
<td>.98</td>
</tr>
<tr>
<td>Week 24 × intervention group with &lt;20% app use frequency</td>
<td>−1.760 (1.250)</td>
<td>.17</td>
<td>−1.760 (1.250)</td>
<td>.16</td>
</tr>
<tr>
<td>Week 24 × intervention group with ≥20% app use frequency</td>
<td>−0.572 (0.986)</td>
<td>.56</td>
<td>−0.572 (0.986)</td>
<td>.56</td>
</tr>
<tr>
<td>HECSI&lt;sup&gt;c&lt;/sup&gt;</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Week 0</td>
<td>Ref</td>
<td>Ref</td>
<td>Ref</td>
<td>Ref</td>
</tr>
<tr>
<td>Week 12</td>
<td>−0.185 (0.181)</td>
<td>.31</td>
<td>−0.185 (0.181)</td>
<td>.31</td>
</tr>
<tr>
<td>Week 24</td>
<td>−0.286 (0.181)</td>
<td>.11</td>
<td>−0.286 (0.181)</td>
<td>.11</td>
</tr>
</tbody>
</table>

<sup>a</sup> Adjusted for age, sex, and disease duration.

<sup>b</sup> Reference level.

<sup>c</sup> Adjusted for age and sex.
Male Patients Profit More From the Intervention Regarding the Clinical Outcome

In a further subgroup analysis of the intervention group in regard to the sex-specific development of the HECSI, we found a significant improvement in the HECSI compared with baseline only for male participants (V2: r = -1.06; P = .008; V3: r = -1.21; P = .003).

Correlation of the eHECSI With the HECSI

Correlating the eHECSI assessed on the basis of pictures taken by the patients of their hands and feet with the HECSI recorded by physicians during regular personal visits, the eHECSI correlated strongly with the in-person–assessed HECSI (r = 0.898; P = .002) even when the quality of the images was not that good. If the pictures were of good quality, the correlation of the eHECSI with the HECSI was also highly significant (r = 0.875; P < .001).

Discussion

Principal Findings

In our intervention study, we showed that the use of our monitoring app in combination with a patient education session has a significant effect on quality of life, pain, activity, and clinical outcome if the app is not used more than once every 5 weeks. In addition, men seem to profit more from app use frequency than women regarding the clinical outcome.

We first analyzed differences between the intervention and control groups in regard to amelioration of quality of life, pain, activity, and eczema. All our study patients, independent of group membership, had less pain, showed an enhanced quality of life, and participated more actively in life; in addition, their skin condition improved over time. Although the intervention group showed a stronger improvement at all times, the difference between the 2 groups never reached significance. As our patients received a physician’s appointment every 3 months regardless of their skin condition, we conclude that the regular physician-patient contact was crucial for the amelioration of the disease in both groups. This aligns with the observations of Riedl et al [18] who showed that regular physician-patient contact leads to improvement in subjective and objective symptoms. Direct physician-patient contact seems to be more effective than an educational program combined with a monitoring app in the short term regarding our whole study population. In this case, the final evaluation of the study data at week 60 will provide better knowledge about the long-term effects achieved by our intervention.

In our previous intervention study involving a 60-week monitoring app for patients with psoriasis, we were able to show that patient education in combination with a monitoring app resulted in a significant amelioration of depressive and anxiety symptoms in patients who used the app fewer than once a month [17]. In that study, we concluded that patients who were chronically ill do not wish to be reminded of their disease too often. Moreover, it seemed that patients do not want to invest too much time in documenting their disease because they already need to spend considerable time in taking care of their eczematous skin. Furthermore, in this study, an app use frequency of fewer than once every 5 weeks led to a significant amelioration of quality of life, pain, activity, and extent of eczema in the subgroup using the app fewer than once a month (<20% app use frequency) compared with the control group. The mainstay of hand and foot eczema management is still topical therapy, which needs to be applied several times a day. For patients with psoriasis, process aspects such as application time have been associated with nonadherence and a negative impact on quality of life [19,20]. In line with this observation, Retzl er et al [21] showed that topical treatment regimens in patients with atopic dermatitis have a detrimental effect on quality of life that increases with treatment duration and frequency of application. Therefore, an additional time-consuming burden imposed on patients with hand and foot eczema such as a too-frequent app-based documentation of their skin disease might generate no additional benefits regarding quality of life and disease outcome. It should be noted that the collected data do not allow differentiating whether patients who used the app less frequently simply experienced an improvement in their skin condition. This group could have profited solely from the patient education, which enhanced knowledge, provided in the study. This observation is in concordance with the study by Ahn et al [22], who were able to show that patient

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**Table 1: Correlation of the eHECSI With the HECSI**

<table>
<thead>
<tr>
<th>Assessment</th>
<th>Ref</th>
<th>Ref</th>
<th>Ref</th>
<th>Ref</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control group</td>
<td>Ref</td>
<td>Ref</td>
<td>Ref</td>
<td>Ref</td>
</tr>
<tr>
<td>Intervention group with &lt;20% app use frequency</td>
<td>0.383 (0.399)</td>
<td>.34</td>
<td>0.466 (0.371)</td>
<td>.21</td>
</tr>
<tr>
<td>Intervention group with ≥20% app use frequency</td>
<td>0.037 (0.314)</td>
<td>.91</td>
<td>-0.160 (0.296)</td>
<td>.59</td>
</tr>
<tr>
<td>Week 0 × control group</td>
<td>Ref</td>
<td>Ref</td>
<td>Ref</td>
<td>Ref</td>
</tr>
<tr>
<td>Week 12 × intervention group with &lt;20% app use frequency</td>
<td>-0.990 (0.423)</td>
<td>.02</td>
<td>-0.990 (0.423)</td>
<td>.02</td>
</tr>
<tr>
<td>Week 12 × intervention group with ≥20% app use frequency</td>
<td>0.026 (0.333)</td>
<td>.94</td>
<td>0.026 (0.333)</td>
<td>.94</td>
</tr>
<tr>
<td>Week 24 × intervention group with &lt;20% app use frequency</td>
<td>-0.652 (0.423)</td>
<td>.12</td>
<td>-0.652 (0.423)</td>
<td>.12</td>
</tr>
<tr>
<td>Week 24 × intervention group with ≥20% app use frequency</td>
<td>-0.310 (0.333)</td>
<td>.35</td>
<td>-0.310 (0.333)</td>
<td>.35</td>
</tr>
</tbody>
</table>

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*DLQI: Dermatology Life Quality Index.
Ref: reference value.
HECSI: Hand Eczema Severity Index.*
education and web-based resources in dermatology increase compliance and adherence to therapy. We cannot rule out that the education provided by the 2 dermatological specialists led to the assessed significant improvement in the subgroup using the app fewer than once every 5 weeks, but in our previous study [12] for patients with psoriasis, the education alone had no effect on the outcome. Therefore, we assume that the same is true for patients with chronic hand and foot eczema.

We additionally assessed whether patients reduce the app use frequency as their outcomes improve, but the subgroup with <20% app use frequency showed lower app use frequency from the start, with no decrease in the use in the course of time.

By contrast, the app provided in the study allowed direct contact between patients and their treating physicians, which probably reassured patients and improved quality of life in the intervention group when using the app fewer than once a week. We believe that the mere possibility of being able to contact the supervising physician if needed rather than the frequency of physician-patient contact is decisive to improved quality of life. In our clinical perception, frequent physician’s appointments to obtain a follow-up prescription may become a burden, in particular for younger patients who have less time because of their jobs. Such patients might benefit significantly from additional teledermatological care.

Another finding of our study was that the HECSI of male participants decreased faster than those of female participants, independent of app use frequency, although women show higher adherence to topical therapy [23]. We assume that men may benefit more from a constant reminder to apply their topical therapy provided by an eHealth device even when they avoid frequent documentation of their eczema in the app. A positive benefit for reminder apps has already been demonstrated for therapy adherence in patients with cardiovascular disease [24]. Further studies addressing this point are needed in patients with hand and foot eczema.

One of the study’s great strengths was that we were able to show that telemedical care can at least partially replace personal care in patients with hand and foot eczema because the analysis of pictures taken by the patients correlates strongly with that of the in vivo images. Therefore, the HECSI assessed in the face-to-face visit correlated significantly with the eHECSI. This is surely not the case for all dermatological diseases in which the disease can affect the whole body, especially the genital area and the capillitium. A study by Zabludovska et al [25] concluded that only significant changes were detected by photographs; however, in the study, the number of participants was very small (N=33). Whether photographs can be used to monitor the progression of chronic hand eczema and reliably determine HECSI should be further investigated.

Our study includes some limitations. A major limitation is the monocentric design and the small study cohort, which limits generalizability of the results. In particular, the group with <20% app use frequency is very small, which could have led to missed or overinterpreted differences between the groups, especially as we compared this subgroup of the intervention group with the control group. Further studies are necessary to verify our findings on a broader scale.

Conclusions
Overall, our intervention had a positive effect on quality of life, pain, activity, and possibly the clinical outcome in a subgroup of patients with hand and foot eczema.

We were able to show that a monitoring app for patients with hand and foot eczema that allows direct contact with their treating physicians combined with patient education may have the potential to improve the eczema outcome of these patients, especially if the app is not used too frequently. We believe that a monitoring app such as the one presented in this study has the potential to improve patient care and should be implemented in daily practice. However, because of the small number of participants, especially in the subgroups of the intervention group, as well as missing data on treatment adherence of the control group, these data need to be re-examined in a larger sample with consideration of individual factors.

Acknowledgments
The authors express special thanks to the team of the dermatology department of the University Hospital Mannheim. This work was sponsored by Novartis Pharma GmbH.

Conflicts of Interest
AS received honoraria for presentations and as a member of the advisory boards of LEO Pharma, Novartis GmbH, and Almirall Hermal GmbH. AS is the CEO and owner of Derma Intelligence GmbH, which developed DermaScope Mobile.

Multimedia Appendix 1
CONSORT-eHEALTH checklist (V 1.6.1).
[PDF File (Adobe PDF File), 2536 KB - mhealth_v11i1e38506_app1.pdf]

References


**Abbreviations**

**DiGA:** German acronym for Digital Health Applications

https://mhealth.jmir.org/2023/11/e38506

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*(page number not for citation purposes)*
**DLQI:** Dermatology Life Quality Index
**eHECSI:** electronic Hand Eczema Severity Index
**HECSI:** Hand Eczema Severity Index
**NRS:** numeric rating scale
**V:** visit time point

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Effectiveness of a Sodium-Reduction Smartphone App and Reduced-Sodium Salt to Lower Sodium Intake in Adults With Hypertension: Findings From the Salt Alternatives Randomized Controlled Trial

Helen Eyles1, PhD; Jacqueline Grey1, BPED; Yannan Jiang1, PhD; Elaine Umali1, MPH; Rachael McLean2, PhD; Lisa Te Morenga3, PhD; Bruce Neal1, PhD; Anthony Rodgers4, PhD; Robert N Doughty5, MD; Cliona Ni Mhurchu1, PhD

1National Institute for Health Innovation, The University of Auckland, Auckland, New Zealand
2Department of Preventive and Social Medicine, University of Otago, Dunedin, New Zealand
3Research Centre for Hauora and Health, Massey University Wellington, Wellington, New Zealand
4The George Institute for Global Health, University of New South Wales, Sydney, Australia
5Department of Medicine, The University of Auckland, Auckland, New Zealand

Corresponding Author:
Helen Eyles, PhD
National Institute for Health Innovation
The University of Auckland
School of Population Health, Grafton Campus, Faculty of Medical and Health Sciences
22-30 Park Avenue, Private Bag 92019, Auckland Mail Centre 1142
Auckland, 1023
New Zealand
Phone: 64 9 923 4658
Email: h.eyles@auckland.ac.nz

Abstract

Background: Even modest reductions in blood pressure (BP) can have an important impact on population-level morbidity and mortality from cardiovascular disease. There are 2 promising approaches: the SaltSwitch smartphone app, which enables users to scan the bar code of a packaged food using their smartphone camera and receive an immediate, interpretive traffic light nutrition label on-screen alongside a list of healthier, lower-salt options in the same food category; and reduced-sodium salts (RSSs), which are an alternative to regular table salt that are lower in sodium and higher in potassium but have a similar mouthfeel, taste, and flavor.

Objective: Our aim was to determine whether a 12-week intervention with a sodium-reduction package comprising the SaltSwitch smartphone app and an RSS could reduce urinary sodium excretion in adults with high BP.

Methods: A 2-arm parallel randomized controlled trial was conducted in New Zealand (target n=326). Following a 2-week baseline period, adults who owned a smartphone and had high BP (≥140/85 mm Hg) were randomized in a 1:1 ratio to the intervention (SaltSwitch smartphone app + RSS) or control (generic heart-healthy eating information from The Heart Foundation of New Zealand). The primary outcome was 24-hour urinary sodium excretion at 12 weeks estimated via spot urine. Secondary outcomes were urinary potassium excretion, BP, sodium content of food purchases, and intervention use and acceptability. Intervention effects were assessed blinded using intention-to-treat analyses with generalized linear regression adjusting for baseline outcome measures, age, and ethnicity.

Results: A total of 168 adults were randomized (n=84, 50% per group) between June 2019 and February 2020. Challenges associated with the COVID-19 pandemic and smartphone technology detrimentally affected recruitment. The adjusted mean difference between groups was 547 (95% CI −331 to 1424) mg for estimated 24-hour urinary sodium excretion, 132 (95% CI −1083 to 1347) mg for urinary potassium excretion, −0.66 (95% CI −3.48 to 2.16) mm Hg for systolic BP, and 73 (95% CI −21 to 168) mg per 100 g for the sodium content of food purchases. Most intervention participants reported using the SaltSwitch app (48/64, 75%) and RSS (60/64, 94%). SaltSwitch was used on 6 shopping occasions, and approximately 1/2 tsp per week of RSS was consumed per household during the intervention.
Conclusions: In this randomized controlled trial of a salt-reduction package, we found no evidence that dietary sodium intake was reduced in adults with high BP. These negative findings may be owing to lower-than-anticipated engagement with the trial intervention package. However, implementation and COVID-19–related challenges meant that the trial was underpowered, and it is possible that a real effect may have been missed.

Trial Registration: Australian New Zealand Clinical Trials Registry ACTRN12619000352101; https://www.anzctr.org.au/Trial/Registration/TrialReview.aspx?id=377044 and Universal Trial U11111-1225-4471

(IntJMIR Mhealth Uhealth 2023;11:e43675) doi:10.2196/43675

KEYWORDS
mobile health; mHealth; smartphone; smartphone app; cardiovascular disease; sodium; salt; blood pressure; technology; reduced-sodium salt; mobile phone

Introduction

Background
High blood pressure (BP) is the leading cause of premature and preventable death worldwide [1], mostly owing to its effect on cardiovascular disease (CVD). The relationship between high BP and sodium intake is widely recognized, with long-term reduction of dietary sodium resulting in a decrease in BP regardless of hypertension status, sex, ethnic group, or use of BP-lowering medication [2].

Even modest reductions in BP can have important impacts on population-level morbidity and mortality from CVD [2]. Therefore, in 2013, the World Health Organization (WHO) proposed a target for member states to achieve a 30% relative reduction in population sodium intake toward 2000 mg per day by 2025 [3], and at least 96 countries worldwide are working toward this target through a formal national sodium-reduction strategy [4]. In Aotearoa New Zealand (NZ), an ethnically diverse country of approximately 5 million, adults consume 40% more sodium than WHO recommendations (3373 mg per day) [5,6], and 1 in 5 adults has high BP [7]. Furthermore, high BP and cardiovascular conditions are unequally distributed, with populations traditionally underserved by the health care system, including those from lower-income groups, Māori (indigenous New Zealanders) whānau (families), and Pacific communities, having a higher burden [7]. Although NZ does not have a national sodium-reduction strategy, The Heart Foundation has been working with the food industry for more than a decade to remove sodium from low-cost, high-volume foods [8]. In addition, the Ministry for Primary Industries launched the Health Star Rating front-of-pack nutrition label in 2014 to help consumers make healthier food choices [21].

SaltSwitch does not address discretionary salt. In contrast, RSSs, or salt substitutes, provide an alternative to regular table salt as some of the sodium chloride has been replaced by potassium salts or other minerals; they are lower in sodium and higher in potassium but have a similar mouthfeel, taste, and flavor. There is evidence from a 2022 Cochrane meta-analysis including 26 RCTs and 34,961 participants showing that the use of an RSS can reduce sodium chloride in the diet by 3% to 77% [16]. A subset of 12 RCTs in the review measured BP, with 20 reporting data appropriate for meta-analysis; these studies found that RSSs can reduce systolic BP (SBP) by a mean difference of −4.76 (95% CI −6.01 to −3.5) mm Hg [17]. The wide range of effects was investigated in subgroup analyses, but there was low statistical power, and it was not possible to determine whether some types of RSS interventions were likely to be more effective than others or whether particular populations were most likely to benefit. Furthermore, none of the included studies were from countries where discretionary salt use contributed <25% to dietary sodium intake, such as in NZ.

However, SaltSwitch does not address discretionary salt. In contrast, RSSs, or salt substitutes, provide an alternative to regular table salt as some of the sodium chloride has been replaced by potassium salts or other minerals; they are lower in sodium and higher in potassium but have a similar mouthfeel, taste, and flavor. There is evidence from a 2022 Cochrane meta-analysis including 26 RCTs and 34,961 participants showing that the use of an RSS can reduce sodium chloride in the diet by 3% to 77% [16]. A subset of 12 RCTs in the review measured BP, with 20 reporting data appropriate for meta-analysis; these studies found that RSSs can reduce systolic BP (SBP) by a mean difference of −4.76 (95% CI −6.01 to −3.5) mm Hg [17]. The wide range of effects was investigated in subgroup analyses, but there was low statistical power, and it was not possible to determine whether some types of RSS interventions were likely to be more effective than others or whether particular populations were most likely to benefit. Furthermore, none of the included studies were from countries where discretionary salt use contributed <25% to dietary sodium intake, such as in NZ.
Objectives
The primary aim of the Salt Alternatives Study (SALTS) was to determine whether 12 weeks of intervention with a sodium-reduction package (SaltSwitch app + RSS) could reduce estimated 24-hour urinary sodium excretion in adults with high BP (ACTRN12619000352101; Universal Trial U1111-1225-4471).

Methods

Study Design
SALTS was a 2-arm parallel RCT conducted in NZ between May 2019 and February 2021. A 2-week baseline period was followed by a 12-week intervention period.

Ethics Approval
The trial protocol [18] was approved by the NZ Health and Disability Ethics Committees in February 2019 for a period of 3 years (18/NTB/239), and the trial was prospectively registered in the Australian New Zealand Clinical Trials Registry (ACTRN12619000352101).

Participants and Recruitment

Participants
Eligible participants were adults aged ≥18 years who owned a smartphone, had a seated SBP of ≥140 mm Hg or diastolic BP (DBP) of ≥85 mm Hg, planned to undertake household grocery shopping during the trial period, and could read and understand English. The exclusion criteria were SBP of >200 mm Hg; DBP of >120 mm Hg; using an RSS; using the SaltSwitch app; contraindication to altering sodium or potassium intake in the diet; taking furosemide, regular prednisone, or nonsteroidal anti-inflammatory drugs; having had a stroke or cardiovascular event in the previous 6 months; diagnosis of heart failure; planning on being away from home for ≥2 of the subsequent 14 weeks; or inability to provide informed consent. Participants were also excluded at the end of the baseline period if they did not return a spot (casual) urine sample and provide at least 6 home-based BP measures during the baseline period.

Recruitment
Participants were recruited from 2 large NZ cities: Auckland and Wellington. Recruitment settings were (1) face to face at community events such as night markets, outside pharmacies, in shopping malls, and via a mobile BP clinic run by the Stroke Foundation of NZ; (2) referrals from general practitioners (GPs).
and pharmacists; (3) email invitations sent to staff at the University of Auckland; (4) six Facebook advertising campaigns; (5) two market research panels, Dynata and Horizon; and (6) HealthMatch, a clinical trial participant recruitment company. Specific engagement strategies were adopted to attract participants from Māori whānau and Pacific communities, including attendance at events with Ngāti Whāitu Orākei (tangata whenua [indigenous people] of Tūmaki Makaurau or Auckland), hauora (well-being) health checks, local markets, and working directly with Pacific health organizations. All participants provided informed consent via the study smartphone app.

**Randomization and Blinding**

Eligible participants were randomly assigned in a 1:1 ratio to receive either the sodium-reduction intervention package (SaltSwitch smartphone app + RSS) or the control (generic heart-healthy eating information). Randomization was stratified by ethnicity (Māori and non-Māori) and age (<55 and ≥55 years) using permuted block randomization with variable block sizes of 2 or 4. Participants from Māori whānau and Pacific communities were not grouped for randomization as Pacific communities comprise a smaller proportion of the population and have a lower response rate [19] and Māori are the tangata whenua (original inhabitants) of Aotearoa NZ. The allocation sequence was generated by the study statistician (YJ) using computer-generated randomization lists and concealed in a secure database hosted on REDCap (Research Electronic Data Capture; Vanderbilt University) [20] until the point of randomization. Participants were assigned to trial groups by study research assistants using a REDCap software survey form. As the intervention required dietary change from participants and technology support from the study staff, it was not possible to blind participants or all study staff members to the allocation group. However, the lead study researchers (HE, RM, LTM, BN, AR, RND, and CNM) and trial statistician (YJ) were blinded until trial completion.

**Intervention and Control**

**Intervention**

Participants randomized to the intervention received a dietary sodium-reduction package including (1) access to the SaltSwitch smartphone app and (2) a supply of an RSS (as a salt substitute). To encourage the use of SaltSwitch and the RSS, intervention participants were sent weekly reminder notifications to their smartphones. Participants were advised to use the SaltSwitch app whenever they shopped for packaged food brought into the home and to use the RSS in all instances where they would usually use traditional table salt. However, no further dietary advice was provided.

The SaltSwitch app (Figure 1) enables users to scan the bar code of a packaged food using their smartphone camera and receive an immediate, interpretive traffic light nutrition label on-screen alongside a list of healthier, lower-salt options in the same food category. Users can also directly compare the salt content and healthiness of 2 or more foods and create a list of frequently scanned products. SaltSwitch was developed by the George Institute for Global Health [21] and adapted for NZ using the brand-specific Nutritrack (National Institute for Health Innovation) food composition database [22]. Nutritrack is updated annually via cross-sectional surveys of all packaged foods displaying a nutrition information panel sold at the 4 main supermarket chains in NZ (Countdown, New World, PAK'nSAVE, and Four Square) [22]. The Nutritrack database covers approximately 75% of all supermarket food purchases each year. The SaltSwitch food composition data were updated once during the trial. Once downloaded, the SaltSwitch app guided participants through a brief tutorial on how to use the app but did not provide any information on which products to scan. An older, out-of-date version of the SaltSwitch app was available in the NZ Apple and Android app stores during the trial as a component of the NZ FoodSwitch app [21].

The RSS (salt substitute) was manufactured by NuTek Food Science and was a blend of potassium and sea salt, which provided a 75% reduction in sodium compared with regular table salt (74.5% potassium chloride, 24.5% sodium chloride, and 1% silicon dioxide). Intervention participants were sent two 79-g containers of the RSS in plain packaging. The RSS provided to trial participants was not available for commercial sale in NZ during the trial. However, Mrs Rodgers Low Sodium Salt, comprising 49% sodium chloride and 46% potassium and magnesium chloride, was available for sale in some supermarkets.

**Control**

Participants randomized to the control group received a link to generic heart-healthy eating advice developed by the Heart Foundation of NZ sent to control participants’ smartphones during week 1 of the 12-week intervention period. The generic advice was centered on a heart-healthy visual food guide showing the proportion of each type of food to eat each day. The web pages and links also included examples of food types such as grain foods and starchy vegetables, tips on how to achieve a heart-healthy eating pattern, how to read food labels, and how to cut back on salt.

**Study Procedures**

**The Study Smartphone App**

A customized study smartphone app was created to assist with the self-return of urine and BP measures and self-completion of questionnaires and support participants with their trial journey (Figures 2 and 3). The following features were included: consent, questionnaires, video tutorials, notification reminders for urine and BP collection, a barcode scanner for packaged foods, study contact information, and (posttrial) information about the intervention package.
Referral, Screening, and Consent

Referrals were completed by study research assistants and health care providers using a web form [23] with fields for name, mobile number, email address, smartphone ownership, height, weight, and BP. Height was recorded to the nearest 1 cm, and weight was recorded to the nearest 100 g. Following 5 minutes of rest, the referrers took 3 BP measures on the left arm, and the average of the last 2 was automatically calculated. Individuals were advised to follow up their BP measurements with their GP if their measured SBP was ≥200 mm Hg or DBP was ≥85 mm Hg. Researchers used a standard stadiometer to measure height, a Salter electronic scale to measure weight, and an automated BP monitor [24] to measure BP. The equipment used by health care providers varied. Verbal consent was requested to enable the completed referral forms to be sent to the study researchers.

Early referrals did not attend any trial visits in person. However, from August 2019, referrals were offered a screening visit to assist with the use of the study technology. Screening and enrollment were completed by study research assistants via phone or in person using a web form [23]. Participants who met all screening criteria were sent an SMS text message with a link to download the study smartphone app (Figures 2, 3, and the following sections) and complete consent, after which they were provided with a Blipcare Wi-Fi–enabled BP monitor manufactured by Carematix Inc [24], equipment to collect and return 2 spot urine samples, and instructions for data collection. Phone support was also provided.

Baseline

The 2-week baseline period was designed to familiarize participants with trial technologies and collect baseline outcome data. The baseline questionnaire was hosted on REDCap [20] and included date of birth, address, ethnicity, qualifications, employment, household income, behavior regarding dietary salt (excluding total discretionary salt use), existing health conditions, number of household members sharing groceries, concurrent medications, and preferred times for BP measurement reminders. At baseline, participants were asked to scan the bar codes of all packaged foods purchased during the 2-week period.
take BP measures in the morning and evening during the second week, and return a spot urine sample from any day during the second week. Potential participants who failed to return all baseline data by 2 weeks after enrollment received a follow-up support phone call; nonresponders 2 weeks after this call were considered lost to follow-up.

**Follow-up**

During the 12-week intervention period, participants were asked to scan the bar codes of all packaged food purchases (weeks 11 and 12), take BP measures in the morning and evening, collect and return a spot urine sample, and complete the follow-up questionnaire (all during week 12). The follow-up questionnaire was hosted on REDCap [20] and included all baseline questions in addition to questions related to the use of meal kits, recent cardiovascular or adverse events, and self-measured body weight. Intervention participants also answered questions about the use and acceptability of the intervention package and the amount of leftover RSS. All participants were provided with a summary of their BP measures, information on where to purchase an RSS, and access to the SaltSwitch smartphone app (removed 3 months after the last participant completed the trial) on trial completion.

**Outcomes**

**Primary Outcome: Estimated 24-Hour Urinary Sodium Excretion**

Urinary sodium excretion was measured as a proxy for sodium intake. To reduce participant burden, under- and overcollection, and a low response rate, urinary sodium excretion was estimated via a spot (casual) urine sample rather than measured using a gold-standard 24-hour urine collection [25]. Spot urine samples were collected at any time of day except the first void, chilled by participants, and frozen at −18 °C on receipt. Urine samples were thawed at room temperature, vortexed, and analyzed in batches. Urinary sodium and potassium levels were determined on a Roche Hitachi Cobas C311 unit biochemical analyzer using an ion-selective electrode. Urinary creatinine level was determined through Jaffe reaction using alkaline picrate (Roche Hitachi Cobas C311 analyzer). The concentration of sodium was converted to an estimated 24-hour sodium excretion using a standard urine volume of 1.99 L based on previously reported data for approximately 100 NZ adults [26].

**Secondary Outcomes**

**Estimated 24-Hour Potassium Excretion**

The 24-hour potassium excretion was estimated using the same methods as for the estimated 24-hour sodium excretion.

**BP: SBP, DBP, and BP Control**

BP was measured using a Blipcare Wi-Fi–enabled BP monitor programmed to automatically send readings back to study servers via an application programming interface [24]. Participants collected BP measurements in triplicate 1 minute apart on the left arm after 5 minutes of rest [27] in the morning and evening. Reminder notifications were sent to participants’ smartphones, and if no measures were received, researchers followed up with a phone call and additional notifications. Participants who returned <6 BP measures at baseline were excluded. The definition for BP control (≤135/85 mm Hg) was lower than that used for referral purposes as the latter was taken at home and the former was taken in the community [28].

**Sodium Content of Packaged Food Purchases**

Bar codes for packaged foods purchased for home consumption were collected using a scanning feature in the study smartphone app (Figures 2 and 3). The sodium content of household food purchases was calculated by linking bar codes with Nutritracker [22], the brand-specific NZ food composition database used in the SaltSwitch app (see the Intervention section). Weekly reminder notifications were sent to the participants’ smartphones, and if no measures were received, researchers followed up with a phone call and additional notifications.

**Use and Acceptability of the Intervention Package**

Data on the use and acceptability of the SaltSwitch smartphone app and the RSS were collected via the follow-up questionnaire. Bar codes scanned when using the SaltSwitch app were monitored using Google Analytics (for participants who had mobile data available). All intervention participants were asked to record how many teaspoons of RSS they had left at the end of the intervention period.

**Safety and Adverse Events**

Participants who reported abnormal BP measures after randomization were telephoned or sent an SMS text message advising them to visit their GP. Abnormal BP measures were defined as (1) consistently elevated SBP (>180 mm Hg for 3 consecutive days, including any missing days), (2) consistently low SBP (<90 mm Hg for 3 consecutive days, including any missing days), or (3) major changes in SBP from baseline (>20 mm Hg). The salt-reduction package was considered low risk. Therefore, only serious adverse events were collected via the follow-up questionnaire and reported to the Ethics Committee annually. A qualified medical representative was authorized to determine whether adverse events were considered serious.

**Statistical Analysis**

**Sample Size**

A total of 326 participants (163 per group) were estimated to provide 80% power at a 5% level of significance (2-sided) to detect a minimum effect size of 462 mg of sodium in the primary outcome between the 2 groups, allowing for a 10% loss to follow-up. The expected effect size was estimated from the SaltSwitch pilot study data, where estimations of 24-hour urinary sodium excretion were calculated using spot urine samples and a standard urine volume of 1.99 L with an SD of 1400 mg per day (ACTRN12614000206628) [15].

**Main Comparative Analyses**

All participant data collected at baseline and week 12 were summarized using descriptive statistics for the intervention and control groups separately. Continuous variables were presented as mean and SD, whereas categorical variables were reported as frequencies and percentages. The trial evaluation was performed on an intention-to-treat basis, including all eligible participants in the group to which they were randomized. Multiple imputation methods were used for...
missing primary outcome data in the primary intention-to-treat analysis using the Markov chain Monte Carlo method and assuming that the data were missing at random. No imputation was considered on secondary outcomes. Sensitivity analysis was conducted on the primary outcome (1) without imputation and (2) using the International Cooperative Study on Salt and Blood Pressure formula [29] rather than a standard volume to estimate 24-hour sodium excretion. Linear regression was used for continuous outcomes adjusting for baseline outcome value, age, and ethnicity (stratification factors). The model-adjusted mean difference between the 2 groups was estimated with a 95% CI and P value. Logistic regression was used for categorical outcomes, and the estimated group difference was reported as the odds ratio. Owing to the small sample size, no subgroup analysis was considered.

The definition of valid data for spot (casual) urine samples was a collection at baseline during week −1 (−2 weeks to +2 weeks) and at follow-up during week 12 (−1 week to +1 week). Valid BP measurements at baseline were those taken during weeks −2 and −1 (−2 weeks to +2 weeks) and at follow-up during week 12 (−1 week to +1 week). The average SBP and DBP were calculated using a minimum of 6 readings at each time point. Valid bar code data to estimate the sodium content of household food purchases at baseline were scanned during week −1 (−2 weeks to +2 weeks) and at follow-up during week 12 (−1 week to +1 week). The average sodium content of food purchases was calculated for all bar codes received.

Statistical analyses were performed using SAS (version 9.4; SAS Institute). All statistical tests were 2-sided at a 5% significance level.

Changes in Response to the Challenges of the COVID-19 Pandemic

As recommended by Perlis et al [30], we outline the challenges associated with the COVID-19 pandemic and how these affected the SALTS trial. In NZ, there were strict lockdown periods from March 2020 to June 2020, from August 2020 to October 2020, in February 2021, and from August 2021 to November 2021. During these times, most postreferral and data collection procedures could be completed using remote technology. However, lockdown periods prevented enrolled participants from returning spot urine samples as couriers were only available for essential activities, and the university campus was closed, meaning that samples could not be received. Lockdown periods also substantially compromised recruitment as they prevented the collection of face-to-face BP measures necessary for new referrals. Consequently, recruitment was put on hold during these times. Furthermore, potential participants who had been referred and identified as eligible were unable to start the trial during lockdowns as it was not possible for researchers to courier the Wi-Fi–enabled BP monitor and equipment to collect urine samples; as a result, a considerable number of eligible participants lost interest and declined to take part, and recruitment was further compromised (see the Recruitment section).

Results

Trial results are reported according to the CONSORT (Consolidated Standards of Reporting Trials) 2010 guidelines for parallel-group randomized trials [31].

Recruitment

Recruitment took place over 16 months, starting on May 30, 2019, and finishing on October 2, 2019. The last participant was randomized in February 2020. A total of 442 potentially eligible participants were referred, of whom 312 (70.6%) were screened for initial eligibility, 86 (19.5%) declined to participate, and 44 (10%) were unable to be contacted (Figure 4). Of the 312 screened participants, 144 (46.2%) were ineligible as they changed their mind during baseline (n=69, 22.1%), did not meet the screening criteria (n=29, 9.3%), were unable to be contacted (n=27, 8.7%), or did not provide the required baseline data (n=19, 6.1%). The remaining 53.8% (168/312) of the initially screened eligible participants were randomized and took part in the trial; of those, the largest number was from market research panels (55/168, 32.7%) followed by face-to-face events (24/168, 14.3%). The final participant completed the trial on March 20, 2021 [31,32].
Baseline Characteristics of Trial Participants

A total of 84 (50%) of the 168 participants were randomized to the intervention group, and the remaining 84 (50%) were randomized to the control group. A participant in the control group withdrew, stating that they were no longer interested in taking part. A total of 14.3% (24/168) of the participants identified as Māori, and 7.1% (12/168) identified as Pacific (7/84, 8% in the control group and 5/84, 6% in the intervention group). All participant characteristics were similar between groups (Table 1).
Table 1. Baseline characteristics of the trial participants (N=168).

<table>
<thead>
<tr>
<th>Baseline characteristics</th>
<th>Control group (n=84)</th>
<th>Intervention group (n=84)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age (years), mean (SD)</strong></td>
<td>55 (13)</td>
<td>54 (13)</td>
</tr>
<tr>
<td>18 to 54, n (%)</td>
<td>38 (45)</td>
<td>37 (44)</td>
</tr>
<tr>
<td>≥55, n (%)</td>
<td>46 (55)</td>
<td>47 (56)</td>
</tr>
<tr>
<td><strong>Gender, n (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Men</td>
<td>41 (49)</td>
<td>36 (43)</td>
</tr>
<tr>
<td>Women</td>
<td>36 (43)</td>
<td>38 (45)</td>
</tr>
<tr>
<td>Nonbinary or not specified</td>
<td>7 (8)</td>
<td>10 (12)</td>
</tr>
<tr>
<td><strong>Region, n (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Auckland</td>
<td>71 (85)</td>
<td>76 (90)</td>
</tr>
<tr>
<td>Other New Zealand</td>
<td>13 (15)</td>
<td>8 (10)</td>
</tr>
<tr>
<td><strong>Smartphone ownership, n (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>iPhone</td>
<td>32 (38)</td>
<td>41 (49)</td>
</tr>
<tr>
<td>Android</td>
<td>52 (62)</td>
<td>43 (51)</td>
</tr>
<tr>
<td><em><em>Prioritized ethnicity</em>, n (%)</em>*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Māori</td>
<td>12 (14)</td>
<td>12 (14)</td>
</tr>
<tr>
<td>Pacific</td>
<td>7 (8)</td>
<td>5 (6)</td>
</tr>
<tr>
<td>Asian</td>
<td>14 (17)</td>
<td>15 (18)</td>
</tr>
<tr>
<td>European or other</td>
<td>51 (61)</td>
<td>52 (62)</td>
</tr>
<tr>
<td><strong>Highest qualification, n (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>5 (6)</td>
<td>1 (1)</td>
</tr>
<tr>
<td>Secondary</td>
<td>11 (13)</td>
<td>10 (12)</td>
</tr>
<tr>
<td>University degree, polytechnic, trade, or diploma</td>
<td>44 (52)</td>
<td>43 (51)</td>
</tr>
<tr>
<td>Postgraduate degree</td>
<td>21 (25)</td>
<td>27 (32)</td>
</tr>
<tr>
<td>Other</td>
<td>3 (4)</td>
<td>3 (4)</td>
</tr>
<tr>
<td><strong>Employment status, n (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full- or part-time employment</td>
<td>57 (68)</td>
<td>58 (69)</td>
</tr>
<tr>
<td>Retired or full-time homemaker</td>
<td>17 (20)</td>
<td>14 (17)</td>
</tr>
<tr>
<td>Unemployed or student</td>
<td>9 (11)</td>
<td>12 (14)</td>
</tr>
<tr>
<td>Decline to answer</td>
<td>1 (1)</td>
<td>0 (0)</td>
</tr>
<tr>
<td><strong>Annual household income (NZ $ [US $]), n (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≤60,000 (US $37,826.7)</td>
<td>20 (24)</td>
<td>18 (21)</td>
</tr>
<tr>
<td>60,001 to 100,000 (US $37,827.33 to US $63,036.80)</td>
<td>21 (25)</td>
<td>21 (25)</td>
</tr>
<tr>
<td>≥100,001 (≥US $63,037.43)</td>
<td>30 (36)</td>
<td>34 (40)</td>
</tr>
<tr>
<td>Declined to answer</td>
<td>13 (15)</td>
<td>11 (13)</td>
</tr>
<tr>
<td><strong>Behaviors regarding dietary salt, n (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Add salt to food</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Always or often</td>
<td>35 (42)</td>
<td>35 (42)</td>
</tr>
<tr>
<td>Sometimes</td>
<td>23 (27)</td>
<td>19 (23)</td>
</tr>
<tr>
<td>Rarely or never</td>
<td>26 (31)</td>
<td>30 (36)</td>
</tr>
<tr>
<td>Salt added during cooking</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Always or often</td>
<td>52 (62)</td>
<td>54 (64)</td>
</tr>
<tr>
<td></td>
<td>Control group (n=84)</td>
<td>Intervention group (n=84)</td>
</tr>
<tr>
<td>-----------------------------</td>
<td>----------------------</td>
<td>--------------------------</td>
</tr>
<tr>
<td>Sometimes</td>
<td>23 (27)</td>
<td>16 (19)</td>
</tr>
<tr>
<td>Rarely or never</td>
<td>9 (11)</td>
<td>14 (17)</td>
</tr>
<tr>
<td>Saltshaker placed on table</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Always or often</td>
<td>27 (32)</td>
<td>28 (33)</td>
</tr>
<tr>
<td>Sometimes</td>
<td>16 (19)</td>
<td>14 (17)</td>
</tr>
<tr>
<td>Rarely or never</td>
<td>40 (48)</td>
<td>42 (50)</td>
</tr>
<tr>
<td>Do not know</td>
<td>1 (1)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Trying to cut down the amount of salt consumed</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>39 (46)</td>
<td>34 (40)</td>
</tr>
<tr>
<td>Yes</td>
<td>40 (48)</td>
<td>36 (43)</td>
</tr>
<tr>
<td>Do not know</td>
<td>5 (6)</td>
<td>14 (17)</td>
</tr>
<tr>
<td>Look at nutrition information on food packages</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Always or more often than not</td>
<td>29 (35)</td>
<td>25 (30)</td>
</tr>
<tr>
<td>Occasionally</td>
<td>38 (45)</td>
<td>50 (60)</td>
</tr>
<tr>
<td>Never</td>
<td>17 (20)</td>
<td>9 (11)</td>
</tr>
<tr>
<td>Baseline clinical measures</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Height (cm), mean (SD)</td>
<td>169 (10)</td>
<td>168 (9)</td>
</tr>
<tr>
<td>Weight (kg), mean (SD)</td>
<td>88 (19)</td>
<td>89 (18)</td>
</tr>
<tr>
<td>BMI (kg/m²), mean (SD)</td>
<td>31 (6)</td>
<td>31 (5)</td>
</tr>
<tr>
<td>Blood pressure (mm Hg)b, mean (SD)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Systolic</td>
<td>142 (13)</td>
<td>143 (16)</td>
</tr>
<tr>
<td>Diastolic</td>
<td>86 (9)</td>
<td>86 (9)</td>
</tr>
<tr>
<td>Estimated 24-hour urine excretion (mg per day)c, mean (SD)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sodium</td>
<td>3107 (1917)</td>
<td>3616 (2280)</td>
</tr>
<tr>
<td>Potassium</td>
<td>3601 (2202)</td>
<td>4232 (2659)</td>
</tr>
<tr>
<td>Current health conditiond, n (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Diabetes</td>
<td>12 (14)</td>
<td>10 (12)</td>
</tr>
<tr>
<td>High cholesterol</td>
<td>26 (31)</td>
<td>29 (35)</td>
</tr>
<tr>
<td>High blood pressure</td>
<td>54 (64)</td>
<td>60 (71)</td>
</tr>
</tbody>
</table>

aParticipants were allocated to a single ethnic group in the following order of priority even if they identified with more than one ethnicity: Māori, Pacific, Asian, and European or other.
bValid blood pressure data only (ie, received within 1 week before and 2 weeks after randomization date and including a minimum of 6 readings).
cValid urine data only (ie, received within 1 week before and 2 weeks after randomization date); n=73 for the control group and n=77 for the intervention group. Estimated from the concentration of 1 spot urine sample and a standard volume of 1.99 L, with no adjustment for electrolytes not excreted via urine.
dAs advised by a health professional.

Return of Trial Outcome Data

Valid urine samples for the estimation of sodium and potassium excretion were returned by 89.3% (150/168) of the participants at baseline and 45.2% (76/168) of the participants at follow-up. More participants in the control group compared with the intervention group returned a valid urine sample at baseline (77/84, 92% vs 73/84, 87%, respectively; Table 2). Valid BP data were returned by 93.5% (157/168) of the participants at baseline and 83.3% (140/168) of the participants at follow-up. Valid bar code data for the estimation of the sodium content of household food purchases were returned by 76.2% (128/168) of the participants at baseline and 22% (37/168) of the participants at follow-up. The baseline questionnaire was completed by 100% (168/168) of the participants, and the follow-up questionnaire was completed by 76.2% (128/168) of the participants. The rate of return of follow-up data was consistent across ethnic groups except for the follow-up questionnaire, which was returned by 67% (24/36) of the participants identifying as Māori or Pacific and 78.8% (104/132) of the participants identifying as all other ethnicities.
Table 2. Estimates of the effect of the salt-reduction intervention package on urinary sodium and potassium excretion, blood pressure, and the sodium content of household packaged food purchases at 12 weeks (N=168).

<table>
<thead>
<tr>
<th></th>
<th>Control group (n=84)</th>
<th>Intervention group (n=84)</th>
<th>Adjusted difference at 12 weeks&lt;sup&gt;a&lt;/sup&gt; (95% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Participants with valid data, n (%)&lt;sup&gt;b&lt;/sup&gt;</td>
<td>Participants with valid data, n (%)&lt;sup&gt;b&lt;/sup&gt;</td>
<td>Participants with valid data, n (%)&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td><strong>Primary outcome: estimated 24-hour sodium excretion (mg per day)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard volume</td>
<td>73 (87)</td>
<td>3107 (1917)</td>
<td>38 (45)</td>
</tr>
<tr>
<td>Multiple imputitions (primary)&lt;sup&gt;c&lt;/sup&gt;</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No imputation&lt;sup&gt;d&lt;/sup&gt;</td>
<td>65 (77)</td>
<td>3324 (813)</td>
<td>35 (42)</td>
</tr>
<tr>
<td><strong>Secondary outcomes</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estimated 24-hour potassium urination excretion (mg per day)</td>
<td>73 (87)</td>
<td>3601 (2202)</td>
<td>38 (45)</td>
</tr>
<tr>
<td>Systolic blood pressure (mm Hg)&lt;sup&gt;e&lt;/sup&gt;</td>
<td>78 (93)</td>
<td>142 (13)</td>
<td>60 (71)</td>
</tr>
<tr>
<td>Diastolic blood pressure (mm Hg)&lt;sup&gt;e&lt;/sup&gt;</td>
<td>78 (93)</td>
<td>86 (9)</td>
<td>60 (71)</td>
</tr>
<tr>
<td>Sodium content of household food purchases (mg per 100 g)&lt;sup&gt;e&lt;/sup&gt;</td>
<td>67 (80)</td>
<td>346 (427)</td>
<td>20 (24)</td>
</tr>
</tbody>
</table>

<sup>a</sup>Linear regression models adjusted for baseline outcome, age in years, and Māori or Pacific ethnicity.

<sup>b</sup>Valid urine, blood pressure (BP), and food purchasing data were collected within 1 week before or 2 weeks after randomization (for baseline) and 1 week before or 2 weeks after week 12 (for follow-up). For BP, a minimum of 6 readings during these time frames was considered valid. For food purchases, a minimum of 10 products scanned during these time frames was considered valid.

<sup>c</sup>Estimated 24-hour sodium excretion from spot urine using a standard volume of 1.99 L. Multiple imputations used on missing primary outcome data through an intention-to-treat analysis using the Markov chain Monte Carlo method and assuming data were missing at random.

<sup>d</sup>24-hour sodium excretion from spot urine using a standard volume of 1.99 L. No imputation for missing data.

<sup>e</sup>INTERSALT: International Cooperative Study on Salt and Blood Pressure.

<sup>f</sup>24-hour sodium excretion estimated using the INTERSALT formula. No imputation for missing data.

<sup>g</sup>BP control was defined as <135/85 mm Hg. The mean number of valid days for all BP measures at baseline was 12 (SD 6) in the control group and 13 (SD 7) in the intervention group. The corresponding values at week 12 were 8 (SD 3) and 9 (SD 5), respectively. The mean number of valid readings for all BP measures at baseline was 31 (SD 21) in the control group and 37 (SD 24) in the intervention group. The corresponding values at week 12 were 19 (SD 12) and 24 (SD 16), respectively.

<sup>h</sup>The mean number of food products scanned at baseline was 27 (SD 18) in the control group and 24 (SD 18) in the intervention group. The corresponding values at week 12 were 18 (SD 16) and 13 (SD 12), respectively.

**Primary Outcome: Estimated 24-Hour Urinary Sodium Excretion**

The mean estimated 24-hour urinary sodium excretion at 12 weeks was 3935 (SD 2268) mg per day in the intervention group and 3193 (SD 2284) mg per day in the control group (Table 2). There was no significant difference between the groups in estimated 24-hour sodium excretion at 12 weeks (adjusted mean difference=547 mg per day, 95% CI −331 to 1424; Table 2).

Sensitivity analyses were consistent with the primary analysis, with no significant differences observed in the mean difference between groups where no imputation was used or where 24-hour urinary sodium excretion was estimated using the International Cooperative Study on Salt and Blood Pressure formula [29] rather than a standard volume of 1.99 L (Table 2).
Secondary Outcomes

Estimated 24-Hour Urinary Potassium Excretion
The mean estimated 24-hour urinary potassium excretion at 12 weeks was 4210 (SD 2334) mg per day in the intervention group and 4078 (SD 2945) mg per day in the control group (Table 2). There was no significant difference between the groups in estimated 24-hour potassium excretion at 12 weeks (adjusted mean difference=132 mg per day, 95% CI −1083 to 1347; Table 2).

BP: SBP, DBP, and BP Control
The mean SBP for the intervention and control groups at 12 weeks was 139 (SD 12) mm Hg and 138 (SD 15) mm Hg, respectively (Table 2). The corresponding figures for DBP were 84 (SD 8) mm Hg and 84 (SD 10) mm Hg, respectively. No significant difference was observed between the groups for SBP or DBP at 12 weeks. The adjusted mean difference between groups was −0.7 (95% CI −3.5 to 2.2) mm Hg for SBP and −0.4 (95% CI −2.2 to 1.5) mm Hg for DBP (Table 2). The mean number of participants achieving BP control at 12 weeks in the intervention and control groups was 23 (SD 27) and 17 (SD 20), respectively. There was no significant difference between the groups in the odds of achieving BP control (adjusted odds ratio 1.0, 95% CI 0.45-2.1).

Sodium Content of Packaged Food Purchases
The mean number of all bar codes scanned at baseline was 24 (SD 18) for the intervention group and 27 (SD 18) for the control group. The corresponding mean values for the follow-up period were 13 (SD 12) and 18 (SD 16), respectively. There was no significant difference between the groups in the sodium content of packaged foods purchased (adjusted mean difference=73, 95% CI −21 to 168 mg per 100 g; Table 2).

Use and Acceptability of the Intervention Package
A total of 76% (64/84) of the intervention participants provided use and acceptability data; of these 64 participants, 48 (75%) reported using SaltSwitch when shopping, with 25 (52%) of them reporting that they used the app “at least half to every time” they shopped (Table 3). Google Analytics data were available for 96% (46/48) of the SaltSwitch users, who scanned a mean of 29 (SD 40) products during the 12-week intervention period over a mean of 6 (SD 6) shopping occasions. The most common responses from the 56% (27/48) of participants who reported what they “liked most” or “least” about SaltSwitch were that it helped with making lower-salt food choices and thinking about salt in food in general (5/27, 19%) but needed more products to be available in the app to scan (10/27, 37%).

A total of 94% (60/64) of the intervention participants who provided data used the RSS, with 69% (44/64) stating that between half and all the discretionary salt they consumed during the 12-week study period was the RSS. Of those who reported using less than half or none of the RSS (20/64, 31%), 20% (4/20) stated that this was because the taste was unacceptable (Table 3). Participants used a mean of approximately 37.2 g (6.5 tsp) of RSS over the 12-week intervention period, and 44% (28/64) stated that their study salt was consumed by other household members.
Table 3. Use and acceptability of the salt-reduction intervention package (n=64).

<table>
<thead>
<tr>
<th>SaltSwitch smartphone app, n (%)</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Used the SaltSwitch app when grocery shopping over the past 12 weeks (n=64)</td>
<td>48 (75)</td>
</tr>
<tr>
<td>How often used? (n=48)</td>
<td></td>
</tr>
<tr>
<td>More than half to every time</td>
<td>15 (31)</td>
</tr>
<tr>
<td>Half of the time</td>
<td>10 (21)</td>
</tr>
<tr>
<td>A handful of times to less than half of the time</td>
<td>22 (46)</td>
</tr>
<tr>
<td>Did not answer</td>
<td>1 (2)</td>
</tr>
<tr>
<td>How easy to use? (n=48)</td>
<td></td>
</tr>
<tr>
<td>Very easy to somewhat easy</td>
<td>33 (69)</td>
</tr>
<tr>
<td>Neither easy nor difficult</td>
<td>9 (19)</td>
</tr>
<tr>
<td>Somewhat difficult to very difficult</td>
<td>5 (10)</td>
</tr>
<tr>
<td>Did not answer</td>
<td>1 (2)</td>
</tr>
<tr>
<td>Think SaltSwitch is a good way to help shoppers make lower-salt food choices (n=64)</td>
<td>52 (81)</td>
</tr>
</tbody>
</table>

Reduced-sodium salt (study salt)

<table>
<thead>
<tr>
<th>Amount of salt consumed over the past 12 weeks that was study salt (n=64), n (%)</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>All or nearly all</td>
<td>35 (55)</td>
</tr>
<tr>
<td>Half</td>
<td>9 (14)</td>
</tr>
<tr>
<td>Less than half</td>
<td>16 (25)</td>
</tr>
<tr>
<td>None</td>
<td>4 (6)</td>
</tr>
<tr>
<td>If less than half or none, what was the main reason for this? (n=20), n (%)</td>
<td></td>
</tr>
<tr>
<td>Taste unacceptable</td>
<td>4 (20)</td>
</tr>
<tr>
<td>Unwilling or other reason</td>
<td>16 (80)</td>
</tr>
<tr>
<td>Teaspoons of salt left at end of study (n=56), mean (SD)</td>
<td>19.8 (19.9)</td>
</tr>
<tr>
<td>Other household members used the study salt (n=64), n (%)</td>
<td>28 (44)</td>
</tr>
<tr>
<td>How many household members used the study salt? (n=28), n (%)</td>
<td></td>
</tr>
<tr>
<td>1 to 2</td>
<td>17 (61)</td>
</tr>
<tr>
<td>3</td>
<td>4 (14)</td>
</tr>
<tr>
<td>≥4</td>
<td>7 (25)</td>
</tr>
</tbody>
</table>

\[a\] A total of 64 intervention participants returned the follow-up questionnaire.

\[b\] Intervention participants were provided with 158 g or approximately 26.3 tsp of salt.

**Effects for Māori and Pacific Participants**

Owing to the low engagement and recruitment of participants from Māori whānau (28/168, 16.7%) and Pacific communities (13/168, 7.7%), it was not possible to estimate differences in effects separately for these groups.

**Adverse Events**

No serious adverse events were reported during the trial period.

**Challenges Associated With the Use of Trial Technology**

Technology was used in the SALTS trial to streamline study processes, deliver the intervention, collect outcome data, and communicate with participants. Information on the challenges encountered owing to the use of technology, which affected all 4 stages of the SALTS trial and CONSORT flow diagram, [31] is summarized in Table 4 and has been reported elsewhere [32]. However, briefly, during enrollment and allocation of participants (stages 1 and 2), many participants lacked confidence in their ability to download the study smartphone app and connect the Wi-Fi–enabled BP monitor. During this stage, inefficiencies were also experienced by the researchers as the study data management system could not directly exchange information with the referral form and participant tracking systems. During stage 3 (follow-up and collection of outcome data), the study app performed inconsistently across different smartphone models and operating systems, and some participants did not switch on their phone notifications, meaning that they missed important study reminders. Finally, during
stage 4 (data analysis), some participants did not complete the follow-up questionnaire or return BP measures within the time frames for valid data as prespecified in the study protocol [31].

Table 4. Challenges associated with the use of technology and future recommendations.

<table>
<thead>
<tr>
<th>Trial stage</th>
<th>Technology challenge</th>
<th>Future recommendations</th>
</tr>
</thead>
</table>
| Enrollment and allocation of patients | • Not all smartphone owners use smartphone apps, and use may be lower in older populations.  
  • Face-to-face support may be required for confident connection and use of technologies such as smartphone apps and other Wi-Fi-enabled devices.  
  • Interoperability, or the exchange of information between technologies, is critical to harness the efficiencies they offer. | • Complete background research on the population of interest to understand their use of smartphone technology before using it widely in a research study.  
  • Plan for flexibility in the study design to enable face-to-face support for familiarization with study technology, particularly during the early phases.  
  • Incorporate funds and time in the study setup phase to ensure that technologies that need to exchange information with one another can do so correctly and efficiently. For example, ensure that web-based forms exchange data with data management systems and data management systems exchange data with participant booking systems. If funds and time cannot be included, consider the use of simple existing tools such as survey software and an ad hoc SMS text messaging service. |
| Following up participants and collecting outcome data | • Technology can behave in unanticipated ways in response to the variety of smartphone models and operating systems on the market, and it can be difficult to replicate “live” trial conditions for all individual circumstances.  
  • Not all smartphone users like or read notifications. | • Create technology test plans and implement them during all phases of the trial, from early development to the completion of the last participant. When testing technology, use Apple and Android phones and include different operating systems. Have a “soft” launch to enable rigorous early testing with a small group of real participants. To avoid the impacts of software fixes on unrelated functionality, build technology in separate blocks of code that only connect where necessary.  
  • Where possible, use SMS text messages rather than notifications to convey key study information to participants, particularly for those with limited Wi-Fi or data. |
| Data analysis | • The flexibility that technology provides to return outcome data at the participants’ convenience can increase the time frame for data return and the variability in measures. | • Set realistic time frames or windows for participants to return remote data to researchers. For example, for participants returning a casual urine sample by courier, a realistic number of days will be needed to provide the participant with options, they may need a reminder messages, or there could be courier delays. Set time frames for each outcome that is collected remotely and specify these before study start in the statistical analysis plan.  
  • In addition to using standardized methods for the collection of clinical outcome data, consider whether other aspects of outcome data collection should also be standardized. For example, blood pressure measures vary considerably between and within individuals and from day to day and even hour to hour; in this case, standardizing the time for data collection (eg, 8 AM), rather than allowing participants to choose a time in the morning that suits them, will result in reduced variation in blood pressure measures across the sample. |

Discussion

Principal Findings

In this RCT, we found no evidence that 12 weeks of intervention with a salt-reduction package reduced estimated 24-hour urinary sodium excretion in adults with high BP. The estimated mean sodium excretion was higher in the intervention group than in the control group at 12 weeks; however, the CI for the mean difference was wide, suggesting no real difference. In addition, we found no effect of the intervention package on any secondary outcome, including estimated 24-hour urinary potassium excretion and BP. Although most intervention participants reported using the SaltSwitch app (48/64, 75%) and the RSS (60/64, 94%) during the 12-week intervention period and acceptability of the intervention was high, the intervention dose was low; participants reported using SaltSwitch on less than half of shopping occasions and consuming only approximately 1/2 tsp of RSS per household per week during the intervention period. The low recruitment of participants from Māori whānau and Pacific communities meant that it was not possible to estimate differences in effects separately for these groups.

Limitations

In addition to the low intervention dose, important limitations of the SALTS trial were the reduced study power, low number of participants from Māori whānau and Pacific communities, lower-than-anticipated engagement with trial technologies, and use of a spot rather than 24-hour urine sample for estimation of the primary outcome. Implementation and COVID-19 challenges
meant that the trial was substantially underpowered, and thus, it is possible that a real effect may have been missed. Although a larger trial would have enabled the study hypothesis to be tested as intended, it is possible that the null trial findings would have been similar because of the limited use of intervention components. Given the high acceptability, the reason for the low consumption of the RSS by trial participants is not clear, but the low use of discretionary salt at baseline by trial participants may have been a factor. The ease of use and acceptability of SaltSwitch were also high, but reported use was low, with the reasons most reported by participants for not using the intervention app more often being the use of web-based grocery shopping instead, others completing the grocery shopping, difficulty in downloading or using SaltSwitch, and lack of time.

Despite adopting specific recruitment strategies to attract and engage Māori whānau and Pacific communities, we randomized only 14.3% (24/168) and 7.1% (12/168) of the total participants from these groups, respectively. Although we were able to attend numerous face-to-face events with Māori communities and work directly with Pacific health organizations, a capacity-building approach led by Māori for Māori and by Pacific for Pacific where these groups take an active part in the research would likely have been more effective [33].

Challenges associated with the considerable use of technology in the trial also affected recruitment, engagement, and return of outcome data. However, it is difficult to know the magnitude of the effect related to these challenges as technology provides certain inherent efficiencies and enabled researchers to continue some aspects of the trial during COVID-19 lockdowns.

The use of spot urine rather than gold-standard 24-hour urine samples may have affected the ability to identify a difference in sodium intake between the intervention and control groups [34]. Although 24-hour urine samples are considered too burdensome for nonclinical study populations, future similar research would benefit from a subsample of participants providing a 24-hour urine sample, which would provide some information on the consistency of effects.

Caution should also be exercised when generalizing the findings of the SALTS trial to other population groups. In addition to the low number of participants from Māori whānau and Pacific communities, the study sample was highly educated; many were already trying to cut down on the amount of salt they consumed and using nutrition information on food packages to make healthier choices. Furthermore, 1 in 3 referrals declined to take part or were unable to be contacted, and the inclusion-to-randomization rate (calculated from the 59 referrals who were initially eligible and completed the baseline questionnaire but were not randomized) was lowest for those from Māori whānau (24/52, 46%) and Pacific communities (12/17, 71%; conversion rates for Asian and European or other were 29/36, 81% and 103/132, 78%, respectively). Possible reasons for why almost half of Māori referrals (24/52, 46%) and approximately 40% of Pacific referrals (12/17, 71%) did not continue in the study include the collective cultures of these groups misaligning with the individual framing of the intervention and the lack of face-to-face contact [32].

smartphone apps offer benefits, including lower scale-up costs, personalized health information, real-time delivery of advice, and remote assessment of outcomes, there is evidence indicating that face-to-face relationships are a key component for achieving social connection and digital inclusion, both of which are vital to reducing inequities [35,36].

Strengths

Nonetheless, the SALTS trial is one of the few RCTs of a smartphone app to promote dietary sodium reduction in adults [13]. To date, most mHealth interventions aimed at reducing sodium consumption have focused on improving knowledge and awareness of dietary salt intake using SMS text messaging. The use of more innovative technologies and rigorously designed trials were identified as key recommendations for future research in a 2019 systematic review [14]. Furthermore, SALTS is one of a limited number of trials testing an RSS in a country with a predominantly Western diet where packaged foods contribute most (>50%) of sodium to dietary intake [37].

Comparison With Prior Work

The null findings of the SALTS trial are inconsistent with those of 2 recent systematic reviews of mHealth interventions that specifically target dietary salt reduction. The first was a 2019 systematic review of the effectiveness of mHealth technologies for salt reduction and included 6 RCTs and 5 quasi-experimental studies; 8 of 11 studies produced positive results [14], and 2 of the RCTs stated salt consumption as the primary outcome (one of which was a pilot of the SaltSwitch app [15]), finding significant reductions in intake as estimated by a spot (casual) urine sample. However, both trials were small (ie, <100 participants). The results of a more recent (2020) RCT of the “LowSalt4Life” just-in-time adaptive mobile app for adults with hypertension were also positive, with a significant reduction in estimated 24-hour urinary sodium excretion compared with usual dietary advice [38]. A 2019 systematic review examining the effectiveness of electronic health interventions for BP control also found a significant overall reduction in sodium intake (n=15 trials) [13].

The reasons why the SaltSwitch app was ineffective compared with previous studies are difficult to determine as the intervention components associated with effectiveness were not investigated. However, in contrast to the SALTS intervention, most previous studies were co-designed or included at least one of the following behavior change techniques: system-generated feedback based on current behaviors, goal setting, regular motivational SMS text messages, or face-to-face support from a health care provider in addition to interaction through an electronic device [13]. A recent (2020) systematic review of mHealth RCTs supports the inclusion of behavior change techniques, with prompts or cues, general personalization, goal setting, and action planning found to be significantly associated with positive change [39]. The SaltSwap app included only one of these techniques (prompts or cues to use the app), which may help explain its lack of efficacy. The feasibility of an app called SaltSwap combined with a brief behavioral intervention was recently explored in adults with high BP in the United Kingdom. Although researchers found no evidence that the intervention reduced dietary salt intake, findings of a future
adequately powered trial will provide further information on the effectiveness of mHealth interventions based on behavioral theory [40]. The contrasting positive findings of the SALTS pilot trial also suggest that individual-level behavior change interventions may be more beneficial for highly motivated clinical populations [15,41]. Approaches likely to be more successful at the population level include those outlined by the WHO in their Surveillance, Harness Industry, Adopt Standards for Labelling and Marketing, Knowledge, Environment technical package for salt reduction (i.e., regular measuring and monitoring of population salt use, reformulation of foods and meals to contain less salt, effective food labeling and marketing, education campaigns, and supporting settings such as hospitals and universities to promote healthy eating [42]).

The null findings of the SALTS trial are also inconsistent with evidence from a 2022 Cochrane meta-analysis, which showed that the use of an RSS can reduce urinary sodium excretion by up to 1730 mg per day [17]. However, none of the included studies were from countries such as NZ, where discretionary salt use contributes <25% to dietary sodium intake, and there were insufficient data in the review to determine whether the type of RSS or study population affected effectiveness. The limited use of the RSS by participants in the SALTS trial suggests that, in Aotearoa NZ, it may be more efficacious to focus on the use of RSSs in packaged foods rather than or as an adjunct to a replacement for traditional table salt. That said, RSSs may still be helpful for specific communities or in settings where most food is cooked or prepared in the home or on-site. In settings where RSSs are found to be effective, political actions to support implementation include understanding the path to market and removing cost and accessibility barriers for consumers and food companies [43].

Conclusions

In summary, our trial found no evidence of the effectiveness of a salt-reduction intervention package comprising a smartphone app and RSS on estimated 24-hour sodium excretion (or any secondary outcome assessed) in adults with high BP. The trial was underpowered because of challenges associated with the implementation of trial technologies and the COVID-19 pandemic, meaning that it is possible that a real effect may have been missed. Furthermore, because of low engagement and recruitment, it was not possible to determine potential effects for Māori whānau or Pacific communities. However, it is also possible that a larger trial in the same study population would produce similar results given the low intervention dose. Nonetheless, further research may be warranted to explore the efficacy of SaltSwitch for secondary prevention in highly motivated clinical populations such as those who have had a recent cardiac event. Further research should also be undertaken to explore the use of RSSs in packaged foods, especially for countries such as NZ, where these foods contribute >50% to population sodium intake, and in specific communities or in settings where most food is cooked in the home or prepared on-site. Finally, the challenges associated with the design and delivery of effective individual-level behavioral interventions highlight the need for comprehensive policies and programs, including improvements to food environments and systems, in addition to supportive tools for behavior change—this is critical if we are to achieve meaningful reductions in population sodium intake.

Acknowledgments

The authors are indebted to their trial participants. They would also like to thank their study project coordinator (Diane Wood) and research assistants (Neela Bhana, Bruce Kidd, and Shistata Shrestha); Nhung Ngheim, who helped with the development of an early plan for economic analysis; Tahu-Pōtiki Te Maro-Doran, who assisted with recruitment in Wellington; Green Cross Health and The Stroke Foundation of New Zealand for support with recruitment; student and staff volunteers who helped with recruitment during the Stroke Foundation “Big Blood Pressure Check” and at Ngāti Whāau events (Shai Alsia, Daria Faulconbridge, Bruce Kidd, Xinye Li, Jenny Lin, Magda Rosin, Huang Silver, Summer Wright, and Lina Yousif); Koda Web Design who developed the Salt Alternatives Study smartphone app and database; staff at the National Institute for Health Innovation involved in data management, software, budgets, and contracts (Manoj Alwis, Karen Carter, Sarah Douglas, John Faatui, Michelle Jenkins, Pragya Nandan, Deepak Pandey, Mahfuz Rahman, and Peter Tsai); and Gina Gastrillon and Fraser Taylor, who facilitated the development of the New Zealand version of the SaltSwitch smartphone app. This research was also supported (in part) by the provision of Salt for Life 100 Dietary Alternative Salt free of charge by NuTek. Funding was provided by the Health Research Council of New Zealand program grant (#18/672). HE is funded by a Heart Foundation of New Zealand Senior Fellowship grant (#1843). RND is supported by the Heart Foundation Chair of Heart Health. The funder had no role in the study design; collection, analysis, or interpretation of the data; writing of the report; or decision to submit the manuscript for publication.

Authors’ Contributions

HE, BN, and CNM contributed to conceptualization. YJ, JG, EU, and RM contributed to data curation. YJ contributed to formal analysis. HE and CNM acquired funding. HE, JG, EU, and LTM contributed to investigation. HE, JG, EU, RM, LTM, BN, AR, RND, and CNM contributed to methodology. JG and EU were responsible for project administration. JG and EU contributed to resources. HE, BN, AR, RND, and CNM supervised the study. YJ and RM validated the data. HE and YJ contributed to visualization. HE wrote the original draft. HE, JG, UM, RM, LTM, BN, AR, RND, and CNM reviewed and edited the manuscript.

Conflicts of Interest

None declared.
Multimedia Appendix 1
CONSORT-EHEALTH (Consolidated Standards of Reporting Trials of Electronic and Mobile Health Applications and Online Telehealth) questionnaire V1.6.1.

References


Abbreviations

BP: blood pressure
CONSORT: Consolidated Standards of Reporting Trials
CVD: cardiovascular disease
DBP: diastolic blood pressure
GP: general practitioner
mHealth: mobile health
NZ: New Zealand
RCT: randomized controlled trial
REDCap: Research Electronic Data Capture
RSS: reduced-sodium salt
SALTS: Salt Alternatives Study
SBP: systolic blood pressure
WHO: World Health Organization

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The Effect of a mHealth App (KENPO-app) for Specific Health Guidance on Weight Changes in Adults With Obesity and Hypertension: Pilot Randomized Controlled Trial

Naoki Sakane1, MD, PhD; Akiko Suganuma1, BB; Masayuki Domichi1, BBIS; Shin Sukino1, BNS; Keiko Abe1, BHNS; Akiyoshi Fujisaki2, MS; Ai Kanazawa3, BS; Mamiko Sugimoto3, BS

1Division of Preventive Medicine, Clinical Research Institute, National Hospital Organization Kyoto Medical Center, Kyoto, Japan
2Technology Development HQ, OMRON HEALTHCARE Co., Ltd., Kyoto, Japan
3Cardiovascular Disease Business Planning Strategy HQ, OMRON HEALTHCARE Co., Ltd., Kyoto, Japan

Corresponding Author:
Naoki Sakane, MD, PhD
Division of Preventive Medicine
Clinical Research Institute
National Hospital Organization Kyoto Medical Center
1-1 Mukaihata-cho, Fukakusa
Fushimi-ku
Kyoto, 612-8555
Japan
Phone: 81 75 641 9161
Fax: 81 75 645 2781
Email: nsakane@gf6.so-net.ne.jp

Abstract

Background: Commercial smartphone apps that promote self-monitoring of weight loss are widely available. The development of disease-specific apps has begun, but there is no app for specific health guidance (SHG) to prevent metabolic syndrome, type 2 diabetes, and cardiovascular diseases in middle-aged adults in Japan.

Objective: This study aimed to determine the efficacy of an SHG mobile health app in facilitating weight loss in Japanese adults with obesity and hypertension.

Methods: In a 12-week, statistician-blinded, randomized parallel controlled trial, 78 overweight and obese men aged 40-69 years were assigned in a 1:1 ratio to either the usual support plus KENPO-app group (intervention group) or the active control group. KENPO-app (release April 10, 2019; OMRON Healthcare Co., Ltd.) was developed by the study team and focus groups and uses behavior change techniques (ie, self-monitoring and goal-setting theory). This app was developed for SHG based on the four specific health checkups and guidance system in Japan: (1) focusing primarily on achieving the target (weight loss of ≥2 kg); (2) assessing healthy eating, exercise habits, smoking habits, relaxation, and self-weighing; (3) providing information on the results of specific health checkups; and (4) starting an intervention period of 6 months with the interim assessment at 3 months. The initial assessment explored the following: personality traits (4 types), health checkup data concerns (10 items), symptom concerns (10 items), and the aim of the intervention (weight loss, improving fitness, symptoms, laboratory data). Chatbot-supported health information on health and health behavior was selected from 392 quizzes based on app data and was provided to participants. The KENPO-app had chatbot-supported feedback and information provision combined with a self-monitoring tool (weight, steps, and blood pressure). Data on active exercise, healthy eating, and healthy lifestyle habits were obtained using a web-based self-administered questionnaire at baseline and 12 weeks.

Results: The trial’s retention rate was 95% (74/78). The adherence to daily self-weighing, wearing the pedometer, and blood pressure monitoring in the KENPO-app group was significantly higher than those in the active control group. Compared with the active control group, the median body weight and BMI of the intervention group significantly decreased at 3 months (–0.4, IQR –2.0 to 0.6 kg vs –1.1, IQR –2.7 to –0.5 kg; P=.03; –0.1, IQR –0.6 to 0.3 kg vs –0.4, IQR –0.8 to –0.2 kg; P=.02, respectively). The intervention increased the percentage of participants who self-reported taking ≥8000 steps, eating vegetables before rice, eating slowly, and relaxing. Personality traits were associated with the degree of weight loss in the intervention group.

Conclusions: The SHG-specific KENPO-app was feasible and induced modest but significant weight loss in adults with obesity.
**Introduction**

In 2008, all health insurers in Japan were mandated to provide specific health guidance (SHG) to prevent metabolic syndrome, type 2 diabetes, and cardiovascular diseases in middle-aged adults in Japan [1-6]. During the first implementation stage, between 2008 and 2012, the nationwide implementation goal was 45%. However, after reassessment in 2019, the actual implementation rate was far lower at 23.2%. During the second stage, between 2013 and 2017, the flow of the SHG process was reviewed. During the COVID-19 pandemic, self-quarantine was associated with unhealthy eating habits, sedentary behavior, and weight gain [7,8]. In addition, the efficacy of SHG was small, and repeater eligibility for SHG was a problematic issue [9]. During the third stage, between 2019 to 2023, SHG using information and communications technology (ICT) was initially introduced in 2021. For the fourth stage (2024-), the evaluation of the outcome (ie, ≥2 kg of weight loss) will be performed, and a mobile health (mHealth) care app will be introduced for SHG. Overall, research evidence suggests that mobile apps and wearables are effective self-regulating tools for weight loss in the Western population, but a discrepancy exists [10,11]. Commercial smartphone apps that promote the self-monitoring of weight loss are widely available. The development of disease-specific apps has begun. Several apps are used for real-world SHG, but there is no app specified for SHG. Therefore, we developed the SHG-specific mHealth app (KENPO-app), and this study aimed to determine its efficacy in facilitating weight loss in Japanese adults with obesity and hypertension.

**Methods**

**Study Design**

This study was a 12-week, statistician-blinded, parallel-group, randomized controlled trial (RCT) of adults with obesity and hypertension. The data were obtained between October 2021 and May 2022.

**Ethics Approval**

The study protocol was approved by the institutional review board of Kyoto Medical Center (NO.21-057), and the protocol of the study was registered at the University Hospital Medical Information Network Center (UMIN000046263).

**Participants**

Participants were recruited from the screening panel of the Omron monitor recruitment site for product development and research in Japan. Therefore, participants may have relatively higher computer/internet literacy. We held an online information session for this trial. Inclusion criteria were as follows: age 40-64 years, BMI≥25 kg/m², systolic blood pressure (SBP) ≥130 mm Hg or diastolic blood pressure (DBP) ≥85 mm Hg, smartphone users capable of installing apps, and individuals capable of communicating online. Exclusion criteria were as follows: receiving SHG at present, taking antihypertensive medicine, contraindication for healthy eating and active exercise by a doctor, pregnant or breastfeeding women, and inappropriate cases (ie, severe psychiatric disorders) as determined by a research doctor.

**Randomization and Masking**

The independent statistician randomly allocated participants into one of two intervention arms according to sex-, age-, SBP-, and BMI-stratified block randomization (seed=1221 and block size=2). We adopted a single-blind approach; thus, the effectiveness was assessed by blinded researchers who were unaware of the randomization results.

**Self-monitoring Tool**

Participants in both groups received a Bluetooth weighing scale (HBF-227T, OMRON Healthcare Co, Ltd), pedometer (HJA-405T, OMRON Healthcare Co, Ltd), and upper arm blood pressure (BP) monitor (HCR-7501T, OMRON Healthcare Co, Ltd).

**The Active Control Group**

The participants in the active control group received the usual support. The usual support was based on intensive SHG, and the participants in both groups received initial online face-to-face counseling by a health care professional (ie, a registered dietician) who had completed the established Ministry of Health, Labor and Welfare (MHLW) training course. Participants were briefed about their health condition and lifestyle through a review of their SHG results. They were instructed to set achievable personalized behavioral goals. After the initial counseling, a health care professional provided email support three times at 2, 6, and 12 weeks. Implementation points according to the MHLW in the active control group were comparable to the required points of ≥180 in the SHG. Daily recording of body weight and steps were recommended. Measurements of BP in the morning and evening were also recommended.

**mHealth KENPO-app**

KENPO-app (release April 10, 2019; OMRON Healthcare Co, Ltd) was developed using behavior change techniques (ie, self-monitoring and goal-setting theory) by the study team and focus groups. This app was developed for SHG based on the four specific health checkups and guidance system in Japan: (1) focusing on achieving the primary target (weight loss of ≥2 kg); (2) assessing healthy eating, exercise habits, smoking habits, relaxation, and self-weighing; (3) providing information on the
results of specific health checkups; and (4) starting an intervention period of 6 months with the interim assessment at 3 months. The initial assessment explored the following: personality traits (4 types), concerns about health checkup data (10 items), concerns about symptoms (10 items), and the aim of the intervention (weight loss, improving fitness, symptoms, laboratory data; Figures 1 and 2). Saeki et al [12] reported a cluster analysis that showed 4 clusters in a total of 1500 people aged 15-75 years. They classified personality traits into four types: “Challenger” (self-realization and a sense of growth; fact-based extrovert), “Entertainer” (connection and gratitude; relationship introvert), “Communicator” (optimism; relationship introvert), and “Walker” (do things at my own pace; fact-based introvert). The targeted behavioral goals were as follows: exercise habits (10 items), healthy eating habits (10 items), lifestyle habits (10 items), and daily steps (5000, 7000, 8000, and 10,000 steps). The self-administrated questionnaire on exercise, healthy eating, and lifestyle habits had three choices: “not confident,” “ready to change,” and “already have been.” Chatbot-supported health information on health and health behavior was selected from 392 quizzes based on app data that was provided to participants (Textbox 1). Participants accessed the KENPO-app from the App Store or Google Play. Self-weighing twice was recommended. We did not perform revisions or updates during the study period. Safety and security procedures included privacy considerations and the availability of a hotline.

Figure 1. Screenshot and initial assessment of KENPO-app system. (A) KENPO-app at APP Store; (B) KENPO-app at Google Play; (C) initial assessment items.

Figure 2. Outline of KENPO-app system.
Textbox 1. The contents of the KENPO-app study.

<table>
<thead>
<tr>
<th>Input to the app</th>
<th>Self-monitoring (before initial specific health guidance [SHG])</th>
<th>Online initial SHG</th>
<th>Self-monitoring (after initial SHG)</th>
<th>Quiz on health</th>
<th>Input to the app (12 weeks)</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Initial assessment (laboratory data, symptoms, and clinical goals)</td>
<td>• Pedometer, weight, and blood pressure, and behavioral agenda</td>
<td>• SHG based on app data and personality trait</td>
<td>• Pedometer, weight, and blood pressure, and behavioral agenda</td>
<td>• Chatbot-supported feedback of app data and sign of weight regain</td>
<td>• Final assessment (laboratory data, symptoms, objective)</td>
</tr>
<tr>
<td>• Personality trait</td>
<td></td>
<td></td>
<td>• Chatbot-supported quiz on health and health behavior</td>
<td></td>
<td>• Behavioral agenda (exercise, dietary, and lifestyle habits)</td>
</tr>
<tr>
<td>• Setting weight loss goal</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Targeting behavioral agenda (exercise, dietary, lifestyle habits, daily steps)</td>
<td></td>
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</tbody>
</table>

Outcome
The outcome included changes in body weight and BMI. Weight measurements were uploaded to the cloud where the data were obtained, and the 7-day average weight was calculated. Other outcomes included changes in SBP, DBP, and adherence to the device. The frequency of weight, BP, and step uploads was recorded as a measure of adherence. Data on active exercise habits (10 items), healthy eating habits (10 items), and healthy lifestyle habits (10 items) were obtained using a web-based self-administered questionnaire at baseline and 12 weeks. Quality assurance was performed through standard operating procedures and benchmarking. Adherence to the apps was defined based on the sending rate of body weight measurements, and an attrition diagram was made.

Statistical Analysis
Data are expressed as the mean (SD), median (IQR), range, or number. Blinded data were analyzed using the R software version 4.0.0. (R Foundation for Statistical Computing) on an intention-to-treat basis by the statistician. Statistical analysis of quantitative data was performed using the Shapiro-Wilk test, Mann-Whitney U test, Student t test, and Spearman rank test. Categorical data were analyzed using Fisher exact test or exact binomial test. Those cases with missing data were omitted in the relevant analysis. Sensitivity analysis was performed using multiple imputation. There was no previous study related to our hypothesis. Therefore, the sample size was estimated as 52 people with an effect size of 0.8 (large effect size) for a pilot or feasibility study. With a dropout rate of approximately 30%, 80 people were required. The level of statistical significance was set at $P<.05$.

Results
Participants and Adherence
After 80 participants were screened, we enrolled 78 participants and excluded 2. Of the 78 participants, the mean age was 52.0 (SD 6.5) years, and 55% (n=43) were male. Those who had full- and part-time jobs accounted for 65% (n=51) and 19% (n=15) of the sample, respectively. Participants were assigned to either the KENPO-app group (intervention group; n=39) or the active control group (n=39). There were no differences in age (mean 52.5, SD 6.6 years vs mean 51.4, SD 6.4 years; $P=.47$), male sex ratio (56.4% vs 53.8%; $P>.99$), BMI (mean 27.5, SD 1.9 km/m² vs mean 27.9, SD 2.3 km/m²; $P=.41$), or SBP (mean 138.3, SD 12.7 mm Hg vs mean 136.2, SD 17.5 mm Hg; $P=.55$) between the groups. Two participants in the intervention group did not receive the intervention before the initial web-based consultation. We could not contact 1 participant after the intervention for unknown reasons in the active control group. As indicated in the CONSORT flow diagram, one participant was deleted from the analysis due to device failures in the active control group (Figure 3). The trial retention was 95% (74/78). Figure 4A shows the self-weighing attrition diagram. The adherence to daily self-weighing, wearing the pedometer, and BP monitoring in the KENPO-app group was significantly higher than those in the active control group. Two participants in the intervention group did not receive the intervention before the initial web-based consultation. We could not contact 1 participant after the intervention for unknown reasons in the active control group. As indicated in the CONSORT flow diagram, one participant was deleted from the analysis due to device failures in the active control group (Figure 3). The trial retention was 95% (74/78). Figure 4A shows the self-weighing attrition diagram. The adherence to daily self-weighing, wearing the pedometer, and BP monitoring in the KENPO-app group was significantly higher than those in the active control group. Participants in the KENPO-app group had the following health checkup data concerns: hyperglycemia 27% (n=10),
hypertriglyceridemia 57% (n=21), and low high-density lipoprotein cholesterol 24% (n=9).

**Figure 3.** CONSORT flow diagram of KENPO-app study.

**Figure 4.** Attrition diagram on self-weighing and mean changes in body weight during the study period.

**Outcome**

**Figure 4** shows the weight changes during the study (mean –2.0, SD 0.6 kg in the intervention group vs mean –0.8, SD 0.3 kg in the active control group at the 12-week follow-up). The distribution of the weight changes was not normal as assessed by the Shapiro-Wilk test. Compared with the active control group, the median body weight and BMI of the intervention group significantly decreased at 3 months (–0.4, IQR –2.0 to 0.6 kg vs –1.1, IQR –2.7 to –0.5 kg; \( P = .03 \); –0.1, IQR –0.6 to 0.3 kg vs mean –0.4, IQR –0.8 to –0.2 kg; \( P = .02 \), respectively). The sensitivity analysis confirmed the results. The odds ratio for achieving \( \geq 3\% \) and 2% weight loss was 1.58 (95% CI 0.47-5.63) and 2.27 (95% CI 0.79-6.85), respectively. Personality traits were associated with the degree of weight loss in the KENPO-app group. Compared with “challenger” (n=7),
“walker” (n=6) had significantly greater weight loss (median –0.50, IQR –0.65 to 0.40 kg vs median –3.10, IQR –4.42 to –2.00; \( P = .02 \)), but there was no difference in weight change among “challenger,” “communicator,” and “entertainer.” The adherence to daily self-weighing and BP monitoring in the intervention group was significantly higher than in the active control group (daily self-weighing: mean 79.3%, SD 10.5% vs mean 68.6%, SD 22.1%; \( P = .01 \); BP monitoring: mean 78.0%, SD 11.4% vs mean 58.8%, SD 31.6%; \( P = .001 \), respectively). Similarly, adherence to daily steps was higher in the intervention group than in the active control group (mean 75.7%, SD 13.4% vs mean 68.2%; \( P = .09 \)). Only adherence to self-weighing in the morning and evening was negatively correlated with changes in body weight in the intervention group, although adherence to daily self-weighing and daily steps in both groups was not.

SBP decreased in the intervention group (from mean 138, SD 13 mm Hg to mean 135, SD 10 mm Hg; \( P = .02 \)), but this was not significantly different from the active control group. There were no changes in DBP observed in the intervention group.

**Healthy Behavior**

The percentage of participants who reported ≥8000 steps per day, slow eating speed, vegetable intake before rice, selecting a healthy menu, and relaxation in the intervention group increased after the 12-week study period, while the percentage of eating breakfast and reducing snacks in the active control group increased (Table 1). The rate of achieving ≥8000 steps based on the pedometer after the intervention tended to be higher than that in the active control group (58.8% vs 32.4%; \( P = .05 \)). There were no severe adverse events or technical problems.
Table 1. Healthy lifestyle and symptoms during the study period according to the group.

<table>
<thead>
<tr>
<th>Item</th>
<th>Intervention group (n=39), n (%)</th>
<th>Control group (n=39), n (%)</th>
<th>P value</th>
<th>Pre</th>
<th>Post</th>
<th>P value</th>
<th>Pre</th>
<th>Post</th>
<th>P value</th>
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<td><strong>Active exercise habits</strong></td>
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<td></td>
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<tr>
<td>Use of stairs instead of the escalators</td>
<td>5 (14)</td>
<td>8 (22)</td>
<td>.45</td>
<td>9 (24)</td>
<td>14 (38)</td>
<td>.13</td>
<td></td>
<td></td>
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<tr>
<td>Walking ≥8000 steps</td>
<td>6 (16)</td>
<td>13 (35)</td>
<td>.046</td>
<td>9 (24)</td>
<td>8 (22)</td>
<td>&gt;.99</td>
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<td>At least 30 min of brisk daily walks</td>
<td>4 (11)</td>
<td>9 (24)</td>
<td>.18</td>
<td>6 (16)</td>
<td>6 (16)</td>
<td>&gt;.99</td>
<td></td>
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<td>Do gymnastics/stretching everyday</td>
<td>3 (8)</td>
<td>6 (16)</td>
<td>.37</td>
<td>2 (5)</td>
<td>8 (22)</td>
<td>.08</td>
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<tr>
<td>Do not stay home and do nothing on holiday</td>
<td>3 (8)</td>
<td>7 (19)</td>
<td>.22</td>
<td>7 (19)</td>
<td>12 (32)</td>
<td>.18</td>
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<td>Stand up and exercise once an hour</td>
<td>8 (22)</td>
<td>13 (35)</td>
<td>.18</td>
<td>9 (24)</td>
<td>9 (24)</td>
<td>&gt;.99</td>
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<tr>
<td>Do housework (cooking, cleaning, etc)</td>
<td>15 (41)</td>
<td>18 (49)</td>
<td>.37</td>
<td>24 (65)</td>
<td>25 (68)</td>
<td>&gt;.99</td>
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<td>Resistance training ≥3 times per week</td>
<td>1 (3)</td>
<td>2 (5)</td>
<td>&gt;.99</td>
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<td>2 (5)</td>
<td>&gt;.99</td>
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<td>Use the gym or pool at least once per week</td>
<td>1 (3)</td>
<td>1 (3)</td>
<td>&gt;.99</td>
<td>0 (0)</td>
<td>1 (3)</td>
<td>&gt;.99</td>
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<td>Play sports at least once a week</td>
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<td>4 (11)</td>
<td>.13</td>
<td>3 (8)</td>
<td>4 (11)</td>
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<td><strong>Healthy eating habits</strong></td>
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<td>Eat moderately</td>
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<td>7 (19)</td>
<td>.08</td>
<td>6 (16)</td>
<td>10 (27)</td>
<td>.22</td>
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<td>Eat breakfast</td>
<td>22 (60)</td>
<td>22 (60)</td>
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<td>31 (84)</td>
<td>.04</td>
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<td>Eat vegetable first</td>
<td>12 (32)</td>
<td>23 (62)</td>
<td>.01</td>
<td>22 (60)</td>
<td>26 (70)</td>
<td>.22</td>
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<td>Eat slowly and well</td>
<td>1 (3)</td>
<td>9 (24)</td>
<td>.01</td>
<td>13 (35)</td>
<td>16 (43)</td>
<td>.37</td>
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<tr>
<td>Eat with nutritional balance in mind</td>
<td>4 (11)</td>
<td>9 (24)</td>
<td>.13</td>
<td>12 (32)</td>
<td>15 (41)</td>
<td>.45</td>
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<td>Do not overeat carbohydrates</td>
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<td>5 (14)</td>
<td>.13</td>
<td>9 (24)</td>
<td>14 (38)</td>
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<td>Eat fried food up to 3 times per week</td>
<td>1 (3)</td>
<td>6 (16)</td>
<td>.07</td>
<td>12 (32)</td>
<td>16 (43)</td>
<td>.29</td>
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<tr>
<td>Reduce salt</td>
<td>1 (3)</td>
<td>6 (16)</td>
<td>.07</td>
<td>11 (30)</td>
<td>12 (32)</td>
<td>&gt;.99</td>
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<td>Reduce sweet buns and delicatessen bread</td>
<td>7 (19)</td>
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<td>.72</td>
<td>11 (30)</td>
<td>14 (38)</td>
<td>.37</td>
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<td>Reduce eating in dinner</td>
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<td>4 (11)</td>
<td>.25</td>
<td>8 (22)</td>
<td>13 (35)</td>
<td>.13</td>
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<td>Reduce sugar-sweetened beverages</td>
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<td>14 (38)</td>
<td>.15</td>
<td>20 (54)</td>
<td>23 (62)</td>
<td>.45</td>
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<tr>
<td>Reduce sweets</td>
<td>4 (11)</td>
<td>5 (14)</td>
<td>&gt;.99</td>
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<td>Check food labels</td>
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<td>12 (32)</td>
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<td>Choose healthy menu</td>
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<td>9 (24)</td>
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<tr>
<td>Do not eat anything 2 h before bedtime</td>
<td>9 (24)</td>
<td>15 (41)</td>
<td>.08</td>
<td>13 (35)</td>
<td>14 (38)</td>
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<td>Go to bed early</td>
<td>8 (22)</td>
<td>12 (32)</td>
<td>.39</td>
<td>10 (27)</td>
<td>10 (27)</td>
<td>&gt;.99</td>
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<tr>
<td>Try to have alcohol-free days</td>
<td>26 (70)</td>
<td>30 (81)</td>
<td>.29</td>
<td>27 (73)</td>
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<td>.62</td>
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<td>Reduce alcohol drinks</td>
<td>27 (73)</td>
<td>28 (76)</td>
<td>&gt;.99</td>
<td>24 (65)</td>
<td>25 (68)</td>
<td>&gt;.99</td>
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<td>Stop smoking</td>
<td>33 (89)</td>
<td>32 (87)</td>
<td>&gt;.99</td>
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<td>&gt;.99</td>
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<td>Relaxation</td>
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<td>16 (43)</td>
<td>.02</td>
<td>15 (41)</td>
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<td>Headache</td>
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<td>3 (8)</td>
<td>.07</td>
<td>8 (22)</td>
<td>7 (19)</td>
<td>&gt;.99</td>
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<td>Shoulder stiffness</td>
<td>23 (62)</td>
<td>12 (32)</td>
<td>.006</td>
<td>21 (57)</td>
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<td>1 (3)</td>
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<td>7 (19)</td>
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<td>Lumbaro</td>
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<td>17 (46)</td>
<td>15 (41)</td>
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<td>Knee pain</td>
<td>13 (35)</td>
<td>8 (22)</td>
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<td>6 (16)</td>
<td>5 (14)</td>
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<td>Constipation</td>
<td>7 (19)</td>
<td>0 (0)</td>
<td>.02</td>
<td>8 (22)</td>
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<td>&gt;.99</td>
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<td>Chillness</td>
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<td>2 (5)</td>
<td>.02</td>
<td>13 (35)</td>
<td>4 (11)</td>
<td>.02</td>
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</table>
Discussion

Principal Findings
This is the first study to confirm the effectiveness of the SHG-specific KENPO-app in obese adults with hypertension. The mHealth KENPO-app is feasible and can produce modest but significant weight loss. Compared with standard care, the mHealth app produced modest weight loss (−1.0 kg to −2.4 kg of body weight) in obese adults with diabetes [13]. The meta-analysis by Ang et al [14], including 17 articles for Asian populations, indicated that the effect size of the RCTs for weight change was small to moderate. The effect size of our results was also small to moderate. In this study, we observed a significant change in SBP. Although mHealth apps are effective in reducing weight, they were ineffective in lowering BP in 160 adults with ≥2 cardiovascular risk factors [15]. Further examination, including a large sample size, is required to confirm these issues in the future.

Adherence and Weight Change
Self-monitoring of weight was a significant predictor of weight loss [16-18]. In this study, self-weighing twice a day (in the morning and evening) was negatively correlated with weight change, although daily self-weighing was not. We previously reported that self-weighing twice per day plus daily target setting and feedback were more effective in promoting weight loss than one daily self-measurement [19]. Self-weighing twice a day is a recommendation in clinical practice.

Healthy Behavior and Weight Loss
The current consensus states that obtaining less than 5000 steps per day is sedentary behavior, whereas obtaining >8000 steps indicates an active exercise habit [20]. A meta-analysis by Flores Mateo et al [21] indicated that the mHealth app was associated with significant changes in body weight and BMI of −1.04 kg and −0.43 kg/m², respectively, compared with the control group. However, there was no significant difference in physical activity between the groups. On the other hand, Richardson et al [22] performed a meta-analysis on pedometer-based interventions without caloric restriction, with a pooled estimated change in body weight of −1.3 kg. In this study, the KENPO-app increased the proportion of ≥8000 steps (self-reported).

Moreover, slow eating speed, vegetable intake before rice, selection of a healthy menu, and relaxation in the intervention group increased after the intervention. Fast eating speed is positively associated with obesity [23,24]. For weight loss strategies, the recommendation of increased vegetable consumption is often used [25]. Meal sequence, such as eating vegetables before rice, reduces postprandial glycemic and weight loss effects [26]. In a meta-analysis by Tapsell et al [27], 5 participants reported greater weight loss, 9 reported no difference, 1 showed weight gain, and 1 reported a positive association between weight loss and high vegetable consumption. Comprehensive healthy eating may have resulted in significant weight loss in the study.

Personality Traits and Weight Changes
Personality traits are an important factor in health behaviors. Interestingly, personality traits were associated with the degree of weight change in this study. Specific aspects of personality (ie, agreeableness) are relevant to weight loss maintenance [28,29]. People with greater openness and conscientiousness were associated with greater compliance with self-care [30]. Personality traits such as neuroticism, agreeableness, and conscientiousness are associated with self-weighing frequency, dietary habits, support, and difficulties during the weight loss process [31]. Further examinations including the big five personality traits (neuroticism, extraversion, openness, agreeableness, and conscientiousness) and large sample sizes are required to confirm these issues in the future.

Strength and Limitations
The strengths of this study include the SHG-specific mHealth app, objective measurement of data, and a high retention rate. Although mHealth apps for weight management are popular and widely available, many apps lack professional content expertise. Encouraging app development based on evidence-based online approaches would ensure content quality, allowing health care professionals to recommend their use [32]. However, there are several limitations, including the short-term (12 weeks) and lack of laboratory data. Careful attention should be paid to interpretations regarding the results because of the lack of blinding. In this study, health and ICT literacy may be higher compared to participants in the real-world needing SHG. We did not analyze the cost-effectiveness. Further examinations including cost-effective analysis are required to confirm these issues in real-world SHG. The generalizability of the findings is limited to other populations due to it being in the Japanese language and being an SHG-specific app.

In conclusion, the SHG-specific KENPO-app was feasible and induced significant weight loss in Japanese adults with obesity and hypertension.
Acknowledgments
This study was partly supported by the Japan Society for the Promotion of Science KAKENHI (grant 22K11253) and the Japan Agency for Medical Research and Development DOUKI-APP Study (grant 21ek0210124). This study was funded by OMRON Healthcare Co, Ltd.

Conflicts of Interest
None declared.

Multimedia Appendix 1
CONSORT-eHEALTH checklist (V 1.6.1).

References


Abbreviations

BP: blood pressure
DBP: diastolic blood pressure
ICT: information and communications technology
mHealth: mobile health
MHLW: Ministry of Health, Labor and Welfare
RCT: randomized controlled trial
SBP: systolic blood pressure
SHG: specific health guidance
Sakane et al

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Improving Kidney Outcomes in Patients With Nondiabetic Chronic Kidney Disease Through an Artificial Intelligence–Based Health Coaching Mobile App: Retrospective Cohort Study

Wei Liu1,2*, MD; Xiaojuan Yu3,4,5,6*, MD; Jiangyuan Wang7*, MD; Tianmeng Zhou7, MS; Ting Yu2,8, MM; Xuyong Chen7, MD; Shasha Xie7, MD; Fuman Han3,4,5,6, MD; Zi Wang3,4,5,6, MD

1Department of Nephropathy, Anqing Municipal Hospital, Anqing, China
2Anqing Medical Center of Anhui Medical University, Anqing, China
3Renal Division, Department of Medicine, Peking University First Hospital, Beijing, China
4Institute of Nephrology, Peking University, Beijing, China
5Key Laboratory of Renal Disease, Ministry of Health, Beijing, China
6Key Laboratory of Chronic Kidney Disease Prevention and Treatment, Ministry of Education, Beijing, China
7Beijing Kidney Health Technology Co., Ltd, Beijing, China
8Fifth Clinical Medical College, Anhui Medical University, Hefei, China
*these authors contributed equally

Abstract

Background: Chronic kidney disease (CKD) is a global health burden. However, the efficacy of different modes of eHealth care in facilitating self-management for patients with CKD is unclear.

Objective: The aim of this study was to evaluate the effectiveness of a mobile app–based intelligent care system in improving the kidney outcomes of patients with CKD.

Methods: Our study was a retrospective analysis based on the KidneyOnline intelligent system developed in China. Patients with CKD but not dependent on dialysis who registered on the KidneyOnline app between January 2017 and January 2021 were screened. Patients in the KidneyOnline intelligent system group and those in the conventional care group were 1:1 matched according to their baseline characteristics. The intervention group received center-based follow-up combined with the KidneyOnline intelligent patient care system, which was a nurse-led, patient-oriented collaborative management system. Health-related data uploaded by the patients were integrated using deep learning optical character recognition (OCR). Artificial intelligence (AI)–generated personalized recipes, lifestyle intervention suggestions, early warnings, real-time questions and answers, and personalized follow-up plans were also provided. Patients in the conventional group could get professional suggestions from the nephrologists through regular clinical visits, but they did not have access to the service provided by AI and the health coach team. Patients were followed for at least 3 months after recruitment or until death or start of renal replacement therapy.

Results: A total of 2060 eligible patients who registered on the KidneyOnline app from 2017 to 2021 were enrolled for the analysis. Of those, 902 (43.8%) patients were assessed for survival analysis after propensity score matching, with 451 (50%) patients in the KidneyOnline intelligent patient care system group and 451 (50%) patients in the conventional care group. After a mean follow-up period of 15.8 (SD 9.5) months, the primary composite kidney outcome occurred in 28 (6%) participants in the KidneyOnline intelligent patient care system group and 32 (7%) in the conventional care group, with a hazard ratio of 0.391 (95% CI 0.231-0.660; P <.001). Subgroup survival analysis demonstrated that the KidneyOnline care system significantly reduced
the risk of composite kidney outcome, irrespective of age, sex, baseline estimated glomerular filtration rate (eGFR), and proteinuria. In addition, the mean arterial pressure (MAP) significantly decreased from 88.9 (SD 10.5) mmHg at baseline to 85.6 (SD 7.9) mmHg at 6 months ($P<.001$) in the KidneyOnline intelligent patient care system group and from 89.3 (SD 11.1) mmHg to 87.5 (SD 8.2) mmHg ($P=.002$) in the conventional CKD care group.

**Conclusions:** The utilization of the KidneyOnline intelligent care system was associated with reduced risk of unfavorable kidney outcomes in nondiabetic patients with CKD.

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**KEYWORDS**
chronic kidney disease; self-management; mobile apps; end-stage kidney disease; eHealth intervention; kidney; efficacy; eHealth care; dialysis; deep-learning; artificial intelligence; patient care

**Introduction**

Chronic kidney disease (CKD) is a worldwide public health concern and is increasingly becoming a global economic burden [1]. Both end-stage kidney disease (ESKD) and a reduction of estimated glomerular filtration rate (eGFR) are associated with hospitalization, cardiovascular events, and risk of death [2]. The prevalence of CKD in China was reported to be 10.8% in 2012, while only 12.5% of Chinese adults were aware of CKD as a medical problem [3]. Patients with CKD are often accompanied by comorbidities such as hypertension, diabetes, and heart disease. Providing care for patients with CKD involves a multidisciplinary team of physicians, nurses, dieticians, and social workers. Interventions to improve the outcomes of patients with CKD include lifestyle modification, antihypertensive medication, lipid modification, and glycemic control in patients with diabetes mellitus [4]. Achieving better health outcomes for patients with CKD requires patients to be aware of CKD and to engage in treatment and management plans [5]. Telehealth apps provide new opportunities to enhance self-management, behavior change, and medication adherence in a convenient way, thus reducing health complications and improving the overall kidney survival time.

There has been growing interest from physicians and other health care providers to use novel health-related mobile apps for patients in their fields of interest. Telehealth educational apps are more flexible and adaptable to patients’ preferences than paper-based or in-person health education. However, according to a systematic review, CKD-related apps accounted for only 1% of the total number of available apps in 2017 [6]. In addition, as opposed to in-person health consultations, telehealth programs usually do not offer patients the chance to ask their providers or educators questions immediately, which hampers the popularity and uptake of newly developed mobile apps.

Up to now, most studies describing the effectiveness of eHealth interventions on patients with CKD were from North America [7]. Moreover, the studies had relatively small sample sizes and only investigated changes in participants’ clinical parameters in a short period of time. Importantly, there has been a lack of studies assessing eHealth interventions using hard kidney end points. The objective of this study is to evaluate the effectiveness of a novel nurse-led, real-time communicating, app-based intelligent patient care system in China between 2017 and 2021 from real-world data.

**Methods**

**Study Design and Participants**

This study was a retrospective cohort analysis based on a mobile app called KidneyOnline in China. The KidneyOnline app offered a platform with free materials and resources about CKD. Patients received recruitment information about the KidneyOnline app within WeChat; subsequently, they downloaded the app and became active app users. The KidneyOnline intelligent patient care system was embedded in the app, and users made their own decision about whether to join the intelligent care system. Informed patient consent forms were signed by the patients within the KidneyOnline app. All app users between January 2017 and January 2021 were screened according to the recruitment criteria, and eligible patients were grouped according to their original choice.

Patients were enrolled if they (1) were over 18 years old; (2) fulfilled the diagnosis of CKD (ie, eGFR <60 mL/min/1.73 m² or eGFR < 90 mL/min/1.73 m² but with albuminuria or hematuria for at least 3 months or as defined using other clinically indicated criteria); (3) uploaded 2 pieces of data upon registration with an interval of at least 3 months; (4) were free of dialysis, with a baseline eGFR >15mL/min/1.73 m²; and (5) were able and willing to provide informed consent. Patients were excluded if (1) they or their relatives were unable to use a smartphone, (2) they intended to start dialysis or have a kidney transplant within the next 3 months, (3) there was a lack of baseline or follow-up data, or (4) they refused to communicate with the health coach team. Study participants were followed for at least 3 months after recruitment until death or the start of renal replacement therapy.

**Intervention**

The KidneyOnline intelligent patient care system was a nurse-led, patient-oriented collaborative management system as an adjunct to regular clinic visits for patients with CKD (Figure 1). The intelligent system was empowered by artificial intelligence (AI) and a health coach team, which consisted of a group of experienced nurses trained by nephrologists, dieticians, and social workers. The system consisted of a smartphone app for patients, a web-based clinical dashboard app for health care providers, and a data server for information management (Figure 1).
Participants in the KidneyOnline intelligent patient care group were able to experience at least 5 aspects of service provided by the system, which are detailed in Textbox 1 (Figure 2).

Patients in the conventional care group only had access to the health-related educational materials provided by the app. They could get professional suggestions from the nephrologists through regular clinical visits, but they did not have access to the service provided by AI and the health coach team.

Figure 1. Framework of KidneyOnline intelligent care system. AI: artificial intelligence; KDIGO: Kidney Disease: Improving Global Outcomes (clinical practice guidelines).

Textbox 1. The 5 aspects of service provided to patients by the KidneyOnline system.

1. Interpretation of disease condition and corresponding guidance. The intelligent care system helped explain patients’ diagnoses and medication prescriptions, analyze and interpret lab results, and remind patients about medication precautions. The system also provided guidance on lifestyle interventions, including diet, exercise, and sleep. Patients could receive artificial intelligence (AI)–generated personalized recipes based on their disease condition and food preferences, and they were able to make food diaries to see if the nutrition requirements were met.

2. Regular check-ups. The intelligent care system followed each patient regularly to check if the patient was in good condition, assure if the recent BP was well-controlled, evaluate whether the patient’s current medication was reasonable, and assess whether the patient’s dietary intake was reasonable.

3. Early warnings. Through the algorithm, the intelligent system was able to identify risks associated with lab results and certain medications and make early warnings to minimize these risks. If abnormal lab results requiring immediate attention were identified, the system would send a medical alert to both the patient and the health coach. The health coach would take the initiative to contact the patient and make suggestions, including reminding the patient about medications, providing guidance on diet, exercise, and other lifestyle aspects, and reminding the patient to consult with doctors.

4. Real-time question-and-answer fields empowered by knowledge graphs. We established a renal knowledge graph according to the Kidney Disease: Improving Global Outcomes (KDIGO) guidelines for chronic kidney disease (CKD), which provided intelligent search and human-computer dialogues to enhance the efficiency and professional competency of the health coach team. Empowered by the graphs, the health coaches promptly provided real-time answers to any questions the patients had (Multimedia Appendix 1). These include laboratory results analysis, medication precautions, dietary guidance, exercise guidance, advice on coping with unexpected situations, advice on the correct way to take medicine to avoid kidney injuries, and so forth.

5. Clinical reminders. According to the patient's overall condition, the intelligent system could generate a personalized follow-up plan, reminding the patient to go to the doctor at regular intervals, helping them sort out test items they need to finish, and checking follow-up results to confirm whether the follow-up visit was completed.
Data Collection
The foundation of this intelligent system was built upon the structurization of patients’ health-related data using deep learning optical character recognition (OCR). Conventionally, patients’ health data came from a variety of sources, including (1) patients’ self-reported signs and symptoms; (2) data from intelligent home devices such as sphygmomanometer, and (3) patients’ past medical history, clinical notes, drug prescriptions, lab results, pathological reports, imagological exams, and so on. In the KidneyOnline intelligent system, patients uploaded those data simply by taking photos, and the intelligent system extracted the data efficiently by utilizing deep learning OCR. Combined with manual verification, a structured database was built so that patients’ health-related data could be integrated and analyzed quantitatively.

The participants took photos of their medical records, laboratory test results, and clinical prescriptions and uploaded them on the mobile app. All electronic data and photographs were uploaded instantly to a secure, cloud-based server. To comply with security and privacy regulations, patients’ smartphones were password-protected, and data were encrypted. Only the researchers were able to access the data on a cloud storage platform.

Outcomes
The primary outcome of our study was the first occurrence of either a 30% decrease in eGFR or an incidence of ESKD. Secondary end points included changes in 24-hour proteinuria and changes in mean arterial pressure (MAP). eGFR results were calculated by using the Chronic Kidney Disease Epidemiology Collaboration (CKD-EPI) formula. Blood pressure data were collected through the app based on home blood pressure measurements uploaded by the patients, using either mercury or an electronic sphygmomanometer.

Ethics Approval
This study was approved by the local research ethics board from Anqing Municipal Hospital (2022-033) and was conducted according to the Declaration of Helsinki.

Statistical Analysis
Reporting Descriptive Data
The distributional properties of data were expressed as mean (SD) for continuous variables with a normal distribution or median (IQR) for variables with a skewed distribution. For continuous data, the independent or paired Student t test was used for within-group and between-group comparisons; for categorical variables with percentages, the chi-square or McNemar test was used. Clinical parameters including 24-hour proteinuria and MAP during the follow-up were compared using Student t tests (for normally distributed continuous variables) and Wilcoxon signed-rank tests (for nonnormally distributed continuous variables).

Propensity Score Matching
To balance the confounding factors between the KidneyOnline intelligent patient care system group and the conventional CKD care group, 1:1 propensity score matching (PSM) was performed using nearest neighbor algorithms with a 0.9 caliper width of 0.02 pooled standard deviations. Matching was based on baseline characteristics of age, sex, BMI, baseline eGFR, MAP, and proteinuria levels.

Assessment of the Benefits of KidneyOnline
For survival analysis, both the Kaplan-Meier method and Cox proportional hazards model were used. The Kaplan-Meier
method was applied to evaluate the cumulative incidence of primary outcomes in both groups following PSM. Additionally, the Cox proportional hazards model was utilized to identify predictive factors associated with the outcomes. For matched data after PSM, the Cox proportional hazards model with gamma frailty was used. All missing information was treated as missing data without imputation. Subgroup analyses were performed after stratifying according to the median age (<33 years vs ≥33 years), sex, kidney function (eGFR <60 mL/min/1.73 m² vs ≥60 mL/min/1.73 m²), and proteinuria (<1 g/24 h vs ≥1 g/24 h, <3 g/24 h vs ≥3 g/24 h), as well as the median value of baseline MAP (<88.7 mmHg vs ≥88.7 mmHg). Statistical analyses were performed using Python and Lifelines, an open-access survival analysis library written in Python. A 2-sided \( P < .05 \) was considered statistically significant.

**Results**

**Baseline Characteristics**

Between January 2017 and January 2021, 78,007 potentially eligible patients were screened. Among them, 2060 (2.6%) were eligible for our analysis according to the inclusion and exclusion criteria. There were 1600 (77.7%) patients in the KidneyOnline intelligent patient care system group and 460 (22.3%) patients in the conventional care group (Figure 3). Among the 2060 patients enrolled in our study, the mean age was 35.6 (SD 9.5) years, 1175 (57%) were female, and they had an average BMI of 22.7 (SD 4.2) kg/m². Upon registration, the mean eGFR was 88.6 (SD 31.3) mL/min/1.73 m², and the mean proteinuria level was 1.4 (SD 1.8) g/24 h. The average MAP was 89 (SD 11) mmHg. During the follow-up period, 1539 (75%) patients were treated with a renin-angiotensin-aldosterone system blocker (RASB), 524 (25%) were treated with steroids, and 418 (20%) were treated with immunosuppressants. Compared with patients in the conventional care group, patients in the KidneyOnline intelligent patient care system group had a more favorable BMI (mean 22.5, SD 4 kg/m² vs mean 23.2, SD 4.8 kg/m²; \( P = .004 \)) and lighter 24-hour proteinuria (median 0.7, IQR 0.3-1.6 g/24 h vs median 0.9, IQR 0.3-1.9 g/24 h; \( P = .033 \)) but worse baseline kidney function (mean 87.8, SD 31.3 mL/min/1.73 m² vs mean 91.5, SD 31.4 mL/min/1.73 m²; \( P = .024 \)). There were no significant differences in the context of RASB and steroids or immunosuppressants usage between the 2 groups (Table 1).

**Figure 3.** Flow diagram of patient enrollment for the analysis. eGFR: estimated glomerular filtration rate.
Table 1. Baseline and follow-up characteristics of patients in the whole cohort.

<table>
<thead>
<tr>
<th>Demographics</th>
<th>Total (N=2060)</th>
<th>Conventional care group (n=460)</th>
<th>KidneyOnline care group (n=1600)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years), mean (SD)</td>
<td>35.6 (9.5)</td>
<td>35.3 (9.6)</td>
<td>35.8 (9.5)</td>
<td>.32</td>
</tr>
<tr>
<td>Sex, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>1175 (57)</td>
<td>248 (53.9)</td>
<td>927 (57.9)</td>
<td>.12</td>
</tr>
<tr>
<td>Male</td>
<td>885 (43)</td>
<td>212 (46.1)</td>
<td>673 (42.1)</td>
<td>.12</td>
</tr>
<tr>
<td>BMI (kg/m²), mean (SD)</td>
<td>22.7 (4.2)</td>
<td>23.2 (4.8)</td>
<td>22.5 (4)</td>
<td>.004</td>
</tr>
<tr>
<td>Etiology of CKD⁴, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IgA⁵ nephropathy or IgA vasculitis</td>
<td>945 (45.9)</td>
<td>182 (39.6)</td>
<td>763 (47.7)</td>
<td>.002</td>
</tr>
<tr>
<td>Membranous nephropathy</td>
<td>185 (9)</td>
<td>49 (10.7)</td>
<td>136 (8.5)</td>
<td>.18</td>
</tr>
<tr>
<td>Focal segmental glomerular sclerosis</td>
<td>63 (3.1)</td>
<td>13 (2.8)</td>
<td>50 (3.1)</td>
<td>.86</td>
</tr>
<tr>
<td>Hypertensive nephropathy</td>
<td>53 (2.6)</td>
<td>23 (5)</td>
<td>30 (1.9)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Diabetic nephropathy</td>
<td>7 (0.3)</td>
<td>1 (0.2)</td>
<td>6 (0.4)</td>
<td>.95</td>
</tr>
<tr>
<td>Other types of nephritis</td>
<td>246 (11.9)</td>
<td>50 (10.9)</td>
<td>196 (12.2)</td>
<td>.47</td>
</tr>
<tr>
<td>Unknown etiology</td>
<td>559 (27.1)</td>
<td>141 (30.7)</td>
<td>418 (26.1)</td>
<td>.062</td>
</tr>
<tr>
<td>Kidney transplant recipient</td>
<td>2 (0.1)</td>
<td>1 (0.2)</td>
<td>1 (0.1)</td>
<td>.93</td>
</tr>
<tr>
<td>Laboratory results</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline eGFR⁶ (mL/min/1.73 m²), mean (SD)</td>
<td>88.6 (31.3)</td>
<td>91.5 (31.4)</td>
<td>87.8 (31.3)</td>
<td>.024</td>
</tr>
<tr>
<td>CKD stage 3-4, n (%)</td>
<td>443 (21.5)</td>
<td>88 (19.1)</td>
<td>355 (22.2)</td>
<td>.18</td>
</tr>
<tr>
<td>Baseline proteinuria (g/24 h), median (IQR)</td>
<td>0.8 (0.3-1.7)</td>
<td>0.9 (0.3-1.9)</td>
<td>0.7 (0.3-1.6)</td>
<td>.033</td>
</tr>
<tr>
<td>Baseline MAP⁷ (mmHg), mean (SD)</td>
<td>88.6 (10.9)</td>
<td>89.5 (11.1)</td>
<td>88.4 (10.8)</td>
<td>.051</td>
</tr>
<tr>
<td>Drug therapies, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RASB⁵</td>
<td>1539 (74.7)</td>
<td>333 (72.4)</td>
<td>1206 (75.4)</td>
<td>.19</td>
</tr>
<tr>
<td>Steroids</td>
<td>524 (25.4)</td>
<td>127 (27.6)</td>
<td>397 (24.8)</td>
<td>.23</td>
</tr>
<tr>
<td>Immunosuppressants</td>
<td>418 (20.3)</td>
<td>94 (20.4)</td>
<td>324 (20.3)</td>
<td>.93</td>
</tr>
</tbody>
</table>

⁴CKD: chronic kidney disease.
⁵IgA: immunoglobulin A.
⁶eGFR: estimated glomerular filtration rate.
⁷MAP: mean arterial pressure.
⁸RASB: renin-angiotensin-aldosterone system blocker.

Benefits of KidneyOnline Care System for the Whole Population

After a mean follow-up of 18.1 (SD 9.5) months, the primary composite kidney outcome occurred in 121 (8%) participants in the KidneyOnline intelligent patient care system group and 33 (7%) in the conventional care group, with 86 (5%) versus 21 (5%) and 33 (2%) versus 12 (3%) participants reaching a 30% eGFR decrease and ESKD, respectively.

Multivariate Cox regression with stepwise procedures was used to analyze the risk factors of composite kidney outcome. After adjustments for age, gender, baseline eGFR, proteinuria, MAP, and use of RASB, steroids, and immunosuppressants, individuals in the KidneyOnline care group were less likely to progress to ESKD compared with the conventional group, with a hazard ratio of 0.375 (95% CI 0.221-0.638; P<.001) (Multimedia Appendix 2).

Characteristics of the Individuals After PSM

A 1:1 PSM analysis was performed to balance the selection bias between the 2 groups. A total of 902 patients with 451 (50%) patients in each group were successfully matched. In total, the average age was 35.5 (SD 9.4) years, and 54% (n=487) were female. The average BMI was 22.9 (SD 3.8) kg/m². The baseline MAP was 89.1 (SD 10.8) mmHg, and the 24-hour proteinuria was 0.8 (IQR 0.3-1.8) g/24 h. The baseline eGFR of the 902 patients was 91.9 (SD 30.7) mL/min/1.73 m² (Table 2). Overall, there were 672 (75%) patients who received RASB, 232 (26%) who received steroids, and 197 (22%) who received immunosuppressant therapy. There were no significant
differences in laboratory results and treatments between the KidneyOnline intelligent patient care system and the conventional care group at baseline (Table 2).

**Table 2.** Baseline and follow-up characteristics of patients after propensity score matching (PSM).

<table>
<thead>
<tr>
<th>Demographics</th>
<th>Total (N=902)</th>
<th>Conventional care group (n=451)</th>
<th>KidneyOnline care group (n=451)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demographics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (years), mean (SD)</td>
<td>35.5 (9.4)</td>
<td>35.27 (9.6)</td>
<td>35.67 (9.2)</td>
<td>.51</td>
</tr>
<tr>
<td>Sex, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>487 (54)</td>
<td>244 (54.1)</td>
<td>243 (53.9)</td>
<td>&gt;.99</td>
</tr>
<tr>
<td>Male</td>
<td>415 (46)</td>
<td>207 (45.9)</td>
<td>208 (46.1)</td>
<td>&gt;.99</td>
</tr>
<tr>
<td>BMI (kg/m²), mean (SD)</td>
<td>22.9 (3.8)</td>
<td>22.9 (4.0)</td>
<td>23.0 (3.6)</td>
<td>.90</td>
</tr>
<tr>
<td>Etiology of CKD, n (%)</td>
<td>386 (42.8)</td>
<td>181 (40.1)</td>
<td>205 (45.5)</td>
<td>.13</td>
</tr>
<tr>
<td>IgA nephropathy or IgA vasculitis</td>
<td>95 (10.5)</td>
<td>45 (10)</td>
<td>50 (11.1)</td>
<td>.64</td>
</tr>
<tr>
<td>Membranous nephropathy</td>
<td>23 (2.5)</td>
<td>12 (2.7)</td>
<td>11 (2.4)</td>
<td>&gt;.99</td>
</tr>
<tr>
<td>Focal segmental glomerular sclerosis</td>
<td>29 (3.2)</td>
<td>22 (4.9)</td>
<td>7 (1.6)</td>
<td>.006</td>
</tr>
<tr>
<td>Hypertensive nephropathy</td>
<td>4 (0.4)</td>
<td>1 (0.2)</td>
<td>3 (0.7)</td>
<td>.63</td>
</tr>
<tr>
<td>Diabetic nephropathy</td>
<td>99 (11)</td>
<td>48 (10.6)</td>
<td>51 (11.3)</td>
<td>.84</td>
</tr>
<tr>
<td>Other types of nephritis</td>
<td>265 (29.4)</td>
<td>141 (31.3)</td>
<td>124 (27.5)</td>
<td>.24</td>
</tr>
<tr>
<td>Unknown etiology</td>
<td>1 (0.1)</td>
<td>1 (0.2)</td>
<td>0 (0)</td>
<td>&gt;.99</td>
</tr>
<tr>
<td>Kidney transplant recipient</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Laboratory results</td>
<td>91.9 (30.7)</td>
<td>91.5 (31.3)</td>
<td>92.3 (30.2)</td>
<td>.63</td>
</tr>
<tr>
<td>Baseline eGFRc (mL/min/1.73 m²), mean (SD)</td>
<td>163 (18.1)</td>
<td>86 (19.1)</td>
<td>77 (17.1)</td>
<td>.49</td>
</tr>
<tr>
<td>CKD stage 3-4, n (%)</td>
<td>0.8 (0.3-1.8)</td>
<td>0.8 (0.3-1.8)</td>
<td>0.8 (0.3-1.6)</td>
<td>.29</td>
</tr>
<tr>
<td>Baseline proteinuria (g/24 h), median (IQR)</td>
<td>89.1 (10.8)</td>
<td>89.3 (11.0)</td>
<td>88.9 (10.5)</td>
<td>.56</td>
</tr>
<tr>
<td>Baseline MAPd (mmHg), mean (SD)</td>
<td>672 (74.5)</td>
<td>327 (72.5)</td>
<td>345 (76.5)</td>
<td>.20</td>
</tr>
<tr>
<td>Drug therapies</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RASBe</td>
<td>232 (25.7)</td>
<td>123 (27.3)</td>
<td>109 (24.2)</td>
<td>.32</td>
</tr>
<tr>
<td>Steroids</td>
<td>197 (21.8)</td>
<td>93 (20.6)</td>
<td>104 (23.1)</td>
<td>.41</td>
</tr>
</tbody>
</table>

aCKD: chronic kidney disease.
bIgA: immunoglobulin A.
ceGFR: estimated glomerular filtration rate.
dMAP: mean arterial pressure.
eRASB: renin-angiotensin-aldosterone system blocker.

**Benefits of the KidneyOnline Care System for Propensity-Matched Individuals**

After a mean follow-up period of 15.8 (SD 9.5) months, the primary composite kidney outcome occurred in 28 (6%) participants in the KidneyOnline intelligent patient care system group and in 32 (7%) in the conventional care group, with a hazard ratio (HR) of 0.391 (95% CI 0.231-0.661; P<.001) (Figure 4), with 20 (4%) versus 20 (4%) and 8 (2%) versus 12 (3%) participants reaching a 30% decrease in eGFR and ESKD, respectively. A subgroup analysis showed that the KidneyOnline intelligent patient care system significantly reduced the risk of composite kidney outcome in all subgroups stratified by age (<33 vs ≥33 years), sex, kidney function (eGFR <60 vs ≥60 mL/min/1.73 m²), and proteinuria (<1 vs ≥ g/24 h, <3 vs ≥3 g/24 h). However, the KidneyOnline intelligent patient care system improved the composite kidney outcomes in patients with elevated levels of MAP, but it did not improve composite kidney outcomes in the normal MAP group (Multimedia Appendix 3).
Changes in MAP During Follow-up

Since the KidneyOnline intelligent patient care system showed different effects in different MAP groups, we further analyzed the MAP during follow-up between the KidneyOnline group and the conventional CKD care group. The baseline MAP values were similar between the 2 groups. The MAP significantly decreased from 88.9 (SD 10.5) mmHg at baseline to 85.6 (SD 7.9) mmHg at 6 months \((P < .001)\) in the KidneyOnline group and from 89.3 (SD 11.1) mmHg to 87.5 (SD 8.2) mmHg \((P = .002)\) in the conventional CKD care group. After 6 months, the MAP in the KidneyOnline group participants remained at a lower level compared with that in the conventional CKD care group (Multimedia Appendix 4A). This trend was also observed when participants were stratified according to the median value of MAP (88.7 mmHg) (Multimedia Appendix 4B,C).

Changes in Proteinuria During Follow-up

The mean level of 24-hour proteinuria in the KidneyOnline intelligent patient care system group was not significantly different from the conventional CKD care group at baseline (1.4 vs 1.5 g/24 h, \(P = .36\)). During the follow-up, the mean level of 24-hour proteinuria decreased to 0.8 g/24 h in the KidneyOnline intelligent patient care system group and 0.8 g/24 h in the conventional care group at end of 12 months. There was no significant difference in the mean level of 24-hour proteinuria between the 2 groups by the end of 24 months (0.7 vs 0.7 g/24 h, \(P = .92\)) (Multimedia Appendix 5).

Discussion

Principal Findings

In this study, we described a nurse-led, smartphone-based patient-oriented system designed to help disease management in patients living with stages 1 to 4 of CKD. Our findings demonstrate that this intelligent care system was associated with better blood pressure control and a reduced risk of kidney failure. This provided a novel strategy for promoting a healthy lifestyle and improving kidney prognosis in patients with CKD, regardless of their scheduled consultations.

Comparisons to Prior Work

The incidence and prevalence of CKD have been persistently increasing because of the aging population, who experience a high incidence of metabolic disorders such as hypertension, diabetes, and obesity [8-10]. There have been efforts to find innovative and efficient ways to improve patient outcomes, but the results have been conflicting due to varied intervention facets and intensities. Few studies showed improvement in hard kidney end points or eGFR change. The intervention conducted in the Multifactorial Approach and Superior Treatment Efficacy in Renal Patients With the Aid of Nurse Practitioners (MASTERPLAN) study [11] initially reported negative results of the strict implementation of CKD guidelines to patients with CKD in decreasing the risk of ESKD. Nevertheless, after a prolonged follow-up, Peeters et al [12] demonstrated that additional support by nurse practitioners, including lifestyle intervention, use of mandatory medication, and implementation of CKD guidelines reduced the risk of composite renal endpoints (death, ESKD and 50% increase in serum creatinine) by 20%. The care management performed by nurse practitioners at least quarterly resulted in a decrease in eGFR of 0.45 mL/min/1.73

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Figure 4. Kaplan-Meier curve of primary composite kidney outcomes.

![Kaplan-Meier curve of primary composite kidney outcomes](image-url)
Interestingly, there was an improvement in proteinuria in both the KidneyOnline intelligent care group and the conventional care group. This may be attributed to the KidneyOnline app's educational materials on the benefits of a low-salt diet. In a typical Chinese diet, the salt intake is often much higher than recommended. The KidneyOnline app enabled patients from both groups to access free educational materials on the importance of a low-salt diet, as well as tips on limiting salt intake. Moreover, the KidneyOnline app offered a variety of low-salt diet recipes, which might have helped increase patients' compliance with a low-salt diet. Additionally, there was a high percentage of patients with glomerulonephritis, with 25.7% (n=232) being treated with steroids. The use of steroids and immunosuppressants is another important factor leading to the improvement in proteinuria.

The rate of smartphone ownership has exploded in China during the last 10 years. Telehealth apps provide new opportunities to enhance self-management, behavior change, and medication adherence not only for people living in urban areas but also for those in rural areas. As Duan et al [24] have shown, the prevalence of CKD in China's rural areas was 16.4% between 2015 and 2017. Education level, personal income, alcohol consumption, and hypertension were all risk factors associated with insufficient kidney function. The KidneyOnline care system provides a web-based solution for patient-centered care and helps reduce the time and cost associated with long travels to seek medical advice. Thus, our mode of care could facilitate patients' self-management in a cost-effective manner, especially in areas facing a shortage of medical resources.

Strengths and Limitations

To our knowledge, this study was the first to assess the efficacy of a smartphone-based, nurse-led, patient-oriented management system for patients with CKD across China using hard kidney end points. The 4-year observational data from the real world demonstrated the efficacy of this newly developed system. Inevitably, our study had several limitations. First, there were over 70,000 user registrations on our app. Only 2060 patients' records fulfilled our criteria and were eligible for analysis. This could have resulted in selection bias in both groups. Patients with a stronger sense of self-management and motivation were more likely to be included in this study. Second, patients who had severe symptoms or advanced pathological lesions were less likely to choose our patient care system; instead, they received treatments in large hospitals on their first visits. Moreover, patients with minor renal impairment could potentially have a lower probability of joining the KidneyOnline care system. In addition, due to the cost associated with the KidneyOnline care system, patients who joined the system probably had a higher economic status compared with patients in the control group. Nonetheless, we have shown that patients in the KidneyOnline care group experienced better prognoses in terms of composite renal outcomes, irrespective of their age, baseline eGFR, and proteinuria. More data are needed to illustrate the efficacy of our mode of care in those with more impaired kidney function, as well as those with very slight renal impairment. Third, we did not analyze other possible end points related to the utilization of the KidneyOnline care system, such as cardiovascular comorbidities and hospitalization frequencies.

https://mhealth.jmir.org/2023/1/45531

Liu et al

m² per 1.73 m² per year in the intervention group compared with the control group [12]. In a study conducted in Taiwan, Barrett et al [13] showed that multidisciplinary education according to the National Kidney Foundation's Kidney Disease Outcomes Quality Initiative (NKF/KDOQI) guidelines decreased the incidence of dialysis and reduced mortality in predialysis patients with CKD after a mean follow-up of 11.7 months. Recently, in their 3-month-prospective study, Li et al [14] reported that patients with CKD who received diet, exercise, and self-management education delivered via a wearable device and smartphone app experienced a slower rate of eGFR decline than those given only conventional care. These studies suggested that beyond traditional nephrologist-centered clinical consultations, proper education in combination with the careful management of patients with CKD could potentially improve kidney outcomes even in the short term. In the KidneyOnline intelligent patient care system, patients were educated by nurses who received training according to the Kidney Disease: Improving Global Outcomes (KDIGO) guidelines. Other interventions including lifestyle intervention and education were all integrated into the KidneyOnline care system. Our study confirmed previous findings that nurse care could improve the renal outcomes of patients with CKD via patient education, disease interpretation, and lifestyle intervention.

Analysis of Findings

Our study demonstrated that the KidneyOnline care system reduced the risk of composite kidney end points, irrespective of age, baseline eGFR, and proteinuria. This effect was multifactorial. One of the main underlying reasons for this effect was the well-controlled blood pressure, which was significantly lower at 6 months compared with that at the time of enrollment in the KidneyOnline care group, and it remained at a lower level throughout the follow-up period. In China, the prevalence of hypertension is higher in patients with CKD compared with the general population, but awareness of hypertension in patients with CKD was reported to be 80.7% in 2018[15]. Previous studies have shown that adequate control of blood pressure was suboptimal in patients with CKD [16,17]. In fact, refractory hypertension in patients was largely attributed to inadequate adherence to prescribed medication [18]. Low medication adherence was associated with CKD progression [19,20]. It has been established that well-designed mobile apps could effectively improve medication adherence in cardiovascular disease [21,22]. In the KidneyOnline care system group, the trend graph and brief report about blood pressure, real-time online questions and answers, and medication intake suggestions were all potential factors that might have contributed to patients' good adherence. Moreover, constant online communication and laboratory test reminders possibly prompted participants' clinical visits to adjust their medication regimens in time, thus reducing the risk of adverse drug reactions. Finally, healthy lifestyle modifications, including sufficient physical activity, proper BMI control, smoking cessation, and healthy diet habits, were reported to help slow the progression of CKD in patients with preserved kidney function [23]. Participants joining the KidneyOnline care group often gave positive feedback on the smart reminder for helping them organize their diets and make healthy lifestyle choices.
which would help us better evaluate our mode of management for patients with CKD. Additionally, the participants were young and normotensive; there was a high prevalence of glomerulonephritis but a limited number of diabetes cases, and these factors may have limited the feasibility of the KidneyOnline care system for patients with CKD caused by diabetic nephropathy. It is also important to note that our study was conducted in China; because the education and economic levels of patients with CKD vary across countries, a new mode of patient care based on mobile phones in other countries is anticipated.

**Conclusion**

We developed a smartphone-based, nurse-led, patient-oriented management system to facilitate health care for patients with nondiabetic CKD in China. Through multifaceted patient care, our mode of patient management was associated with a reduced risk of composite kidney outcomes. This strengthened the evidence of telehealth interventions to promote kidney health and long-term management for patients with CKD.

**Acknowledgments**

We are grateful to all the patients and controls for their participation in this study.

**Data Availability**

The data sets analyzed in this study are not publicly available due to business confidentiality reasons but are available from the corresponding author upon reasonable request.

**Conflicts of Interest**

Authors JW, TZ, XC, SX, and FH are employed by the Beijing Kidney Health Technology Co Ltd. The remaining authors have no conflicts of interest to declare.

**Multimedia Appendix 1**

Demonstration of KidneyOnline dashboard for patients and health coach team.  
[**PNG File, 279 KB** - mhealth_v11i1e45531_app1.png]

**Multimedia Appendix 2**

Multivariate Cox regression analysis of composite kidney outcome (before patient matching). eGFR: estimated glomerular filtration rate; MAP: mean arterial pressure; RASB: renin-angiotensin-aldosterone system blocker.  
[**PNG File, 344 KB** - mhealth_v11i1e45531_app2.png]

**Multimedia Appendix 3**

Forest plot of the comparison between the 2 different modes of care in different subgroups (after patient matching). eGFR: estimated glomerular filtration rate; MAP: mean arterial pressure.  
[**PNG File, 137 KB** - mhealth_v11i1e45531_app3.png]

**Multimedia Appendix 4**

Changes in mean arterial pressure (MAP) during follow-up in the whole population and subgroups.  
[**PPTX File, 285 KB** - mhealth_v11i1e45531_app4.pptx]

**Multimedia Appendix 5**

Changes in 24-hour proteinuria in the 2 matched groups of patients after propensity score matching (PSM) during follow-up.  
[**PNG File, 124 KB** - mhealth_v11i1e45531_app5.png]

**References**


Abbreviations

AI: artificial intelligence  
CKD: chronic kidney disease  
CKD-EPI: Chronic Kidney Disease Epidemiology Collaboration  
eGFR: estimated glomerular filtration rate  
ESKD: end-stage kidney disease  
HR: hazard ratio  
KDIGO: Kidney Disease: Improving Global Outcomes  
MAP: mean arterial pressure  
NKF/KDOQI: National Kidney Foundation's Kidney Disease Outcomes Quality Initiative  
OCR: optical character recognition  
PSM: propensity score matching  
RASB: renin-angiotensin-aldosterone system blocker

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mHealth Apps Targeting Obesity and Overweight in Young People: App Review and Analysis

Elena Vlahu-Gjorgievska1, PhD; Andrea Burazor1, BSc; Khin Than Win1, PhD; Vladimir Trajkovik2, PhD

1School of Computing and Information Technology, University of Wollongong, Wollongong, Australia
2Faculty of Computer Science and Engineering, Ss Cyril and Methodius University, Skopje, Republic of North Macedonia

Corresponding Author:
Elena Vlahu-Gjorgievska, PhD
School of Computing and Information Technology
University of Wollongong
Northfields Ave
Wollongong, 2522
Australia
Phone: 61 42214606
Email: elenavg@uow.edu.au

Abstract

Background: Overweight and obesity have been linked to several serious health problems and medical conditions. With more than a quarter of the young population having weight problems, the impacts of overweight and obesity on this age group are particularly critical. Mobile health (mHealth) apps that support and encourage positive health behaviors have the potential to achieve better health outcomes. These apps represent a unique opportunity for young people (age range 10-24 years), for whom mobile phones are an indispensable part of their everyday living. However, despite the potential of mHealth apps for improved engagement in health interventions, user adherence to these health interventions in the long term is low.

Objective: The aims of this research were to (1) review and analyze mHealth apps targeting obesity and overweight and (2) propose guidelines for the inclusion of user interface design patterns (UIDPs) in the development of mHealth apps for obese young people that maximizes the impact and retention of behavior change techniques (BCTs).

Methods: A search for apps was conducted in Google Play Store using the following search string: ["best weight loss app for obese teens 2020"] OR ["obesity applications for teens"] OR ["popular weight loss applications"]). The most popular apps available in both Google Play and Apple App Store that fulfilled the requirements within the inclusion criteria were selected for further analysis. The designs of 17 mHealth apps were analyzed for the inclusion of BCTs supported by various UIDPs. Based on the results of the analysis, BCT-UI design guidelines were developed. The usability of the guidelines was presented using a prototype app.

Results: The results of our analysis showed that only half of the BCTs are implemented in the reviewed apps, with a subset of those BCTs being supported by UIDPs. Based on these findings, we propose design guidelines that associate the BCTs with UIDPs. The focus of our guidelines is the implementation of BCTs using design patterns that are impactful for the young people demographics. The UIDPs are classified into 6 categories, with each BCT having one or more design patterns appropriate for its implementation. The applicability of the proposed guidelines is presented by mock-ups of the mHealth app “Morphe,” intended for young people (age range 10-24 years). The presented use cases showcase the 5 main functionalities of Morphe: learn, challenge, statistics, social interaction, and settings.

Conclusions: The app analysis results showed that the implementation of BCTs using UIDPs is underutilized. The purposed guidelines will help developers in designing mHealth apps for young people that are easy to use and support behavior change. Future steps involve the development and deployment of the Morphe app and the validation of its usability and effectiveness.

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KEYWORDS
behavior change techniques; user interface design patterns; mHealth apps; obesity; lifestyle; mobile app; mobile health; mobile phone
Introduction

Obesity has nearly tripled in the last 30 years, with the World Health Organization estimating that around 340 million or 27% of the world’s children and adolescents are overweight or obese [1]. Overweight and obesity have been linked to several serious health problems and medical conditions, including an increase in the risk for noncommunicable diseases such as cardiovascular diseases, diabetes, musculoskeletal disorders, endometrial cancers as well as other types of cancers [1]. Excessive weight and obesity can lead to not only physiological medical complications but also severe psychological effects [2].

The social and emotional well-being and self-esteem of young people are especially impacted during this important developmental phase of life, with these negative consequences tracking well into an individual’s later life [3,4]. Further, there is a general reduction in the intake of certain food groups and nutrients and an increase in the consumption of junk food and sugary drinks [5,6], as well as a significant decrease in engagement in moderate-to-vigorous physical exercises during this transition period between adolescence and adulthood [7]. Therefore, targeting young people (age range 10-24 years) is very important [8].

The assumption that nutrition and physical activity behaviors are mediators of body weight provides the basis for behavioral interventions for obesity, which are largely derived from the principles of classical conditioning and social theories [9]. A person’s behavior is predominantly responsible for maintaining health and plays an important role in the prevention, management, and treatment of overweight and obesity. Behavior change techniques (BCTs) are descriptors (repeatable components of an intervention) designed to enable behavior change by addressing important targets of capability, opportunity, and motivation. The refined taxonomy of BCT—Coventry, Aberdeen, and London-Refined (CALO-RE)—is specifically tailored toward the change of physical activity and promotion of healthy eating behaviors [10].

Mobile phone ownership is ubiquitous, especially among young people. Based on the media use report, 91% of youth between 12 and 15 years of age own a mobile device [11]. The mobile devices are carried by their owners most of the time and are rarely switched off [12]; therefore, they can provide notifications to the users at particular moments, thereby enhancing the engagement and adoption of certain behaviors. These devices can also be used for collecting and analyzing user data, which facilitate the capability to automate certain processes, consequently reducing a user’s cognitive load in navigation and selection activities [13]. These characteristics make mobile phones good candidates for delivering digitally supported obesity interventions.

Mobile health (mHealth) apps present a unique opportunity, particularly for young people, to revolutionize the way health behavior change interventions are delivered [14]. However, despite the potential for improved engagement in long-term interventions [15], health interventions delivered by these devices are short-lived. Literature shows that most users cease using a mHealth app activity within a few uses, and a quarter of mHealth apps are found to be used only 1 time after installation [16].

The factors that impact the adoption of mHealth apps are well-researched, and there is no significant evidence to suggest that adoption alone can improve an individual’s health [16]. The continuation of use where technology supports user engagement in behavior change is the area that can enhance positive outcomes [15]. Thus, the continuation of use of mHealth apps greatly impacts their overall efficacy and potential for success.

The user interface and experience of mobile apps strongly influence users’ perception and satisfaction and have a strong impact on the app’s adoption and continuation of use [17]. The user interface design patterns (UIDPs) are descriptions of the best practices within user interface design. They are general reusable solutions to commonly occurring problems and can ensure that user interfaces flow well and are easy and enjoyable to use. In addition, UIDPs can reduce the cognitive load and improve the overall performance of the app. Furthermore, literature [18] suggests that the overall “look and feel” of apps impacts the adoption by young people, while the perception that health apps were designed primarily for adults was found to be a barrier in using the app. In this context, applying well-known user interface design principles and patterns [19] can improve the efficacy of mHealth apps and contribute toward its continuation of use.

Previous research in this field is primarily focused on mHealth interventions for the adult population without a specific view of the young people demographics [15]. However, evidence suggests that mHealth interventions may be viable in effecting positive health changes in young people as well [20]. The variable results for using mHealth apps by young people could be also explained by the lack of available apps specifically tailored to offer weight management for this group [14]. Additionally, there is a scarcity of research on the impact of UIDPs on the efficacy of BCTs in mHealth apps for obese young people.

The aims of this research were to (1) review and analyze mHealth apps targeting obesity and overweight and (2) propose guidelines for the inclusion of UIDPs in the development of mHealth apps for obese young people.

Methods

The overview of the study methodology is presented in Figure 1. A search for apps was conducted in Google Play Store by using a combination of the following keywords: [“best weight loss app for obese teens 2020”] OR [“obesity applications for teens”] OR [“popular weight loss applications”]. The inclusion criteria for the apps were as follows: free; available in both Google Play and Apple App Store; do not require the use of external devices; appropriate for individuals between 10 and 24 years of age; and app’s primary purpose (app category, tags, and description) is stated as health, nutrition, physical activity improvement, targeting obesity, or specified as a tool for obesity intervention.

https://mhealth.jmir.org/2023/1/e37716

JMI R MHEALTH AND UHEALTH

Vlahu-Gjorgievsk a et al

Methods

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The first 20 most popular apps that met the above described criteria were selected for further analysis. During the app inspection, 3 of the selected apps were found to require in-app purchases to access the key functionality and thus were excluded from the study, leaving 17 apps for analysis. Two researchers installed the apps on separate devices and analyzed the features of the apps independently. When there was a discrepancy in the opinions, all the authors discussed them until a consensus was reached.

The selected mHealth apps were analyzed for the inclusion of BCTs from the CALO-RE taxonomy [10] (Multimedia Appendix 1) in their design, taking into account the UIDPs (selected from [19] and [21] Multimedia Appendix 2) used to support those BCTs. UIDPs were noted only in cases where utilized to implement BCTs or some other key functionalities of the app. The generalist UIDPs such as affordance for tap or swipe or key input patterns were not considered in this analysis. However, any glaring problems with an app’s interface that had the potential to disrupt the user’s experience were noted. Additionally, any features that were not available for free (but only as in-app purchases) were not considered in the analysis.

Based on the results of the review and analysis of the apps, BCT-user interface (BCT-UI) design guidelines classifying UIDPs into 6 categories were developed. Furthermore, using the proposed guidelines, a prototype app called “Morphe” was designed. The purpose of Morphe was to showcase the applicability of the BCT-UI guidelines in the development of mHealth apps targeting young people (age range 10-24 years) with obesity.

Ethical Considerations
As this study does not include experiments on human subjects, no ethical approval was sought.

Results
Review of Apps
Based on the app category, descriptions, and offered features, selected apps were classified into 2 groups: (1) apps focused on physical activity (n=12) and (2) apps focused on nutrition (n=5). Our results (shown in the tables below) and Multimedia Appendix 3 indicate that 20 (out of 40) BCTs listed in the CALO-RE taxonomy were present to some degree in the analyzed apps. The most frequently employed BCTs were related to self-monitoring of behavior (15 apps), followed by prompt practice (9 apps), providing feedback on the performance of the behavior (9 apps), goal setting (behavior) (8 apps), and successful behavior contingent rewards (8 apps). The goal setting of behavior and self-monitoring of behavior were mostly implemented in combination (8 apps) as well as by self-monitoring of behavior with prompt practice (9 apps). The goal setting of behavior and goal setting of behavioral outcome were combined in 5 apps. Six of the BCTs implemented in the apps focused on physical activities were not implemented in the nutrition-focused apps (Table 1).
Table 1. Number of apps implementing each behavior change technique or user interface design pattern.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Apps (n)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Behavior change technique</strong>a</td>
<td></td>
</tr>
<tr>
<td>#16: Self-monitoring of behavior</td>
<td>15</td>
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<td>#19: Provide feedback on performance</td>
<td>9</td>
</tr>
<tr>
<td>#26: Prompt practice</td>
<td>9</td>
</tr>
<tr>
<td>#5: Goal setting (behavior)</td>
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<tr>
<td>#13: Successful behavior contingent rewards</td>
<td>8</td>
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<td>#6: Goal setting (outcome)</td>
<td>7</td>
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<td>#17: Self-monitoring of behavioral outcome</td>
<td>7</td>
</tr>
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<td>#21: Instruction on how to perform behavior</td>
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<tr>
<td>#1: Information provision (general)</td>
<td>6</td>
</tr>
<tr>
<td>#28: Facilitate social comparison</td>
<td>6</td>
</tr>
<tr>
<td>#22: Demonstrate behavior</td>
<td>6b</td>
</tr>
<tr>
<td>#9: Setting graded tasks</td>
<td>5b</td>
</tr>
<tr>
<td>#12: Effort or progress contingent rewards</td>
<td>4</td>
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<tr>
<td>#14: Shaping</td>
<td>4</td>
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<tr>
<td>#29: Plan social support</td>
<td>4</td>
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<tr>
<td>#40: Stimulate anticipation of future rewards</td>
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<td>#4: Information provision (others' behavior)</td>
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<tr>
<td>#3: Information provision (others' approval)</td>
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<tr>
<td>#7: Action planning</td>
<td>1b</td>
</tr>
<tr>
<td>#36: Stress management</td>
<td>1b</td>
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<tr>
<td><strong>User interface design pattern</strong></td>
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<td>Content: Cards</td>
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<tr>
<td>Charts: Sparklines</td>
<td>13</td>
</tr>
<tr>
<td>Content: Filters</td>
<td>11</td>
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<tr>
<td>Gamification-Rewards: Collectibles</td>
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<tr>
<td>Notifications: Triggers</td>
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<tr>
<td>Charts: Drilldown</td>
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<tr>
<td>Content: Search</td>
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<td>Charts: Dashboard</td>
<td>5</td>
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<tr>
<td>Form: Calculator</td>
<td>5</td>
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<tr>
<td>Social: Profile</td>
<td>5</td>
</tr>
<tr>
<td>Content: Article list</td>
<td>5b</td>
</tr>
<tr>
<td>Gamification-Rewards: Praise</td>
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<tr>
<td>Social: Connecting</td>
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<td>Charts: Threshold</td>
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<td>Social: Activity Stream</td>
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<td>Form: Multistep</td>
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<td>Social: Comments</td>
<td>3</td>
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<tr>
<td>Social: Groups</td>
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<tr>
<td>Characteristics</td>
<td>Apps (n)</td>
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<td>Gamification-Rewards: Points</td>
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<tr>
<td>Gamification-Rewards: Unlock features</td>
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<tr>
<td>Gamification: Leaderboard</td>
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<td>Content: Favorites</td>
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<td>Form: Registration with Personalization</td>
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<td>Personalization</td>
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<td>Gamification: Levels</td>
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<td>Social: Reactions</td>
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<td>Charts: Overview plus Data</td>
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<td>Gamification: Appropriate Challenge</td>
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<tr>
<td>Onboarding: Tutorials</td>
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</table>

aBehavior change techniques are listed as per the numbering in the Coventry, Aberdeen, and London-Refined taxonomy.
bBehavior change techniques and user interface design patterns not implemented in apps focused on nutrition.

Our analysis identified several UIDPs used in the implementation of BCTs (Table 1 and Table 2). Information provision was often implemented using cards (14 apps) and complemented with search and filter functionalities. Pattern filters was implemented in 11 apps, and search was included in 8 apps. Favorites was underutilized (only in 2 apps) besides the many obvious opportunities for its implementation. For successful behavior contingent rewards or effort or progress contingent rewards, most apps utilized collectibles (10 apps). Providing feedback was mostly implemented using charts, with sparklines (13 apps) and drilldown (9 apps) included in apps to provide feedback about the performance of the behavior. None of the apps implemented UIDPs such as scarcity, social proof, Kairos, and interactive preview, while tutorials (1 app) and personalization (2 apps) were underutilized. It needs to be noted that 11 of the UIDPs implemented in the apps focused on physical activities were not implemented in the nutrition-focused apps (Table 1).
<table>
<thead>
<tr>
<th>Focus, app name</th>
<th>Type/target group</th>
<th>Behavior change techniques</th>
<th>Total</th>
<th>User interface design patterns</th>
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<td><strong>Physical activity focus</strong></td>
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<td></td>
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<tr>
<td>NFL Play 60</td>
<td>Exergaming</td>
<td>#1-Information provision (general)</td>
<td>5</td>
<td>Onboarding: Tutorials</td>
</tr>
<tr>
<td></td>
<td>Educational target group: age range 6-8/9-12 years</td>
<td>#9-Set graded tasks</td>
<td>Content: Cards</td>
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BCT-UI Design Guidelines

The app analysis results clearly show that implementing BCTs by using UIDPs is underutilized. Only 12 BCTs and 13 UIDPs are implemented in 5 or more apps, of which 3 BCTs and 3 UIDPs are not implemented in the nutrition-focused apps. To overcome this gap and help developers create mHealth apps for obese young people that are easy to use and effective in motivating users to engage in behavior change, we propose BCT-UI design guidelines (presented in Figure 2). These guidelines focus on implementing BCTs using UIDPs that are impactful for the young people demographics. The guidelines use the BCTs from Michie’s CALO-RE framework [10] with selected UIDPs [19,21,22].

Each BCT may have one or more UIDPs appropriate for its implementation. UIDPs are classified into 6 categories (Figure 3). The content represents any display of the information, where the information can be textual or graphical. The presentation of the content can include patterns such as article list, cards, option to mark items as favorites, filter and search to refine or locate content of interest, as well as social proof (that can be presented by textual references). The charts represent how the data can be visually presented, including different types of charts such as dashboard, drilldown, interactive preview, overview plus data, sparklines, or threshold. These user interface patterns can help in visualizing users’ behavioral and outcome goals, action planning, self-monitoring, or present feedback on the performance. The forms category represents umbrella patterns that focus on structure or feature rather than a specific form implementation. In this context, the forms are components that support input from the user. The gamification elements represent the items that deliver rewards or stimulate challenge and competition. In these UIDPs, the rewards can be implemented as collectibles, points, praise, or unlocking specific features and can be used to introduce different challenge levels or create appropriate challenges based on user preferences. The leaderboards as well can be used to facilitate social comparison. The social elements are patterns (activity stream, groups, comments, reactions) that allow users to connect with their peers for social support and comparison. The connection can be anonymous or delivered through social media integration. The “other” category includes patterns that can support delivering prompts of various kinds (such as Kairos and Triggers), tutorials, and general design considerations such as the incorporation of personalization and customization. These UIDPs can be used as nudges to intervene at specific times when the user will be open to receiving advice or performing the goal behavior.

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Use Cases: Using UIDPs to Implement BCTs

The proposed design guidelines offer the utilization of different UIDPs in the implementation of various BCTs. Besides the use cases presented in this section, miscellaneous examples of each pattern in the context of their BCTs are presented in Multimedia Appendix 4. In the given use cases, we have used mock-ups of the Morphe app developed by the authors to showcase the applicability of the proposed BCT-UI guidelines. This app is intended for young people (age 10-24 years) and has 5 main functionalities: learn, challenge, statistics, social interaction, and (user’s) settings. Additionally, the Morphe app uses notifications to nudge the user toward the desired behavior.

Use Case 1: Content Presentation

The presentation of the content in the app is very important for the usability of the app. Content UIDP dictates how app users can access, refine, and interact with app information and experiences. In our Morphe app (Figure 4), the educational content in the “Learn” functionality is presented using the article list pattern. In general, article lists tend to contain multiple rectangular cards used to store and deliver content. Each card contains an image, a title, and a brief description to allow the user to understand what information is contained in the article. Using the favorites pattern, the user can mark the items of interest and have easier access to those articles. Additionally, the combination of using filters and search allow the user to refine the content that is displayed on the screen by category (nutrition, physical activity, obesity) or by keywords.
Use Case 2: User Data

Forms are used to collect data from the user. These data are primarily used to personalize users’ experiences as assisting with goal setting and providing a baseline for behavioral monitoring. The Morphe app uses a multistep form to gather data about the user in the registration process (Figure 5). The multistep patterns allow each option to be accessible by some other means as well. For example, a BMI calculator that displays a weight range overview dependent on weight and height input can be used to help a user define a goal weight or to see their progress toward a goal weight each time they log in their weight.
Use Case 3: Use of Charts
Charts give the user a way of interacting with their data, including goal and performance history and progress. In the context of behavior change, charts can be used to present a review of the behavioral and outcome goals, represent data from periods in which the user achieved their goals, as well as provide feedback on the user’s performance. In the given example (Figure 6), the statistics functionality provides an overview of the user’s effort and progress concerning the set goals. The stats page includes submenus for diet and nutrition (eat submenu item), exercise (move submenu item), and mental health and well-being (mood submenu item). In order to visualize the progress and achievements, a few types of charts are used: dashboard, drilldown, threshold, sparklines, and overview plus data.

Figure 5. Morphe app registration process.

Figure 6. Morphe app statistics.
Use Case 4: Gamification

To engage users in behavior change and achieve their goals, several gamification patterns can be used. The challenge section in the Morphe app (Figure 7) provides access to proposed workouts, challenges, and users’ leaderboards. The workouts submenu allows the user to access workouts and exercises across several categories. Additionally, the user can choose the challenge that is most suitable for achieving a certain goal. As the user progresses throughout the workouts, different features are unlocked as a reward for the effort. Another type of reward is points. The user can be awarded a number of points by winning a physical activity challenge, performing, or making progress toward a goal behavior. In the case of the Morphe app, the points can be used to modify a user’s avatar or “purchase” entry to other challenges. The leaderboard submenu allows the users to view their achievements relative to other users and their friends. This pattern enables the user to compare their achievements with other users, thus identifying their role model and working toward reaching better results.

Figure 7. Morphe app challenge.

Use Case 5: Notifications

There are 2 types of notifications: Kairos and Triggers. Kairos are app nudges that utilize personalization and customization patterns to intervene at specific times when the user will be open to receiving advice or performing the goal behavior. For example, the Morphe app uses Kairos (Figure 8) to let the user know when he/she is close to achieving a particular goal and as such, is more likely to feel motivated to give effort toward it.

Figure 8. Morphe app notifications.

Discussion

Behavior change requires highly motivated users; therefore, mHealth apps need to provide features and functionalities that support users’ intrinsic and extrinsic motivation. The apps can increase users’ intrinsic motivation if activities that are interesting, challenging, and that have aesthetic appeal are introduced, while extrinsic motivation can be underpinned if options perceived as valuable, meaningful, and important by the users are presented [23]. Additionally, the expectation for mHealth interventions is to be able to achieve effectiveness in line with the traditional delivery of behavioral interventions. Therefore, the apps developed to support physical activities and healthy eating habits should be engaging enough to motivate the continuation of use.

The proposed design guidelines aim to provide new design considerations by incorporating and supporting BCTs through the use of the recommended UIDPs in the development of
mHealth apps. The benefits of UIDPs are to make task completion quicker and easier by reducing cognitive load, thus helping users to achieve behavior change and higher engagement with the apps. The self-regulatory BCTs, including self-monitoring of behavior, goal setting of behavior, and providing feedback on the performance, can be used as feedback processes that are very important in self-management and behavior control [24]. These BCTs have been consistently coupled with positive changes in physical activity [25], and interventions have been found to be more effective when individuals utilize these techniques [26-28]. Moreover, using different patterns from the context, charts, forms, personalization, or gamification categories can increase the successful intervention engagement; therefore, people will engage with mHealth apps in the long term.

Research shows that reward-seeking behavior is more prominent among young people because this age group receives less significant positive responses from rewards, driving them to pursue reinforcers that increase dopamine-related circuitry [29]. As Bryan et al [30] indicate, rewards are experienced in the context of other available rewards, and young people may be particularly sensitive to these changing contexts. Additionally, Davidow et al [31] note that “adolescents are notorious for engaging in reward-seeking behaviors,” and much research in the behavioral health field suggests that the most successful rewards for motivating young people are tied to achieving goals that are immediate, simple, and socioculturally reinforced. This represents an important opportunity to support the users’ extrinsic motivation by diversifying the rewards in the apps by using gamification patterns such as the use of a points system, introducing levels, or offering opportunities to unlock new features. These patterns can provide experiences of autonomy, competence, and relatedness by adding fun and excitement to the activities [32]. Although the implementation of the “Training to use prompts” behavior technique and utilizing the “Onboarding: tutorials” design patterns represent a clear opportunity in future app development, training and navigation menus are important in the early stages of app interaction and adoption. However, the provided instructions need to keep the text to a minimum and written to a sixth-grade level [33]; otherwise, it can be difficult to read, presenting a further barrier to engagement.

The literature regarding the social support for BCTs presents opposite findings. Although some research suggests that young people find peer interactions more rewarding [30], others find that young people find social posting not desirable since they do not want to bother their friends or share achievements that they considered to be uninteresting [34]. Another concern is sharing personal or sensitive data with others [35]. In this context, during the development phase of the app, designs that implement social patterns with relative anonymity that will support the young people’s engagement need to be considered. Stress management BCT has been identified as a necessary component for health behavior change, especially for young people with obesity who might have greater levels of stress [36]. UIDPs included in the content group can be useful in the implementation of this behavior technique by providing generic information about mindfulness, stress, and anxiety management.

BCT categories such as “prompt self-talk” or “prompt identification as a role model” can increase user engagement by focusing on intrinsic and social motivation elements that are recorded as having bolstered engagement [37]. However, effective implementation of prompts needs consideration in timing, frequency, and tailoring [38] that can be designed using Karios, Triggers, and Personalization in combination with Gamification or Social Patterns. Further, personalized prompts for a given situation are proven to be more effective in behavior change [39]. Problem-solving solutions for barriers to physical activities can motivate individuals to increase their activity [40]. Therefore, features that could assist users with solving barriers to physical activity, such as well-timed notifications for inclement weather or recommendations for suitable indoor exercises can be beneficial. The proposed design guidelines link the BCTs with UIDPs, which can maximize the impact and increase the adoption and continuation of use of mHealth apps for obese young people. However, the design process of such apps is complex and requires the involvement of relevant stakeholders: public health and clinical experts for content creation, app developers for designing the apps’ features and functionality, and young people as prospective users of the app.

A few limitations in this research need to be noted. The time frame of the app analysis should be considered since there is a possibility that some of the features could be revealed to the user after using the app over a longer period of time. The applicability of the proposed BCT-UI design guidelines was presented by designing the prototype app Morphe. However, the prototype was created without insight from the young people community. Furthermore, the guidelines need to be validated with the real users of an mHealth app targeting young people with obesity.

In conclusion, the analysis of 17 mHealth apps has shown that the utilization of UIDPs in implementing BCTs is limited. Taking into account the importance of BCT and UIDP in improving the efficacy of the mHealth apps, in this paper, we proposed BCT-UI design guidelines. The aim of these guidelines is to support the development of mHealth apps that are easy to use and effective for long-term adoption by young people. Additionally, 5 use cases of the Morphe app targeting overweight and obese young people were presented to showcase the usability of the design guidelines. Future research should involve the development and deployment of the Morphe app and validation of its usability and effectiveness in obesity and overweight management within the young people community. However, since the proposed guidelines are generalized, exploring its utilization in the design of mHealth apps for the management of other health conditions as well as various age groups can be valuable.
Conflicts of Interest
None declared.

Multimedia Appendix 1
Coding constraints of the Coventry, Aberdeen, and London-Refined (CALO-RE) taxonomy of behavior change techniques [10].
[PDF File (Adobe PDF File), 777 KB - mhealth_v11i1e37716_app1.pdf]

Multimedia Appendix 2
User interface design pattern definitions [19,21].
[PDF File (Adobe PDF File), 535 KB - mhealth_v11i1e37716_app2.pdf]

Multimedia Appendix 3
Behavior change techniques implemented in the reviewed apps.
[PDF File (Adobe PDF File), 229 KB - mhealth_v11i1e37716_app3.pdf]

Multimedia Appendix 4
Proposed usage of the user interface design patterns in the context of the behavior change techniques.
[PDF File (Adobe PDF File), 591 KB - mhealth_v11i1e37716_app4.pdf]

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Abbreviations

- BCT: behavior change technique
- BCT-UI: behavior change technique–user interface
- CALO-RE: Coventry, Aberdeen, and London-Refined
- mHealth: mobile health
- UIDP: user interface design pattern

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Loss-Framed Adaptive Microcontingency Management for Preventing Prolonged Sedentariness: Development and Feasibility Study

Woohyeok Choi1, PhD; Uichin Lee2, PhD

1Information & Electronics Research Institute, Korea Advanced Institute of Science & Technology, Daejeon, Republic of Korea
2School of Computing, Korea Advanced Institute of Science & Technology, Daejeon, Republic of Korea

Corresponding Author:
Uichin Lee, PhD
School of Computing
Korea Advanced Institute of Science & Technology
291 Daehak-ro, Yuseong-gu
Daejeon, 34141
Republic of Korea
Phone: 82 42 350 3544
Email: uclee@kaist.edu

Abstract

Background: A growing body of evidence shows that financial incentives can effectively reinforce individualsʼ positive behavior change and improve compliance with health intervention programs. A critical factor in the design of incentive-based interventions is to set a proper incentive magnitude. However, it is highly challenging to determine such magnitudes as the effects of incentive magnitude depend on personal attitudes and contexts.

Objective: This study aimed to illustrate loss-framed adaptive microcontingency management (L-AMCM) and the lessons learned from a feasibility study. L-AMCM discourages an individual’s adverse health behaviors by deducting particular expenses from a regularly assigned budget, where expenses are adaptively estimated based on the individual’s previous responses to varying expenses and contexts.

Methods: We developed a mobile health intervention app for preventing prolonged sedentary lifestyles. This app delivered a behavioral mission (ie, suggesting taking an active break for a while) with an incentive bid when 50 minutes of uninterrupted sedentary behavior happened. Participants were assigned to either the fixed (ie, deducting the monotonous expense for each mission failure) or adaptive (ie, deducting varying expenses estimated by the L-AMCM for each mission failure) incentive group. The intervention lasted 3 weeks.

Results: We recruited 41 participants (n=15, 37% women; fixed incentive group: n=20, 49% of participants; adaptive incentive group: n=21, 51% of participants) whose mean age was 24.0 (SD 3.8; range 19-34) years. Mission success rates did not show statistically significant differences by group (P=.54; fixed incentive group mean 0.66, SD 0.24; adaptive incentive group mean 0.61, SD 0.22). The follow-up analysis of the adaptive incentive group revealed that the influence of incentive magnitudes on mission success was not statistically significant (P=.18; odds ratio 0.98, 95% CI 0.95-1.01). On the basis of the qualitative interviews, such results were possibly because the participants had sufficient intrinsic motivation and less sensitivity to incentive magnitudes.

Conclusions: Although our L-AMCM did not significantly affect users’ mission success rate, this study configures a pioneering work toward adaptively estimating incentives by considering user behaviors and contexts through leveraging mobile sensing and machine learning. We hope that this study inspires researchers to develop incentive-based interventions.

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KEYWORDS
contingency management; incentive; sedentary behavior; sedentariness; behavior change; health promotion; financial incentives; health intervention; user compliance; incentive-based intervention; mobile phone
Introduction

Background

Intrinsic motivation refers to an inherent motive to perform a target behavior [1], whereas extrinsic motivation is a specific type of motivation for obtaining a certain outcome that can be separated from the behavior [2]. Although it is clear that intrinsic motivation is essential for behavior change, numerous studies have presented evidence that extrinsic motivation can also greatly contribute to behavior change. A representative behavioral therapy that uses extrinsic motivation is contingency management, which provides external rewards (typically financial incentives) contingent on the occurrence of behaviors of interest for reinforcing positive behavior change [3]. Such a therapeutic approach has already shown effectiveness on behavior change in various fields, including physical activity promotion and dietary tracking [4-9], prevention of drug abuse [10-17], smoking cessation [18-22], productivity and academic performance [23-25], and driving behavior [26,27]. In addition to its application in academic fields, companies also use financial incentives as core motivators for behavior changes, such as health insurance discount programs for healthy behaviors [28] and a commitment contract that allows the company to send money from a user’s account to a particular person or organization (eg, charities) if one fails to reach a self-defined goal [29].

However, the design of incentives in these contingency management interventions has several issues that hinder the achievement of the goal of these interventions, which is to promote successful behavior change. For example, socioeconomic status probably contributes to incentive effectiveness [30,31]. In addition, the assumption of a trade-off between ability and motivation (namely, users with low and high ability require high and low motivation for behavior change, respectively) may imply that the magnitude of an (extrinsic) motivator should differ by context and one’s physical and cognitive capabilities for eliciting behavior change [32]. Another aspect of incentive design that should be considered is the delay between behavior occurrence and incentive delivery, with a shorter delay having shown greater effectiveness in eliciting behavior change [18,33]. Other potential contributors to the effectiveness of contingency management include incentive framing (eg, providing incentives for positive behaviors vs deducting expenses for negative behaviors) [23,26,34,35], incentive magnitude adjustments throughout the intervention [20,34,36,37], and incentive magnitude certainty (eg, fixed vs lottery incentives) [4,12,38].

Although previous studies have shown the effectiveness of the incentive designs of their proposed contingency management interventions, they had several limitations. For example, positive behavior was not immediately rewarded, and only behavioral outcomes from long-term behavior adherence were rewarded at the end of an intervention (eg, lump-sum provision) [7,21]. In addition, incentive magnitudes were often fixed [23,39] or randomly sampled from a predefined range of incentives [4,38] (ie, they did not change by context at the individual level). Moreover, although several studies have proposed an escalating reinforcer where incentive magnitudes increase at each positive behavior occurrence [20,34,36,37], such a design requires intervention practitioners to configure a detailed plan manually (eg, the amount of incentive increment) based on their domain knowledge.

Objectives

This study proposes a novel incentive-based mobile intervention named loss-framed adaptive microcontingency management (L-AMCM), which immediately discourages users’ microbehaviors that cause adverse health effects by providing a personally and contextually tailored incentive. In more detail, this approach delivers a prompt recommending a positive behavior change when the user is susceptible to health risks. Each prompt presents a particular expense framed as a loss (ie, a loss-framed incentive), in which, if the user does not change their behavior in response to the prompt, that expense is deducted from an individual budget that the intervention regularly allocates. In addition, the deducted amount presented in each prompt is dynamically adjusted based on individuals’ responses to prompts over varying incentives and contexts. To this end, the L-AMCM continuously monitors users’ behavior changes in response to prompts presenting varied contexts and expenses. It iteratively learns an individual’s behavioral model, which describes the likelihood of a behavior change in a given context and at a given expense. On the basis of the learned model, the L-AMCM estimates how much each prompt needs to bid to elicit positive behavior, at least to some extent. To evaluate the feasibility of the L-AMCM, we applied it to a mobile health intervention app that delivers active break missions (ie, standing up and moving around for a while) with an estimated incentive via individuals’ smartphones to discourage prolonged sedentary behavior (ie, 50-minute uninterrupted sitting sessions). This study illustrates the lessons learned regarding its application via a 3-week field study with 41 participants. We hope that this study will provide new research directions for incentive-based mobile interventions.

Methods

Design of the L-AMCM Intervention

Motivating Scenario

Herein, we illustrate an exemplar intervention scenario with microincentives in the domain of prolonged sedentary behavior interventions, similar to those in previous research [40,41]. When users uninterruptedly sit down for a long time, a given health intervention app triggers a prompt containing a behavioral suggestion to break the sedentary period (eg, standing up and moving around for a while) and bids a certain amount of monetary incentive that will be withdrawn from an individually assigned budget if users do not adhere to the suggestion. Users then examine whether the compensation is sufficient to make them adhere to the behavior suggestions in a given context. For example, if they receive the prompt late at night, a period in which they may be feeling somewhat tired, they may choose not to adhere to the suggestion if the incentive is low; they would rather continue engaging in sedentary behavior. However,
if the intervention bids a larger incentive, they may consider accepting the behavioral suggestion. In addition, if the prompt is coincidentally delivered immediately or closely after they have spent some time working very hard at the office and may be feeling the need to refresh, they may be more willing to take an active break even with a lower incentive. However, it is clear that the tendency to accept behavioral suggestions with incentives will differ by user. For example, users who already know the health risks of prolonged sitting sessions may be willing to try with more active break suggestions even with lower incentives.

A core assumption of the presented scenario is that users are more likely to accept the behavioral suggestion as the incentive grows, which stems from the evidence of various studies showing that a larger incentive magnitude corresponds to a larger effect on health behavior change [7,10,18,31,33]. Another assumption is that the incentive magnitude necessary for eliciting behavior change may differ by user and context, which is grounded in the Fogg Behavior Model, a practical framework illustrating the underlying factors relevant to behavior change [32]. In this model, a particular behavior happens through the interplay of an individual’s inherent motivation toward the behavior; an individual’s ability to perform the behavior; and an external prompt that elicits behavior change by reminding the behavior, reinforcing motivation, or simplifying the behavior. In the presented scenario, the amount of incentive plays a role in sparking positive behavior change, and the change in incentive magnitude across users and contexts is based on several important aspects of the Fogg Behavior Model, as shown in Textbox 1.

Textbox 1. Key aspects of the Fogg Behavior Model considered in the proposed incentive mechanism.

- **Fogg Behavior Model key aspects**
  - Motivation and ability have a trade-off relationship (eg, lower ability requires more motivation for behavior change); thus, the amount of incentive necessary for the positive behavior might need to change across different levels of motivation and ability. For example, for people with enough adherence motivation, the amount of incentive required for the behavior change might be smaller compared with less motivated people. In addition, people with less ability might need to be compensated with more incentives for behavior change.
  - Motivation and ability differ among individuals; thus, the amount of incentive required for the behavior change would be different by individual.
  - Ability differs by context; thus, the amount of incentive required for positive behavior change might vary by context.

**Hypothetical User Behavior on Incentives and Contexts**

On the basis of these assumptions, we hypothesized an equation for a user’s behavior occurrence likelihood, \( y \in [0,1] \), with a given incentive magnitude \( r \in \mathbb{R} \) and context \( c \in C \) as follows: \( f: r, c \rightarrow y \) such that \( \forall r, r' \in \mathbb{R} \) and \( c, c' \in C \), \( f(r, c) \leq f(r', c') \) if \( r \leq r' \) and \( c=c' \).

Various functions satisfying the aforementioned equation can be used to model the hypothetical user behavior we propose. This study considers a logistic regression (LR) model as it naturally maps an input into a probability output and is easily implemented and interpreted [42]. Then, assuming a vector of one-hot encoded discrete contexts, \( C=\{c_1, c_2, \ldots, c_n, c_s\} \), and the corresponding coefficients (ie, the effect of context on behavior occurrence likelihood), \( B=\{b_1, b_2, \ldots, b_n, b_0\} \), the hypothesized user behavior can be modeled as follows:

\[
\hat{y} = \frac{1}{1 + e^{-\left(\sum_{i=1}^{n} b_i c_i + b_0\right)}}
\]

where \( b_0 \) indicates the effect of incentive magnitude on behavior occurrence likelihood and \( e \) is an intercept term.

**Estimation of Incentive Magnitude**

The hypothesized user behavior can also be rearranged for estimating the incentive magnitude necessary to elicit a target behavior with a given probability, \( y^- \), as follows:

\[
\hat{y} = \frac{1}{1 + e^{-\left(\sum_{i=1}^{n} b_i c_i + b_0\right)}}
\]

Importantly, incentive providers can choose the \( y^- \) depending on their policies. For example, if greater costs are not of concern, a large \( y^- \) will make users highly likely to comply with the behavior suggestions, whereas \( y^- \) close to a half probability will make adherence to behavior suggestions highly uncertain.
Loss-Framed Incentive

A major characteristic of the proposed incentive mechanism is to bid higher incentives as the target behavior becomes less likely. For example, once a user rejects a behavioral suggestion for a given incentive magnitude and context, our mechanism would assume that such a magnitude is insufficient to elicit behavior change. Therefore, the subsequent behavioral suggestion triggered in an identical context will bid a greater magnitude. Otherwise, the user is offered the same or a smaller incentive at the next behavioral suggestion. Such a characteristic may yield gaming behavior if the user is rewarded for succeeding in behavioral missions (ie, a gain-framed incentive). For example, the user may deliberately reject the current bid suggested by the intervention prompt and maintain an unhealthy state to earn higher incentives at successive bids.

To discourage such behavior, we used a loss-framed incentive (ie, a deposit contract) that deducts estimated amounts during mission failures from budgets paid in advance. Combined with the loss-framed incentive, our incentive mechanism gradually increases the amount deducted if the user consecutively rejects the bids, whereas if the user is more likely to accept the bids and comply with behavioral missions, the amount deducted for mission failures decreases. In such a mechanism, the optimal strategy for obtaining as many incentives as possible is to maintain a healthy behavior (eg, regularly interrupting prolonged sedentariness) to keep behavioral missions (which are designed to deduct incentives from the budget) from being triggered and comply with behavioral missions regardless of incentive amounts if missions are triggered. Not only does this strategy keep budgets without deduction, but it also decreases the amount deducted for mission failures because of unavoidable reasons.

In addition to the prevention of gaming behavior, another reason for using the loss-framed incentive is that the loss-framed incentive is more likely to elicit behavior change than the gain-framed incentive because of people’s tendency to place a greater emphasis on losses than gains, as stated by the prospect theory [43]. In practice, previous studies have demonstrated a better effect of the loss-framed incentive on health outcomes than the gain-framed incentive in a variety of intervention domains, including mitigating smartphone overuse [23], promoting physical activity [35], and improving driving behavior [26].

Implementation of Mobile Health Intervention

Overview

To explore how users respond to the proposed incentive strategy, we implemented a research app prototype named StandUp. This prototype comprises 4 major components: sedentary behavior tracking, context sensing, incentive estimation, and active break mission delivery. The StandUp user interface is presented in Figure 2.
**Sedentary Behavior Tracking**

Our prototype app monitors step counts through the user’s smartphone to detect sedentary behavior. The prototype assumes that the user is stationary when <10 steps are recorded in 1 minute. Moving or taking an active break is defined as >45 steps being recorded within a minute. In contrast, we refrained from exactly determining whether the user is sedentary in these cases. Specifically, 10 and 45 steps correspond to approximately 6.6 m to 7.9 m and 29.7 m to 35.6 m of movement, respectively [44,45]. The rationale behind the hard-coded threshold for step counts (ie, 10 and 45 steps) was derived from an internal pilot test wherein these step numbers corresponded to walking for 30 to 60 seconds, respectively. StandUp schedules an intervention prompt to appear after 50 minutes when users become stationary. In addition, the scheduled prompt is canceled if a substantial movement change (ie, at least 10 steps within a minute) is detected.

**Context Sensing**

Context sensing is used for tailoring incentives to different contexts. As location substantially contributes to users’ decisions to comply with interventions [40], our prototype considers location as the key context variable. Once any stationary event occurs, StandUp retrieves the latitude and longitude of the current location from the smartphone’s GPS sensor.

**Active Break Mission Delivery**

If there is no mobility state change for 50 minutes after an intervention prompt has been scheduled, a user receives a mission that suggests taking an active break in the form of a smartphone notification. Each mission lasts 10 minutes and informs about a specific expense deducted from a budget upon failing that mission, where the budget is individually assigned at the start of every day. The 10-minute threshold for adherence to the mission is based on the finding that people see incoming smartphone notifications within 10 minutes on average from notification arrival even when the ringer mode is set to silent [46].

After the notification appears on the smartphone, StandUp begins to check via sedentary behavior tracking whether a user takes an active break within 10 minutes. If a given mission expires without behavior change (ie, no mobility is detected within 10 minutes of mission delivery), StandUp reminds the user of the amount lost via a notification and deducts the amount from the user’s budget. Otherwise, a message of mission success is displayed on the notification. In the case of mission failures, StandUp reschedules the next active break mission to be delivered after 50 minutes. After each mission is completed, StandUp records the mission result (ie, success vs failure), amount of suggested expenses, and GPS coordinates of the current location. These data are stored in the user’s smartphone’s internal storage and used for incentive estimation in subsequent missions. In addition, they are later uploaded to a server via the Wi-Fi network.

**Incentive Estimation**

StandUp supports either a fixed or adaptive incentive strategy. StandUp with a fixed incentive strategy presents a predefined expense without any estimation. Regarding the adaptive incentive strategy, StandUp obtains the mission results (ie, success or failure), expense bids, and GPS coordinates of the locations where missions were initiated within the most recent 7 days. The continuous GPS coordinates should be transformed into discrete factors for modeling user behaviors in response to varying expenses and locations. We used a geohash for this purpose, which maps all locations on Earth onto rectangular
grids and represents each rectangle as a short alphanumeric string. Our implementation maps GPS coordinates within 150-m by 150-m square grids to a single 7-character geohash string (ie, a 7-bit geohash) so that continuous GPS coordinates are discretized. Geohashed representations of locations are then factorized with one-hot encoding. Consequently, mission results, expense bids, and factored locations were used for user behavior modeling and incentive estimation (Multimedia Appendix 1). In addition, the current implementation sets the probability of expected behavior occurrence (ie, ȳ) to 0.5. Such a parameter may allow the adaptive incentive strategy to actively explore the smaller incentive magnitude that is potentially optimal for eliciting behavior change.

Study Design

For 3 weeks, we conducted a single-blind, between-group study with 2 groups: fixed incentive and adaptive incentive. All participants received US $1.50, which is presented as 100 points in StandUp, as a daily budget each morning during the intervention period. We used this specific value (US $1.50) as it is the median value of the daily incentives used in previous studies on incentive interventions for improving physical activity [31]. The fixed incentive group lost US $0.30 whenever participants failed a given active break mission. In the adaptive incentive group, participants lost an amount of incentive estimated by the proposed incentive strategy, in which the incentive ranged from US $0.30 to $3 with a US $0.30 increment (namely, US $0.30, US $0.60, ..., US $2.70, and US $3) and the closest to the estimated one within that range was bid. For example, if the estimated incentive was US $1.40, the real incentive presented to users was US $1.50. If the daily budget was exhausted, participants did not receive any incentives on that day. The field trial was conducted between April 2020 and May 2020.

Recruitment and Procedures

We recruited participants from our web-based campus community and Facebook. The inclusion criteria were as follows: having a sedentary occupation, spending >6 hours sitting on weekdays, and possessing a smartphone with an Android version 7.00 or higher. The participants were randomly assigned to the fixed and adaptive groups so that there was no significant difference between the groups regarding demographics such as age (P=.72; $t_{38.235}=0.363$) and gender (P>.99; N=41, $\chi^2_{1}<0.0$). Before participating in the field study, they received information on the health risks of prolonged sedentary behavior and how to use StandUp. In addition, we briefly instructed participants in the adaptive group on how incentive amounts were estimated (eg, as they become less likely to adhere to behavioral missions, a larger deducted amount is presented). However, we did not explain the detailed algorithm underlying our incentive mechanism (eg, mathematical equations describing user behaviors in response to incentives and contexts) as we believed it might be difficult for the general population to comprehend.

The first week was the baseline period, with StandUp just displaying the minutes that participants spent in a sedentary state on its dashboard and not delivering any active break missions. This period was intended to minimize the novelty effect of our app on any user behavior. After the baseline period, through SMS text messages, we asked participants to activate the mission delivery option for the second and third weeks. Participants were allowed to choose the start time of the missions from 9 AM to 11:59 AM depending on their preferences. The mission prompts were delivered over 9 hours from the chosen start time (eg, 9 AM-6 PM to 11:59 AM-8:59 PM) every day during the intervention period. Thus, at most, 10 missions were delivered to participants per day if they remained sedentary during the mission activation period.

After the field study, we compensated participants with US $24 for study participation and extra payments for the results of their missions (US $21 extra at maximum). In addition, exit interviews lasting 30 minutes were conducted with each participant to investigate user experiences with StandUp and potential factors relevant to the effectiveness of different incentive strategies.

Exclusion Criteria

To clean the data, we first excluded missions collected at the first date of the intervention period as participants manually activated the active break mission delivery option on the first day of the intervention period (the eighth day of the entire field study) and the missions collected on that date possibly contained noise. In addition, we found that StandUp did not operate for a few days for several participants, resulting in a large loss of mission results. Therefore, we excluded all missions from participants whose data did not show any missions triggered for 2 consecutive days.

Measurements and Data Analysis

The major outcome for evaluating the effectiveness of the proposed incentive strategy was the success rate of active break missions. It was defined as the ratio of the number of successful missions to the number of missions triggered. On the basis of the results of the Shapiro-Wilk normality test, both groups’ success rate was normally distributed (for the fixed incentive group: $P=.08$, and $W=0.905$; for the adaptive incentive group: $P=.51$ and $W=0.953$). Therefore, we compared the means of the success rates of the fixed and adaptive incentive groups using the Welch 2-tailed t test, which is known to have better control over type-1 errors than the Student t test [47].

In addition, we performed follow-up analyses of the adaptive incentive group to investigate in depth the effects of various factors on the mission success rate. First, we conducted a generalized linear mixed model (GLMM) analysis, hypothesizing that the mission success rate may be affected by days passed since the intervention onset, expense bids, and location. A reason for including the days passed since the intervention onset in the GLMM analysis is that repeated provision of intervention prompts during intervention periods would decrease responsiveness to those prompts because of the habituation effect [48]. Other 2 factors, deducted amounts and location, were examined to corroborate a hypothesis regarding our incentive mechanism, namely, that the occurrence of the target behavior would vary by context and incentive.
Before building the GLMM, we preprocessed the location data. First, we converted the GPS coordinates of locations where missions were triggered into 7-bit geohash strings, as our incentive mechanism did. As our participants resided elsewhere, geohashed locations would also be different and, thus, could not be used in the GLMM as a factor. Therefore, we relabeled geohashed locations considering the number of behavioral missions triggered (i.e., the number of times prolonged sedentariness happened) at each location. For example, the top-k location refers to the geohashed location where missions were the kth most frequently triggered out of all geohashed locations. We analyzed the top 5 locations where 90% of the missions were triggered. Consequently, our GLMM included the following fixed effects—expense bids, days passed since the intervention onset, and the top 5 locations where missions were triggered—and the following random intercepts—the participants and top 5 locations within participants (i.e., nested random effects). A detailed formula for the GLMM is presented in Multimedia Appendix 2.

Another follow-up analysis was conducted to examine the distribution of coefficients in the hypothetical user behavior model (i.e., $\beta_0$), which was updated for each behavioral suggestion, to investigate whether our incentive estimation worked as intended.

**Ethics Approval**

This study was approved by the institutional review board of the Korea Advanced Institute of Science and Technology (KH2019-114), and we obtained written consent from all participants.

**Results**

**Population Characteristics**

A total of 41 participants initially took part in the 3-week field trial. The mean age was 24.0 (SD 3.8; range 19-34) years, and there were 37% (15/41) female participants. Most participants were graduate (17/41, 41%) and undergraduate (20/41, 49%) students. The other 10% (4/41) of participants were an office clerk, a graphic designer, a private academy instructor, and a researcher. In addition, of the 41 participants, 20 (49%) and 21 (51%) were assigned to the fixed and adaptive incentive groups, respectively. In total, 2387 missions (n=1021, 42.77% failures) were recorded during the field trial. From the data cleaning, of the 2387 missions, we excluded 179 (7.5%) collected on the first day of the intervention period and 399 (16.72%) from 7 participants for whom StandUp did not operate well. The following analyses were conducted with the remaining 1809 missions (n=684, 37.81% failures) from 34 participants (n=13, 38% female participants; n=17, 50% of participants in each group) whose mean age was 24.2 (SD 4.0; range 19-34) years.

**Comparison of Mission Success Rate**

Participants in the fixed and adaptive incentive groups received 900 (n=347, 38.6% failures) and 909 (n=337, 37.1% failures) active break missions, respectively. Although the fixed incentive group (mean 0.66, SD 0.23) showed a larger success rate than the adaptive incentive group (mean 0.61, SD 0.22), the Welch $t$ test showed that the difference between the groups was not statistically significant ($P=.54; t_{31.85}=0.62$).

**Follow-up Analysis of the Adaptive Incentive Group**

**GLMM Analysis**

As noted previously, most missions in the adaptive group were triggered at the top 5 locations (831/909, 91.4%), in which the top-1 to top-5 locations occupied 60.3% (548/909), 15.4% (140/909), 7.7% (70/909), 4.8% (44/909), and 3.2% (29/909) of the missions, respectively. As shown in Table 1, the GLMM analysis revealed that expense bids did not show statistical significance on mission success ($P=.18; \text{OR}=0.98, 95\% \text{CI} 0.95-1.01$). Meanwhile, the location where missions were fourth most frequently triggered ($P=.04; \text{OR}=0.49, 95\% \text{CI} 0.25-0.96$) and the days passed since the intervention onset ($P=.03; \text{OR}=0.95, 95\% \text{CI} 0.91-0.99$) had a statistically significant influence on mission success.

**Table 1.** Results of the generalized linear mixed model analysis for behavior occurrence likelihood in the adaptive incentive group. Marginal and conditional $R^2$ are 0.030 and 0.312, respectively.

<table>
<thead>
<tr>
<th>Fixed effects</th>
<th>$\beta$ (SE)</th>
<th>z score</th>
<th>OR$^a$ (95% CI)</th>
<th>$P$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.32 (0.46)</td>
<td>2.90</td>
<td>3.75 (1.53-9.18)</td>
<td>.004</td>
</tr>
<tr>
<td>Expense bids</td>
<td>-0.02 (0.02)</td>
<td>-1.33</td>
<td>0.98 (0.95-1.01)</td>
<td>.18</td>
</tr>
<tr>
<td>Top-k location</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top 1</td>
<td>0.24 (0.22)</td>
<td>1.07</td>
<td>1.26 (0.82-1.96)</td>
<td>.29</td>
</tr>
<tr>
<td>Top 2</td>
<td>-0.18 (0.25)</td>
<td>-0.73</td>
<td>0.83 (0.51-1.37)</td>
<td>.47</td>
</tr>
<tr>
<td>Top 3</td>
<td>0.02 (0.30)</td>
<td>0.06</td>
<td>1.02 (0.57-1.82)</td>
<td>.96</td>
</tr>
<tr>
<td>Top 4</td>
<td>-0.71 (0.34)</td>
<td>-2.08</td>
<td>0.49 (0.25-0.96)</td>
<td>.04</td>
</tr>
<tr>
<td>Top 5</td>
<td>0.71 (0.42)</td>
<td>1.66</td>
<td>2.03 (0.88-4.65)</td>
<td>.10</td>
</tr>
<tr>
<td>Days since intervention onset</td>
<td>-0.05 (0.02)</td>
<td>-2.23</td>
<td>0.95 (0.91-0.99)</td>
<td>.03</td>
</tr>
</tbody>
</table>

$^a$OR: odds ratio.
Coefficients Corresponding to Incentive Magnitudes

We further investigated how the proposed incentive strategy estimated the effect of the incentive magnitude for every expense bidding. As shown in Figure 3, we found that $\beta_0$ often became negative where the mean of the coefficient across participants was 0.00 (SD 0.08; 95% CI −0.04 to 0.04). In other words, our incentive strategy often estimated that bidding larger expenses rather inhibited participants’ behavior occurrence likelihood.

Corroborating Statistical Analyses via Interviews

Although our statistical analysis did not show a clear relationship between mission success rate and incentive magnitudes, we discovered 2 major behavioral patterns related to incentives in the qualitative interview analysis. One pattern was that participants randomly accepted behavioral suggestions regardless of the expenses offered. Some participants described being intrinsically motivated toward engaging in the active break as they were aware of the risk of sedentary lifestyles or had already felt that their sitting time was too long. These participants typically tried to accomplish active break missions without checking how much expense was bid, as participant 4 noted:

I’m having lower back pain when I sit down and keep myself focused on studying for an hour or two. While using this app (StandUp), I stood up every 50 minutes and felt that my back pain was greatly alleviated. The main reason I followed the active break suggestions was for health benefits, not the money.

Meanwhile, a participant (participant 8) reported choosing to adhere to the mission after 50 minutes of being in a sedentary state regularly to improve his productivity, in a method similar to the Pomodoro technique:

Perhaps the original purpose of this app (StandUp) is to prevent some cardiovascular diseases by increasing physical activity. However, I used this app for a different reason; I used to be less efficient when focusing on one thing. Once I engaged in an active break mission, I organized my thoughts for a while as I walked. So, I felt that my productivity improved.

Another pattern was that participants adhered to behavioral suggestions only when substantial expenses were presented. Subsequently, participants tended to be less sensitive to minor changes in expenses. Several participants had different criteria for the minimum expense that made them consider mission acceptance. Therefore, these participants tended to reject missions when incentives smaller than their criteria were offered, as participant 5 noted:

I tried to accept missions when this app (StandUp) will take back at least 0.15 USD. Such an amount is like my psychological Maginot line.

Discussion

Principal Findings

Financial incentives have been widely regarded as effective behavior reinforcers in diverse health and behavior change domains [31,33,49-54]. However, to the best of our knowledge, most previous studies on incentive-based health interventions often assumed that users’ responses to incentives were homogeneous; thus, compensation for positive behavior changes was fixed even in different individuals and contexts. In addition, these studies required intervention providers to manually configure incentive strategies based on their domain knowledge. Meanwhile, this study argues against such one-size-fits-all incentive strategies and explores the feasibility of a novel incentive strategy, L-AMCM. It personally and contextually tailors the incentive magnitude to users, which is then immediately suggested to them to reinforce behavior changes.

We hypothesized that we could computationally learn about an individual’s preference for incentives by referring to one’s previous responses to incentives in varying contexts.
We developed a simple mobile health intervention targeted at discouraging prolonged sedentary behaviors by delivering information for users about prolonged sedentariness (ie, 50-minute sitting sessions) and by suggesting, via app notifications, that they take active breaks with a loss-framed, low-cost financial incentive. We assumed that people would be more likely to adhere to the behavior suggestions as the deducted amount grew; this led to an LR-based context-aware incentive adaptation where the deducted amount dynamically changed depending on adherence to the behavioral suggestion across different incentives and contexts. Unfortunately, our 3-week between-group field trial with 41 participants showed that the proposed incentive strategy failed to promote more adherence to health behaviors than a fixed incentive strategy. Furthermore, the follow-up analyses partially confirmed that location influenced behavior occurrence likelihood. However, it was found that behavior occurrence likelihood did not always increase as incentive magnitude increased, possibly because of enough intrinsic motivation and less sensitivity to incentive magnitude.

Lessons Learned
From our findings, we learned lessons that may improve incentive magnitude tailoring for contingency management interventions. As a previous study pointed out that the effect of incentive magnitude on decision-making is small [55], one lesson is that acceptance of behavioral suggestions may not be proportional to incentive magnitude; namely, our results were not concordant with our initial expectations. At least in the sedentary behavior intervention we designed, there may be a case in which users may accept or reject behavior suggestions without regard to incentive magnitude. Although somewhat counterintuitive and radical, we may design different incentive strategies where a user’s behavior occurrence likelihood and incentive magnitude are independent of each other instead of there being a linear relationship between them.

Another lesson is that incentive magnitudes should change in a coarse-grained manner. In this study, incentive magnitudes were set to range from US $0.30 to $3 with a US $0.30 increment; nonetheless, participants reported in the interviews that they were less sensitive to fine-grained changes in incentive magnitudes and that they instead had a rough threshold for considering adherence to behavioral suggestions. Hence, substantial changes in incentive magnitude may be more appropriate for eliciting differential behavioral patterns.

Limitations and Future Work
Our sedentary behavior tracking used step counts obtained from an individual’s smartphone; thus, it has constraints such as requiring participants to always carry their smartphones and move around at least 30 m to detect active break sessions. Unfortunately, these constraints made it impossible to capture behavior change when participants did not carry their smartphones and to differentiate a standing activity that can interrupt sedentariness (eg, standing and stretching or working at a standing desk) from sedentary behavior. Detecting sedentary activity by identifying an individual’s posture (eg, lying, sitting, or upright position) with wearable sensors (eg, a thigh-attached accelerometer) could be an alternative for tracking sedentary behavior with better precision and granularity [56].

Another limitation of this study was that health-related outcomes were not measured. Given that previous studies have demonstrated the health benefits of contingency management [52] and prompt-based interventions [57], we assumed that our prompt-based contingency management intervention probably had a positive impact on health outcomes in our experimental design phases. Under such an assumption, the primary objective of this study was to compare different incentive mechanisms in terms of the occurrence of the desired behavior and not to confirm the general health effects of the proposed intervention. Nonetheless, it would be beneficial to precisely measure health-related outcomes such as time spent in sedentary or physical activity [57,58] to establish not only the general health benefits of our intervention but also to rigorously compare the effects of various incentive mechanisms.

For ease of implementation, the incentive mechanism presented in this study used only geohashed locations as contextual factors. Unfortunately, it is challenging to interpret geohashed locations intuitively; thus, our GLMM analysis only partially confirmed the impact of location on behavior occurrence and did not provide a comprehensive interpretation of these locations. It would be beneficial to assign semantic meaning to geohashed locations (eg, home, workplace, or eatery) to clearly understand which attributes of locations influence behavior occurrence. For example, a future study may ask participants to name their locations semantically after delivering intervention prompts via ecological momentary assessment [40,56]. In addition, there would be other contextual factors (eg, ongoing tasks and social settings [40]) and intrinsic attributes (eg, self-efficacy and perceived enjoyment [59] and affective responses [60] toward the target behavior) that may influence an individual’s response to incentives. Future work may try modeling user behavior with several variables as their results will probably improve our knowledge of appropriate incentive magnitude estimation for contingency management interventions.

Although this study does not reveal the benefits of the L-AMCM in terms of target behavior occurrences over a short intervention period, a long-term and follow-up investigation might disclose intriguing effects on user behaviors, supposing that the L-AMCM works as intended. The mitigation of habituation is one of the potential effects we expect. As with the fixed incentive mechanism, the repeated provision of monotonous incentives (ie, providing stimuli with the same intensity) may diminish the perceived value of incentives over time [61]. In contrast, the unique nature of the L-AMCM to offer varying incentives based on users’ responsiveness to incentives (ie, providing stimuli with varying intensities) may keep users from becoming accustomed to intervention prompts to some extent. Furthermore, it would be an interesting research direction to design multicomponent interventions, including incentive adaptation, by considering challenges specific to sedentary behavior. Previous studies have found, for example, that people tend to identify sedentary behavior as a behavior entailing sitting rather than sedentary behavior itself [62]. Hence, sedentary behavior may be habitual and not purposeful [63], and the time
spent in sedentariness was found to be underestimated [64]. This lower awareness of sedentary behavior may make people less aware of its adverse health effects and the health benefits of breaking up long periods of sedentary behavior, possibly leading to decreased motivation toward interventions for preventing sedentary behavior. As an example of how to make people aware of the health risks associated with prolonged sedentariness, the intervention might provide information on behavioral consequences [65]. For example, our mission prompt can be designed to convey specific health outcomes that may result from accepting or rejecting behavioral missions (e.g., “Taking an active break now can reduce the risk of a cardiovascular disease by XX%”).

This feasibility study considered prolonged sedentary behavior, which can be easily detected with an off-the-shelf smartphone [40,57], to avoid technical challenges irrelevant to the L-AMCM. However, we believe that the L-AMCM might be used in a wide range of intervention domains that satisfy certain criteria. The first (but not mandatory) criterion is that unhealthy behavior needs to happen somewhat frequently so that responses to incentives are collected to some extent within a short period and a behavior model is quickly learned. The other criterion is that health behavior or outcome changes should be monitored following the bidding of incentives to track responses to particular incentives. For example, smoking cessation would be a suitable intervention domain for applying the L-AMCM; smoking episodes occur frequently and can be automatically detected despite some technical challenges (e.g., requiring multiple sensor units such as a wrist-worn sensor for detecting wrist-to-mouth movements and a chest-worn sensor for examining inhalation and exhalation [66]).

Conclusions
This study aimed to devise a novel incentive strategy that adjusts incentive magnitude depending on individuals’ behaviors in different contexts and incentives, as well as explore the feasibility of such a strategy via a field trial. To this end, we first developed the LR-based incentive estimation with the expectation that behavior occurrence likelihood would vary by incentive magnitude and context and increase as the incentive grows. However, the 3-week field study showed that users’ actual behaviors were nonconcordant with our expectations. Thus, the proposed incentive strategy showed no statistically significant differences from the fixed incentive strategy. Interestingly, the follow-up analyses revealed that users might be less sensitive to minor changes in incentive magnitudes. Although the proposed incentive strategy failed to show its effectiveness clearly, we believe that this study was the first step toward incentive adaptation for mobile health interventions and hope that it inspires various other researchers to develop and test adaptive incentive strategies.

Acknowledgments
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Conflicts of Interest
None declared.

Multimedia Appendix 1
An algorithm of a logistic regression–based incentive estimation.
[ PNG File, 74 KB - mhealth_v11i1e41660_app1.png ]

Multimedia Appendix 2
A generalized linear mixed model formula.
[ PNG File, 26 KB - mhealth_v11i1e41660_app2.png ]

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Abbreviations

GLMM: generalized linear mixed model  
L-AMCM: loss-framed adaptive microcontingency management

https://mhealth.jmir.org/2023/1/e41660
LR: logistic regression
OR: odds ratio
Promoting Hand Hygiene During the COVID-19 Pandemic: Parallel Randomized Trial for the Optimization of the Soapp App

Dario Baretta¹, PhD; Melanie Alexandra Amrein¹, PhD; Carole Bäder¹, MSc; Gian Giacomo Ruschetti¹, MSc; Carole Rüttimann¹, BSc; Maria Del Rio Carral², PhD; Carlo Fabian³, MA; Jennifer Inauen¹, PhD

¹Institute of Psychology, University of Bern, Bern, Switzerland
²Institute of Psychology, University of Lausanne, Lausanne, Switzerland
³Institute for Social Work and Health, FHNW School of Social Work, Olten, Switzerland

Corresponding Author:
Dario Baretta, PhD
Institute of Psychology
University of Bern
Fabrikstrasse 8
Bern, 3012
Switzerland
Phone: 41 31 684 58 96
Email: dario.baretta@unibe.ch

Abstract

Background: Hand hygiene is an effective behavior for preventing the spread of the respiratory disease COVID-19 and was included in public health guidelines worldwide. Behavior change interventions addressing hand hygiene have the potential to support the adherence to public health recommendations and, thereby, prevent the spread of COVID-19. However, randomized trials are largely absent during a pandemic; therefore, there is little knowledge about the most effective strategies to promote hand hygiene during an ongoing pandemic. This study addresses this gap by presenting the results of the optimization phase of a Multiphase Optimization Strategy of Soapp, a smartphone app for promoting hand hygiene in the context of the COVID-19 pandemic.

Objective: This study aimed to identify the most effective combination and sequence of 3 theory- and evidence-based intervention modules (habit, motivation, and social norms) for promoting hand hygiene. To this end, 9 versions of Soapp were developed (conditions), and 2 optimization criteria were defined: the condition with the largest increase in hand hygiene at follow-up and condition with the highest engagement, usability, and satisfaction based on quantitative and qualitative analyses.

Methods: This study was a parallel randomized trial with 9 intervention conditions defined by the combination of 2 intervention modules and their sequence. The trial was conducted from March to August 2021 with interested participants from the Swiss general population (N=232; randomized). Randomization was performed using Qualtrics (Qualtrics International Inc), and blinding was ensured. The duration of the intervention was 34 days. The primary outcome was self-reported hand hygiene at follow-up, which was assessed using an electronic diary. The secondary outcomes were user engagement, usability, and satisfaction assessed at follow-up. Nine participants were further invited to participate in semistructured exit interviews. A set of ANOVAs was performed to test the main hypotheses, whereas a thematic analysis was performed to analyze the qualitative data.

Results: The results showed a significant increase in hand hygiene over time across all conditions. There was no interaction effect between time and intervention condition. Similarly, no between-group differences in engagement, usability, and satisfaction emerged. Seven themes (eg, “variety and timeliness of the task load” and “social interaction”) were found in the thematic analysis.

Conclusions: The effectiveness of Soapp in promoting hand hygiene laid the foundation for the next evaluation phase of the app. More generally, the study supported the value of digital interventions in pandemic contexts. The findings showed no differential effect of intervention conditions involving different combinations and sequences of the habit, motivation, and social norms modules on hand hygiene, engagement, usability, and satisfaction. In the absence of quantitative differences, we relied on the results from the thematic analysis to select the best version of Soapp for the evaluation phase.

Trial Registration: ClinicalTrials.gov NCT04830761; https://clinicaltrials.gov/ct2/show/NCT04830761

International Registered Report Identifier (IRRID): RR2-10.1136/bmjopen-2021-055971
Introduction

Background

Hand hygiene is an effective behavior for decreasing the transmission of respiratory illnesses [1,2], including COVID-19 [3]. Therefore, recommendations to perform correct hand hygiene at key times have been included in public health guidelines worldwide to counter the spread of COVID-19 [4]. To facilitate the adoption of public health guidelines, the development and evaluation of effective behavior change interventions was identified as a priority of the COVID-19 research agenda, in particular, owing to the fact that limited or no contextualized evidence was available on the effectiveness of behavior change interventions during pandemics [5]. Although evidence synthesis reports became available during the COVID-19 pandemic (July to December 2020), showing a medium, positive effect of hand hygiene interventions developed to counter the spread of various respiratory viruses (eg, influenza virus, respiratory syncytial virus, and adenovirus) [6], their validity and relevance to the COVID-19 pandemic can be questioned. For example, the reviewed studies included interventions targeted at diverse respiratory infections that did not cause pandemics (eg, influenza, flu, and cold) or lead to the spread of a pandemic of the same magnitude as that of the COVID-19 pandemic (eg, pandemic influenza A H1N1).

The need for research on effective behavior change interventions for promoting hand hygiene during a pandemic was further confirmed by the fluctuation in hand hygiene over the course of the COVID-19 pandemic. At first, results indicated high adherence among the public. During the first wave of the pandemic (ie, between March and May 2020), studies suggested that (1) hand hygiene was one of the most adopted protective behaviors against the spread of COVID-19 [7], and (2) the frequency and correctness of hand hygiene behavior in key situations (ie, after coughing, sneezing, blowing one’s nose and upon reaching home or workplace) improved compared with the period before the pandemic outbreak [8,9]. However, research including longer periods of the pandemic showed a decrease in hand hygiene over time. For example, a study conducted from May 2020 to August 2021 showed that almost one-third of the adults from the general population did not comply with hand hygiene recommendations, and some of them had no intention to change their behavior [10]. In addition, there is evidence of significant associations between hand hygiene and indicators of the pandemic trajectory (eg, the increase in recent cases of COVID-19 morbidity is associated with an increase in the frequency of self-reported hand hygiene) [11]. Taken together, the literature suggests that hand hygiene is not consistently performed throughout a pandemic and is prone to variations over time. Therefore, fostering sustained hand hygiene through effective behavior change interventions represented a public health priority to counter the spread of COVID-19 and future pandemics.

During an ongoing pandemic in which social contact should be limited, digital interventions have the advantage that no personal contact is required for their use; moreover, they can be personalized and potentially be integrated into the daily lives of an unlimited number of people. Interventions based on smartphone apps can deliver behavior change techniques [12] in real life that could lead to substantial population-level impact and long-term health behavior change [13]. However, recent reviews have pointed out that there is limited knowledge about how to effectively promote hand hygiene using digital interventions in the general population [6,14].

To address these research gaps, we devised a Multiphase Optimization Strategy (MOST) [15] to develop and test Soapp, an effective smartphone-based behavior change intervention for promoting hand hygiene during the ongoing COVID-19 pandemic [16]. In the preparation phase, we developed 3 intervention modules—tackling habit, motivation, and social norms—based on behavior change theory and empirical evidence [16].

Aim of This Study

This study focused on the optimization phase of Soapp, which aimed to identify the most effective combination and sequence of the developed intervention modules to be included in the subsequent evaluation phase. As described in the study protocol [16], during the optimization phase, we compared 9 different combinations of the 3 developed modules (ie, habit, motivation, and social norms). Overall, 2 optimization criteria were defined to select the best intervention version for the subsequent evaluation phase. The optimization criteria were as follows: (1) the condition with the largest increase in hand hygiene at key times at follow-up (T3) and (2) the condition with the highest engagement, usability, and satisfaction. Regarding the first criterion, we tested the following preregistered hypotheses [16]:

Hypothesis (H) 1; H1: The intervention groups show a significant increase in correct hand hygiene at key times after 4 weeks (T3) of intervention compared with baseline (T1).

H2: The intervention groups significantly differ in the effects of the intervention on correct hand hygiene behavior at key times (T1-T3).

In case of significant between-group differences in hand hygiene at key times, post hoc tests were performed to determine the most effective condition. In addition, we investigated the unique contribution of each module by testing the following hypotheses that were not preregistered:

H3: The intervention groups with the habit module show a significant increase in correct hand hygiene behavior at key times...
times (T1-T3) compared with the groups without the habit module.

H4: The intervention groups with the motivation module show a significant increase in correct hand hygiene behavior at key times (T1-T3) compared with the groups without the motivation module.

H5: The intervention groups with the social module show a significant increase in correct hand hygiene behavior at key times (T1-T3) compared with the groups without the social module.

The second optimization criterion leveraged a combination of quantitative and qualitative methods to explore the participants’ engagement and satisfaction with the app as well as its usability. This criterion was tested using the following hypotheses:

The intervention groups significantly differ in the engagement with (H6), usability of (H7), and satisfaction (H8) with the intervention (T3).

In addition, semistructured interviews were conducted to explore which aspects and features of Soapp were perceived as more usable and more important for supporting engagement and satisfactory experiences after 34 days of using the app.

As secondary outcomes, we had preregistered a series of hypotheses regarding the psychological mechanisms and health impact of the intervention that did not inform the optimization decision. We have reported these in Multimedia Appendix 1 for completion.

Methods

Study Design

The study design for the optimization phase was a double-blind parallel randomized trial. The participants were randomized to 1 of 9 intervention groups in a 1:1:1:1:1:1:1:1:1 ratio and completed 2 consecutive intervention modules, as shown in Figure 1. The total duration of the optimization study (ie, recruitment and data collection) was set to 6 months (start: March 26, 2021) or until a total of 465 participants were enrolled, whichever came first. The duration of the optimization trial for each participant (ie, time between T1 and T3) was 34 days. At the end of the study, as a part of the second optimization criterion, qualitative interviews were conducted with a subsample to collect in-depth information about the engagement with, usability of, and satisfaction with the intervention.

![Figure 1. Intervention optimization. Red diaries represent baseline (T1) and follow-up (T3) assessments for the primary outcome (hand hygiene). R: randomization.](image)

Ethics Approval

This trial is registered at ClinicalTrials.gov (NCT04830761), and the reporting is in line with the CONSORT (Consolidated Standards of Reporting Trials) guidelines [17] (Multimedia Appendix 2). The trial received ethics approval from the Swiss Ethics Committee of the Canton of Bern (ID: 2021-00164).

Participants

The target population for the Soapp app was German-speaking adults from the Swiss population who were interested in using an app to improve hand hygiene behavior. The inclusion criteria were as follows: (1) being aged at least 18 years, (2) owning a smartphone with mobile access to the internet, (3) being
proficient in the German language, and (4) having signed an electronic informed consent form to participate in the study. As presented in the study protocol [16], the initial target sample size for the optimization phase was 387 participants. The sample size was calculated to perform a repeated-measures ANOVA with a within (time: T1-T3)-between (intervention group) interaction. The sample size was determined using an a priori power analysis with G*Power (Heinrich-Heine-Universität Düsseldorf) [18] (β=.80; α=.05; F_S=0.1). Assuming a 20% attrition during the course of the intervention, the target sample size for the study was raised to 465 participants. However, owing to both trial and project timelines, we stopped recruiting after 5 months for a total study duration of 6 months.

A subsample (n=9) participated in qualitative interviews. The recruitment was based on the participants’ willingness to participate in semistructured interviews, as assessed at the end of the last survey (T3). The aim of the qualitative interview was to recruit an even number of participants per intervention module according to hand hygiene adherence: low adherence, medium adherence, and high adherence to hand hygiene. The participants in the ≤33rd percentile were assigned to the low adherence group (3/9, 33%), participants in between the 34th and 66th percentiles were assigned to the medium adherence group (3/9, 33%), and participants in the ≥67th percentile were assigned to the high adherence group (3/9, 33%). The sample size (n=9) was smaller than that reported in the study protocol (n=15) because the recruitment was stopped when theoretical saturation was achieved (ie, no new themes emerged) [19].

Outcomes

Primary Outcome

The primary outcome of the study (ie, the first optimization criterion), the frequency of correct hand hygiene at key times at T3, was assessed via ecological momentary assessment with the support of an electronic diary embedded in Soapp. On diary days (days 2, 8, 16, 24, and 32), the participants were prompted 5 times per day to indicate whether each of the 13 key times to perform hand hygiene defined by the Swiss Federal Office of Public Health had occurred (eg, upon arriving home and after using the toilet; Multimedia Appendix 1). For each situation that occurred, the participants were asked how often they correctly washed or disinfected their hands in that specific situation. The 5-point response scale ranged from never (1) to always (5). The main outcome was operationalized as the mean reported frequency of correct hand hygiene across all the indicated key times and ranged from 1 to 5. To test the H1 and H2, the assessment points considered for hand hygiene behavior were the first diary filled out on day 2 (T1) and the last diary filled out on day 32 (T3).

Secondary Outcomes

Engagement, usability, and satisfaction (ie, the second optimization criterion) were measured at T3. User engagement was assessed using the digital behavior change interventions (DBCI) Engagement Scale [20], a 7-point Likert scale ranging from not at all (1) to extremely (7; Cronbach α=.78). Intervention usability was assessed using the System Usability Scale [21], a 6-point Likert scale ranging from I do not agree at all (1) to I agree completely (6; Cronbach α=.80). Satisfaction was assessed using the Fragebogen zur Messung der Patientenzufriedenheit (ZUF)-8 [22], a 4-point Likert scale ranging from 0 to 3 (Cronbach α=.89).

Other variables assessed during the study but not relevant to the current report are described in the clinical trial registration, and the corresponding results are presented in Multimedia Appendix 1.

Procedure

The participants were recruited via social media (eg, Facebook [Meta Platforms, Inc] and Instagram [Meta Platforms, Inc]), mailing lists, and leaflets with the help of a market research company and with the aim of recruiting a diverse range of people from the German-speaking adult Swiss general population in terms of gender, age, and socioeconomic status. Interested people who clicked on the campaign link were led to a landing page with the study information. Those who chose to continue were redirected to the study page on REDCap (Research Electronic Data Capture; Vanderbilt University) [23] where they could read and watch a video of the study information, fill out an eligibility and consent survey, and sign the e-consent form. After providing electronic informed consent to participate in the study, the participants received a registration code via email and were guided to download the Soapp app from iTunes (Apple Inc) or Google Play Store (Google LLC) and register on it. The day after the registration, the participants received the T1 questionnaire and were then randomized into one of the intervention groups. Randomization was implemented in Qualtrics (Qualtrics International Inc), which preserved the allocation concealment. In addition, the researchers involved in the study were blinded to the intervention assignment, as the participant identifier was pseudoanonymized before randomization. The day after the randomization, the participants filled out the first-hand hygiene diary. The diary included five 1-minute questionnaires per day to avoid retrospective bias in reporting hand hygiene [24].

The optimization trial lasted 34 days and included two 2-week intervention modules (Figure 1). During the first module, the participants filled out the hand hygiene diary on days 2, 8, and 16. After the first module, the participants received a second questionnaire (T2) and a second intervention module, which followed the same structure as the first. After completing the T2, the participants were offered a small gift (ie, a bar of hand soap and a thank you card) to prevent attrition, which was sent to their homes. During the second intervention module, they filled out the hand hygiene diaries on days 24 and 32. At the end of the second module, the participants received the final questionnaire (T3). The participants were given the chance to win 1 of 3 iPhones (Apple Inc) 12s after both the optimization and evaluation phases of the study were completed. The questionnaires and diaries were integrated into Qualtrics services using Soapp’s application programming interface, and the participants’ data were stored on Qualtrics.

The participants who were given the option and volunteered to participate in the qualitative study were interviewed via telephone by a study team member (CB). This 30-minute interview was recorded and included questions about the
usability of the app and the overall experience with the intervention modules in terms of satisfaction and engagement (Multimedia Appendix 3).

**Intervention**

In the optimization phase, each arm of the parallel randomized trial was characterized by a unique combination and sequence of 2 of the 3 intervention modules: motivation, habit, and social norms (Figure 1). The modules were defined as the outcome of the preparation phase in which a theory- and evidence-based approach was followed. The resulting content is synthesized in Table 1 and detailed in supplemental material 1 of the protocol paper [16].
Table 1. Contents of the modules.

<table>
<thead>
<tr>
<th>Module, TDF domain, and behavioral predictor</th>
<th>Behavior change technique</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic</td>
<td></td>
</tr>
<tr>
<td>Goals</td>
<td></td>
</tr>
<tr>
<td>Intention</td>
<td>1.1 Goal setting (behavior)</td>
</tr>
<tr>
<td>Skills</td>
<td></td>
</tr>
<tr>
<td>Skills</td>
<td>4.1 Instruction on how to perform behavior</td>
</tr>
<tr>
<td>Knowledge</td>
<td></td>
</tr>
<tr>
<td>Knowledge</td>
<td>5.1 Information about health consequences</td>
</tr>
<tr>
<td>Environmental context and resources</td>
<td></td>
</tr>
<tr>
<td>Resources and material resources (availability and management)</td>
<td>1.4 Action planning</td>
</tr>
<tr>
<td>Motivation</td>
<td></td>
</tr>
<tr>
<td>Goals</td>
<td></td>
</tr>
<tr>
<td>Intention</td>
<td>1.1 Goal setting (behavior)</td>
</tr>
<tr>
<td>Beliefs about consequences</td>
<td></td>
</tr>
<tr>
<td>Risk perception</td>
<td>5.1 Information about health consequences</td>
</tr>
<tr>
<td>Attitude</td>
<td>5.2 Salience of consequences</td>
</tr>
<tr>
<td>Outcome expectancies</td>
<td>9.2 Pros and cons</td>
</tr>
<tr>
<td>Intention</td>
<td>5.2 Salience of consequences</td>
</tr>
<tr>
<td>Beliefs about capabilities</td>
<td></td>
</tr>
<tr>
<td>Self-efficacy</td>
<td>1.2 Problem solving</td>
</tr>
<tr>
<td></td>
<td>15.1 Verbal persuasion about capabilities</td>
</tr>
<tr>
<td></td>
<td>15.3 Focus on past success</td>
</tr>
<tr>
<td>Reinforcement</td>
<td></td>
</tr>
<tr>
<td>Intention</td>
<td>10.9 Self-reward</td>
</tr>
<tr>
<td>Habit</td>
<td></td>
</tr>
<tr>
<td>Knowledge</td>
<td></td>
</tr>
<tr>
<td>Knowledge</td>
<td>4.2 Information about antecedents</td>
</tr>
<tr>
<td>Memory, attention, and decision processes</td>
<td></td>
</tr>
<tr>
<td>Action control</td>
<td>2.3 Self-monitoring of behavior</td>
</tr>
<tr>
<td>Goals</td>
<td></td>
</tr>
<tr>
<td>Action planning</td>
<td>1.4 Action planning</td>
</tr>
<tr>
<td></td>
<td>7.1 Prompts and cues</td>
</tr>
<tr>
<td>Skills and goals</td>
<td></td>
</tr>
<tr>
<td>Habit strength</td>
<td>8.1 Behavioral practice and rehearsal</td>
</tr>
<tr>
<td></td>
<td>8.3 Habit formation</td>
</tr>
<tr>
<td>Behavioral regulation</td>
<td></td>
</tr>
<tr>
<td>Habit strength</td>
<td>7.1 Prompts and cues (physical cue)</td>
</tr>
<tr>
<td>Social norms</td>
<td></td>
</tr>
</tbody>
</table>
The modules were delivered to the participants via their personal smartphones through the study app Soapp. They were comparable in terms of user time and extent of content, and each module took 2 weeks to be completed. In addition, each intervention condition included a basic module that provided information on hand hygiene to all the participants. During the configuration process, the Soapp app underwent various iterative testing cycles to refine the content of each module and improve usability. The Soapp app contained all the information required to use it, and there was no direct contact with the study team.

**Data Analysis**

**Handling of Missing Data**

Missing data were handled according to the intention-to-treat (ITT) principle [25]. The ITT analysis included all randomized participants. It ignores noncompliance, protocol deviations from the intervention modules, and anything that occurs after randomization. ITT analysis avoids overoptimistic estimates of the efficacy of an intervention resulting from the removal of noncompliers by accepting that noncompliance and protocol deviations that are likely to occur in practice. In line with previous research [26], missing data for hand hygiene behavior were replaced using the last observation carried forward approach.

**Hypothesis Testing**

To test the hypotheses related to the first optimization criterion, a repeated-measures ANOVA with a within-between interaction was used. The within effect was represented by the difference in hand hygiene between T1 and T3 (H1), whereas the within-between interaction was represented by the change in correct hand hygiene behavior between T1 and T3 across all 9 intervention groups (H2). If the groups differed significantly, post hoc tests were performed to identify the most effective intervention group. To test hypotheses H3, H4, and H5, 3 dummy variables were created: habit exposure, motivation exposure, and social exposure. These variables indicated whether a participant was exposed to the corresponding module during the intervention. Then, 3 repeated-measures ANOVAs, 1 for each dummy variable, with a within-between interaction were performed. Each ANOVA tested the interaction between time and the exposure to a specific module (Table 2). Finally, for the second optimization criterion, three 1-way ANOVAs were performed to test differences across conditions at T3 in terms of engagement (H6), usability (H7), and satisfaction (H8). For all the hypotheses, a set of sensitivity analyses with robust and nonparametric (ie, Kruskal-Wallis test) ANOVAs was performed to account for potential unequal sample sizes and nonnormal distribution of the data.
Table 2. Summary of hypothesis tests.

<table>
<thead>
<tr>
<th>H</th>
<th>Preregistered</th>
<th>Dependent variable</th>
<th>Within factor (time)</th>
<th>Between factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>Yes</td>
<td>Hand hygiene</td>
<td>T1-T3</td>
<td>N/A&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>H2</td>
<td>Yes</td>
<td>Hand hygiene</td>
<td>T1-T3</td>
<td>Intervention groups</td>
</tr>
<tr>
<td>H3</td>
<td>No</td>
<td>Hand hygiene</td>
<td>T1-T3</td>
<td>Habit exposure</td>
</tr>
<tr>
<td>H4</td>
<td>No</td>
<td>Hand hygiene</td>
<td>T1-T3</td>
<td>Motivation exposure</td>
</tr>
<tr>
<td>H5</td>
<td>No</td>
<td>Hand hygiene</td>
<td>T1-T3</td>
<td>Social exposure</td>
</tr>
<tr>
<td>H6</td>
<td>No</td>
<td>Engagement</td>
<td>N/A</td>
<td>Intervention groups</td>
</tr>
<tr>
<td>H7</td>
<td>No</td>
<td>Usability</td>
<td>N/A</td>
<td>Intervention groups</td>
</tr>
<tr>
<td>H8</td>
<td>No</td>
<td>Satisfaction</td>
<td>N/A</td>
<td>Intervention groups</td>
</tr>
</tbody>
</table>

<sup>a</sup>H: hypothesis.
<br><sup>b</sup>N/A: not applicable.

**Analytical Software**

The packages `ez` and `WRS2` from the statistical software R (version 4.1.2; R Foundation for Statistical Computing) were used to perform parametric and robust ANOVAs, respectively. The data and R code used for the main analyses are available on the Open Science Framework repository platform [27].

**Qualitative Analysis**

Postintervention user engagement, usability, and satisfaction were explored using semistructured interviews. The interviews were transcribed verbatim, and the transcripts were analyzed using thematic analysis [28]. Thematic analysis is characterized by six phases: (1) familiarizing oneself with the data, (2) generating initial codes, (3) searching for themes, (4) reviewing themes, (5) defining and naming themes, and (6) producing the report. Data and repeated patterns that were considered pertinent to the aims of the study were coded by a coauthor (CR). New inductive codes were labeled as they were identified during the coding process, and the results of the coding process were iteratively discussed by 2 coauthors (CR and JI). The next stage involved searching for themes; CR reviewed the codes one by one, organizing the findings to combine different codes that focus on similar aspects. The ordered data were reviewed and revised in discussion among 3 coauthors (CR, JI, and DB) and were subsequently organized into themes. The resolution of disagreements and agreement on the final themes was achieved through discussion among CR, JI, and DB. After defining and naming the themes, examples of relevant transcripts were selected to illustrate them. The data were analyzed in their original language to preserve their original meanings. Illustrative quotes were translated by CR. Conclusions were drawn on the possible improvement of Soapp to optimize the effectiveness and usability of the intervention for the evaluation phase.

**Results**

**Overview**

The recruitment for the optimization trial began on March 27, 2021, and ended on July 28, 2021. T3 data were collected between April 29 and August 25, 2021. Because of both trial and project timelines, we stopped the trial 6 months after the start of the study, with the recruitment lasting for 5 months. Overall, 232 participants were recruited and randomized into 1 of the 9 intervention conditions. Among these 232 participants, 14 (6%) participants did not fill out any of the 5 hand hygiene diaries, whereas 27 (11.6%) participants did not complete the first diary at T1. Another (1/232, 0.4%) participant completed the first diary but did not encounter any of the key situations to perform hand hygiene during that day. Therefore, these (42/232, 18.1%) participants were excluded from the analysis because the main outcome (ie, hand hygiene) at T1 was missing. Of the 232 participants who were randomized, 190 (81.9%) filled out the hand hygiene diary at T1, and 118 (62.1%; 50.9% of the randomized participants) of them filled out the hand hygiene diary at T3. Figure 2 shows the participants’ flow through randomization, T1 diary assessment, and T3 diary assessment for each intervention group. For the secondary analysis, we included only those participants who filled out the T3 panel assessment because the dependent variables were assessed only at T3.
Figure 2. Participant recruitment flow. The intervention groups are specified as follows: H-H: habit-habit; H-M: habit-motivation; H-S: habit-social; M-H: motivation-habit; M-M: motivation-motivation; M-S: motivation-social; S-H: social-habit; S-M: social-motivation; and S-S: social-social. T1: baseline; T3: follow-up.

T1 Characteristics
Sociodemographic and hand hygiene behaviors at T1 are reported in Multimedia Appendix 4. The figures refer to the 190 participants who filled out the first diary at T1. The mean age of the participants was 39.9 (SD 15.9) years. Of the 190 participants, 139 (73.2%) were women, 125 (65.8%) had high school qualifications, 101 (53.2%) were employed, and 49 (25.8%) were living alone. Descriptive statistics for hand hygiene behavior (mean 4.01, SD 0.82; median=4.17; skewness=−1.24) suggested that hand hygiene behavior was already high at T1, with a moderate left-tailed distribution.

Dropout analysis was performed to investigate T1 differences between the participants who completed the study and those who dropped out at any point during the intervention. We analyzed all the 232 randomized participants, and those who did not complete the last panel assessment at T3 were categorized as dropouts (n=83, 36%). The results suggested no T1 differences between dropouts and retainers with respect to age ($F_{1,230}=2.17; P=.14$), sex ($\chi^2_1=0.4; P=.55$), hand hygiene ($F_{1,229}=0.24; P=.63$), or intention to increase hand hygiene behavior ($F_{1,230}=0.72; P=.40$).
First Optimization Criterion: Change in Hand Hygiene Behavior

The main effects of time and the interaction between time and the intervention groups are reported in Table 3. The main effect of time ($F_{1,181}=10.95; P=.001$) was statistically significant (H1) whereas the interaction between the intervention groups and time was not (H2). The results pertaining to H3, H4, and H5 suggested no effect of the exposure to a specific module during the course of the intervention. Sensitivity analysis using a robust approach confirmed the same results (Multimedia Appendix 4). In addition, as a part of a further sensitivity analysis, the main hypotheses were tested without applying any missing value imputation algorithm. The results are available in Multimedia Appendix 4 and confirm the time effect and the null findings for the interaction effect.

Table 3. Main effects and interactions among modules on hand hygiene behavior at key times (N=232).

<table>
<thead>
<tr>
<th>H², outcome, and factor</th>
<th>Participants, n (%)</th>
<th>Parametric ANOVA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>F test (df)</td>
</tr>
<tr>
<td>H1 and H2</td>
<td>190 (81.9)</td>
<td></td>
</tr>
<tr>
<td>Hand hygiene</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group</td>
<td>0.33 (8)</td>
<td>.95</td>
</tr>
<tr>
<td>Time (T1-T3)</td>
<td>10.95&lt;sup&gt;d&lt;/sup&gt; (1)</td>
<td>.001</td>
</tr>
<tr>
<td>Time × group</td>
<td>1.19 (8)</td>
<td>.31</td>
</tr>
<tr>
<td>H3</td>
<td>190 (81.9)</td>
<td></td>
</tr>
<tr>
<td>Hand hygiene</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Habit</td>
<td>1.25 (1)</td>
<td>.27</td>
</tr>
<tr>
<td>Time (T1-T3)</td>
<td>10.87 (1)</td>
<td>.001</td>
</tr>
<tr>
<td>Time × habit</td>
<td>1.07 (1)</td>
<td>.30</td>
</tr>
<tr>
<td>H4</td>
<td>190 (81.9)</td>
<td></td>
</tr>
<tr>
<td>Hand hygiene</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Motivation</td>
<td>0.00 (1)</td>
<td>.99</td>
</tr>
<tr>
<td>Time (T1-T3)</td>
<td>10.86 (1)</td>
<td>.001</td>
</tr>
<tr>
<td>Time × motivation</td>
<td>0.94 (1)</td>
<td>.33</td>
</tr>
<tr>
<td>H5</td>
<td>190 (81.9)</td>
<td></td>
</tr>
<tr>
<td>Hand hygiene</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social</td>
<td>0.75 (1)</td>
<td>.39</td>
</tr>
<tr>
<td>Time (T1-T3)</td>
<td>10.83 (1)</td>
<td>.001</td>
</tr>
<tr>
<td>Time × social</td>
<td>0.41 (1)</td>
<td>.52</td>
</tr>
<tr>
<td>H6</td>
<td>148 (63.8)</td>
<td></td>
</tr>
<tr>
<td>Engagement</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group (T3)</td>
<td>2.19 (8)</td>
<td>.03</td>
</tr>
<tr>
<td>H7</td>
<td>148 (63.8)</td>
<td></td>
</tr>
<tr>
<td>Usability</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group (T3)</td>
<td>2.46 (8)</td>
<td>.02</td>
</tr>
<tr>
<td>H8</td>
<td>148 (63.8)</td>
<td></td>
</tr>
<tr>
<td>Satisfaction</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group (T3)</td>
<td>1.46 (8)</td>
<td>.18</td>
</tr>
</tbody>
</table>

<sup>a</sup>H: hypothesis.
<sup>b</sup>Partial eta–squared corresponds to the proportion of variance explained by a variable that is not explained by other variables.
<sup>c</sup>Group: intervention group.
<sup>d</sup>Italicized values indicate significance.
Second Optimization Criterion: Participant Engagement, Usability, and Satisfaction

Quantitative Analysis

The effects of the intervention group on engagement, usability, and satisfaction are shown in Table 3. The results of the parametric ANOVA suggested that the self-reported measures of engagement ($F_{1,139}=2.19; \ P=.03$) and usability ($F_{1,139}=2.46; \ P=.02$) differed across the 9 intervention groups. Nonparametric ANOVA with Kruskal-Wallis test showed significant differences across the intervention groups only for usability ($\chi^2=16.1; \ P=.04$). However, both parametric and nonparametric post hoc score differences in engagement and usability between any pair of intervention groups.

Qualitative Analysis

Overview

Across 9 interviews, 7 themes emerged in relation to the research question (refer to Multimedia Appendix 5 for a summary of the themes and for additional extracts illustrating each theme). The themes were named “user experience and app functionality,” “importance of guidance,” “variety and timeliness of the task load,” “reasons for participation,” “change in awareness of hand hygiene and its implications,” “social interaction,” and “personal relevance.” In addition, the following 2 subthemes were identified as a part of the “social interaction” theme: “personal communication and connectedness” and “social comparison.”

User Experience and App Functionality

The first theme that emerged concerned the user experience with the general aesthetics and functionalities of the app. Overall, satisfaction with the intuitive and simple handling of the app was high. The participants considered the usability to be pleasant. Regarding the app aesthetics, some participants were very satisfied with the simplicity of the layout; however, the majority would have preferred more visual structures:

What I liked in particular? Actually, how things were presented. Just the simplicity—all in all it was very simple. [P7, habit-habit, moderate adherence]

Another point on which most participants agreed was that certain features of the app showed technical flaws, which negatively affected their motivation:

So, when this annoying technical problem occurred—if you were to draw a curve now, it [my motivation] went up quite steadily at the beginning, and then slowly decreased due to this technical problem, and then when it was resolved it [my motivation] got back up again. [P5, motivation-social, high adherence]

Importance of Guidance

Throughout the interviews, the participants regularly highlighted the importance of receiving guidance within the app. Specifically, they mentioned the importance of clarity and meaning regarding the tasks that the app asked them to do:

I also thought it was nice that you kind of knew in the morning “ah today is a day with a big survey,” so that you could already plan “okay, today there are maybe a little bit more push messages coming in and I have to pay a little bit more attention.” [P2, habit-habit, high adherence]

The importance of guidance was also manifested as the need for a better overview of the participants’ journey during the study. For instance, some participants would have liked more background information about the study to better understand the timeline or the reasons behind receiving certain tasks:

And otherwise maybe somehow a little bit more background information about what—why am I being asked these questions, so that I can see even more behind this algorithm and behind this concept and then it would become clearer to me why the same questions keep coming. So, a little bit, so even more background knowledge. [P3, social-habit, low adherence]

Although guidance was acknowledged as important, too much direction was also perceived as overwhelming, for example, very frequent push notifications:

Was that now at 10 o’clock, at 12 o’clock or at 2 o’clock, I do not remember any more in which intervals the push messages came in. At the end, I no longer knew at what point I had received the last push notification—there, I lost overview. [P2, habit-habit, high adherence]

Variety and Timeliness of the Task Load

Variety in daily engagement with the content of the app emerged as a central topic in the interviews. A few participants were satisfied with the degree of variety in the task load and the timing of the content offered by the intervention. However, most participants wished for substantially more variety in the task load and timing, particularly toward the end of the intervention:

Sometimes, it was just quiet, nothing happened. But later, once again it came “today something is happening,” yes, I liked that. [P2, habit-habit, high adherence]

Towards the end, when there were fewer and fewer exercises, I found it almost a bit boring. [P7, habit-habit, moderate adherence]

Reasons for Participation

In most interviews, the participants mentioned their initial reasons for participating in the study. One of the most frequently reported motives was curiosity and an interest in learning something new:

I thought, “yeah, sure, I can wash my hands. But do I know everything when they do a study? I could still learn something at the end, I’m not omniscient.” And that’s actually what mainly motivated me, this openness, I’m curious to see what else there is to learn. [P1, habit-habit, moderate adherence]
The participants also elaborated on why they kept using the app. One of the cited motives was the perceived obligation to complete the study:

Well, it [my motivation] certainly did not increase, it was more a matter of persevering—in the sense of whoever says A must also say B. It was said that you could drop out at any time, but still. [P9, motivation-motivation, low adherence]

Change in Awareness of Hand Hygiene and Its Implications

A further theme was represented by the increase in participants’ hand hygiene awareness owing to the use of the app. The change in awareness seemed to have been generated by the fact that participants paid more attention to the self-monitoring of the target behavior:

That was simply my observation of my reaction then—you observe yourself during these four weeks incredibly—I do not know if you have also heard this from other people, but you start watching yourself. [P5, motivation-social, high adherence]

The change in awareness generated a positive loop that led to an increase in the frequency of hand hygiene behavior together with a shift in perception of the issue of hand hygiene and its implications:

I certainly washed my hands more than I had before. And therefore, I have the feeling that I have certainly benefitted from it [the intervention]. [P4, habit-motivation, high adherence]

Social Interaction

The theme of social interaction came up several times during most interviews. Two subthemes define this main theme according to the different social aspects that came to light during the interviews: personal communication and connectedness and social comparison.

Subtheme 1: Personal Communication and Connectedness

Some participants particularly appreciated that the app communicated with them in a personal manner. This led to a feeling of authenticity; therefore, these participants no longer had the impression of interacting with a machine when using the app:

You can say that there is someone behind it. I never felt alone, it was not a one-way kind of communication. I always knew that behind these tasks was indeed a computer, but I still felt connected in a way. [P2, habit-habit, high adherence]

By contrast, other participants would have preferred an even more human-centered mode of delivery of the app content, for example, receiving direct motivational support from other humans:

Maybe, despite everything, a video or something like that—or actually, as is often the case nowadays: a small video with other participants who motivate you. Because reading statistics and news is something else than when someone speaks directly to you. [P8, social-habit, low adherence]

Some participants described having developed a feeling of connectedness with other app users over time. This led to a sense of community, which made them feel supported:

And then I think I had to answer this question three times. And at the end, I think that was at the final question, I thought “yes, I think it is cool that they are taking part, I do not know them, but I think it is cool that they are taking part, and I feel connected to them.” [P2, habit-habit, high adherence]

Subtheme 2: Social Comparison

The participants who were exposed to the social module shared different opinions regarding the opportunity to compare their behavior with that of other participants, which was a feature of the social module only. Indeed, although some participants expressed avoidance of social comparison and fatigue with the competition it created for them, others were pleased about the comparison with other users:

For me, personally, it was too much with the community and otherwise, because others cannot motivate me. Whether someone somehow achieved 100% or 50%, that is actually relatively indifferent to me. And it does not encourage me to become more or less active or whatever. [P8, social-habit, low adherence]

Wish for Personalization

An issue raised by almost every participant was the lack of personal relevance that the list of key moments for hand hygiene entailed. Being regularly asked about key situations that never occurred for them (eg, not having children or not wearing contact lenses) led to a decrease in motivation to fill out the hand hygiene diaries:

Things are asked again and again, which do not concern you at all. This leads to a decrease in motivation. Now, I have to spend five minutes filling out the form again, even though it does not apply. [P3, social-habit, low adherence]

The desire to personalize the app also came up in relation to other intervention content, such as the number of push notifications:

But maybe in the beginning you should be able to specify “I would rather have a little more [push notifications] or a little less.” But what I have received, however, has been right for me. [P2, habit-habit, high adherence]

Discussion

Principal Findings

As part of a MOST to develop and test a smartphone-based hand hygiene intervention during the COVID-19 pandemic, this intervention optimization parallel randomized trial aimed to identify the best combination of intervention modules to be included in the subsequent evaluation phase of SoApp. The results from the main analyses confirmed that the participants who participated in the study increased the frequency of correct
hand hygiene at key times over time (H1). However, the intervention groups did not differ in their effects on correct hand hygiene at key times (H2). Similarly, the exposure to specific modules was not associated with increased hand hygiene over time (H3, H4, and H5). Taken together, the findings related to the first optimization criterion suggested a promising increase in hand hygiene during the intervention period but did not provide scientific evidence to support the preference of one version of Soapp or a specific module over the others. Similarly, the quantitative results from the second optimization criterion (H6, H7, and H8) did not show any differences in engagement, usability, and satisfaction among the 9 intervention modules at T3.

By contrast, the qualitative results revealed what characteristics and features of Soapp the participants perceived as supportive or, conversely, detrimental in terms of engagement, usability, and satisfaction. The finding that the aesthetics and design of the app are important for participants to better enjoy their interaction with Soapp is in line with a previous study on health-related behavior change [29]. The participants expressed the desire for an app that is simple to use, intuitive, and not cognitively demanding and that allows a smooth use of its functionalities. Such fundamental characteristics are deemed to guarantee satisfactory and engaging user experiences with Soapp. A second relevant aspect raised by the interviewed participants is the desire to receive clear guidance about the tasks that the app proposes and the rationale behind them. The participants also appreciated when they received (1) information regarding the behavior change intervention they committed to and (2) suggestions (eg, tips and problem-solving strategies) on how to adhere to correct hand hygiene. However, to prevent declining engagement, the delivery of guiding content should be balanced and not overwhelming (eg, push notifications). These findings are in line with those found in a previous systematic review and empirical research on engagement with digital behavior change interventions [30-32]. A further topic is variety in the daily interactions with the app and the proposed tasks and activities. A task load that varies daily (ie, days with more tasks and days with fewer tasks) seems to be important for sustaining engagement with Soapp. In addition, the regular provision of content over the course of the intervention was considered an important aspect of the app that might require some improvements. This aspect is of particular relevance, as the receipt of an optimal dose of engagement may increase the effectiveness of digital interventions [30]. Another theme that emerged during the interviews concerned the reasons that led the participants to join and remain engaged with the study. Although curiosity and interest to learn new things were important in triggering initial engagement, perceived obligation was a reason to maintain engagement over time. This result provides further support to participants’ demand for a better distributed workload and content over the course of the use of Soapp. On the content side, as in a previous study about adults’ perspectives on health behavior change apps [33], the participants appreciated those features that foster an increased sense of awareness around the target health-related behavior (ie, hand hygiene) and the resulting benefits. These results are in line with recent research conducted during the COVID-19 pandemic suggesting that self-monitoring is positively associated with hand washing [34]. Interestingly, the participants reported that the awareness formed mostly because of filling out the hand hygiene diaries that were included in the study as assessment tools and not as behavior change techniques (ie, self-monitoring). This aspect underscores how assessment tools and intervention strategies were not distinguished from one another by the participants but were perceived as part of the same user experience. A further theme that was at the center of the participants’ comments regarded social interaction. Consistent with previous findings [30-32,35], features supporting a sense of relatedness owing to both a human-centered communication style (ie, tone of voice) and a feeling of connectedness were considered necessary to create social commitment and, ultimately, for engagement and satisfactory interactions with Soapp. Such a sense of relatedness was generated by the general user experience provided by the app (eg, communication style) and was not related to the features delivered by the social norm module. By contrast, in line with previous findings regarding health-related digital interventions [29,31-33,35], a dual perspective emerged in relation to the features that purposefully provided opportunities for social comparison and were part of the social norms module. Indeed, although some participants expressed avoidance of social comparison because they considered their behavior change journey as a personal dimension of their life, others were pleased about the comparison with other users. Therefore, social comparison features can be seen as a 2-edged sword for engagement, as the preference for such features is expected to vary across individuals. Eventually, the participants believed that receiving more personally relevant content would strengthen their engagement with Soapp. Such comments were partially generated by the participants’ experiences in filling out hand hygiene diaries that refer to key times that are not relevant to them.

Implications for the Evaluation Phase of Soapp

Owing to the null findings of the first optimization criterion, we were not able to identify the best intervention group based on the quantitative analysis of the primary outcome. Similarly, no between-group differences emerged in relation to the second optimization criterion (ie, engagement, usability, and satisfaction). Therefore, we relied on the results of the thematic analysis to derive implications for the evaluation phase of Soapp. The resulting intervention design decisions based on this optimization study are summarized in Table 4.
To overcome this issue and in line with the ITT approach, we made hand hygiene less of a priority for potential participants. The enrollment period flattened in Switzerland, which may have contributed to filling an existing research gap and improving the scientific knowledge on the most effective behavior change strategies to promote hand hygiene during a pandemic. This aspect is extremely relevant because digital interventions do not require personal contact and can be integrated into the daily lives of an unlimited number of people. Furthermore, our findings contributed to filling an existing research gap and improving the scientific knowledge on the most effective behavior change strategies to promote hand hygiene during a pandemic. Ultimately, Soapp represents a promising ready-to-go digital tool to be used in cases of future pandemics.

### Table 4. Intervention design recommendations for the evaluation phase of Soapp.

<table>
<thead>
<tr>
<th>Recommendation</th>
<th>Rationale</th>
</tr>
</thead>
<tbody>
<tr>
<td>The social module is excluded from the next evaluation phase.</td>
<td>Habit and motivation modules seem best suited to leverage some of the themes that emerged during the thematic analysis. For instance, themes such as change in awareness and guidance can be better supported by the app features that characterize these modules (ie, action planning tasks, self-monitoring, opportunity to schedule custom reminder, and video on health implication). In addition, the social module might be detrimental for engagement, as it embeds social comparison features, which were perceived as counterproductive by some users.</td>
</tr>
<tr>
<td>A parallel delivery of modules is preferable over a sequential one.</td>
<td>The specific sequence of intervention modules (ie, habit-motivation vs motivation-habit) was not associated with differences in hand hygiene. Therefore, according to the participants’ needs identified as part of the theme “variety and timeliness of the task load,” a parallel delivery of the selected intervention modules is preferable.</td>
</tr>
<tr>
<td>Define a more even distribution of the intervention content and notifications over the course of the study.</td>
<td>A parallel delivery of the modules would allow to distribute each module’s content and tasks over 32 days instead of 16 days, as done during the optimization phase. Therefore, there is more flexibility to define the timeline of the intervention with the aim of balancing the daily task load and, ultimately, guaranteeing a more suited dose of content over the course of the intervention.</td>
</tr>
</tbody>
</table>

### Limitations
This study is not without limitations. A main weakness is the sample size achieved for testing the main hypotheses. Indeed, an a posteriori achieved power of 0.44 (n=190, 81.9%; α=.05; partial η²=0.01) suggests that the probability of detecting a true effect of the intervention groups was lower than the recommended standard (ie, 0.80). Different factors contributed to the collection of data from a limited sample of 190 participants. First, we stopped recruitment 5 months after the start of the study, although the target sample size was not achieved. As specified in the study protocol, the criterion of discontinuing the enrollment of participants after 5 months was based on the constraints of the project timeline [16]. This resulted in a sample of 232 randomized participants. A second reason is the dropouts between randomization and T1 assessment. The T1 assessment was scheduled for the day after randomization; however, some (42/232, 18.1%) participants who had been randomized did not complete it. Therefore, they were excluded from the main analyses.

A further limitation that affected the analysis of the primary outcome was attrition. Of the 190 participants who filled out the T1 diary, 118 (62.1%) completed the diary at T3, leading to 38% and 49% attrition compared with the T1 and randomization figures, respectively. The attrition rate was higher than the estimated rate (ie, 20%). To account for potential differences between dropouts and retainers, we conducted a dropout analysis to investigate whether they differed in regard to key variables such as age, sex, hand hygiene, and intention to increase hand hygiene behavior. Because no significant differences emerged, we considered the participants who completed the study to be representative of our target population (ie, adults interested in using an app to improve hand hygiene behavior). A possible explanation for attrition could be the possibility that the longitudinal study design with 5 diary days and further quasidaily tasks might have generated an interaction fatigue. In addition, the pandemic trajectory during the enrollment period flattened in Switzerland, which may have made hand hygiene less of a priority for potential participants. To overcome this issue and in line with the ITT approach, we used the last observation carried forward method to replace the missing observations in the T3 diary with the latest available diary assessment. However, it should be noted that this method is based on the assumption that behavior is stable and, therefore, might have introduced bias.

Furthermore, the recruited sample was characterized by a high prevalence of women (ie, 139/190, 73.2%). This imbalance was in line with previous research on hand hygiene during the COVID-19 pandemic [11]. A plausible explanation for this gender imbalance might be that during the COVID-19 pandemic, women tended to show higher levels of worry and fear of the pandemic and were keener to adopt protective behaviors such as hand hygiene [11,36]. Finally, the self-reported measurement of hand hygiene may be biased. The use of an electronic diary to measure hand hygiene behavior at key times should have had limited retrospective bias. However, social desirability cannot be disregarded. In addition, thematic analysis indicated that the diary may have worked as an unintentional behavior change technique (ie, self-monitoring).

### Conclusions
This study described the optimization phase of Soapp, a smartphone app for promoting hand hygiene in the context of the COVID-19 pandemic. By leveraging digital technologies and MOST, we addressed the call raised by public health experts for developing evidence-based behavior change interventions that are designed and optimized to be effective in a pandemic context [5]. In this regard, we provided support for the feasibility and effectiveness of digital interventions promoting hand hygiene behavior during an ongoing pandemic. This aspect is extremely relevant because digital interventions do not require personal contact and can be integrated into the daily lives of an unlimited number of people. Furthermore, our findings contributed to filling an existing research gap and improving the scientific knowledge on the most effective behavior change strategies to promote hand hygiene during a pandemic. Ultimately, Soapp represents a promising ready-to-go digital tool to be used in cases of future pandemics.
Acknowledgments

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Authors' Contributions

DB was involved in formal analysis and the writing of the original draft. MAA contributed to conceptualization and methodology. MDRC and CF contributed to qualitative methodology. GGR contributed to resource accumulation and data curation. CB contributed to resource accumulation, data curation, and qualitative methodology. CR was involved in formal qualitative analysis and the writing of the qualitative report. JI contributed to funding acquisition, conceptualization, methodology, formal qualitative analysis, and supervision. All the authors were involved in discussion and in writing, reviewing, and editing the manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Hand hygiene items and secondary hypothesis testing. [DOCX File, 267 KB - mhealth_v11i1e43241_app1.docx ]

Multimedia Appendix 2

CONSORT (Consolidated Standards of Reporting Trials) checklist. [DOCX File, 41 KB - mhealth_v11i1e43241_app2.docx ]

Multimedia Appendix 3

Qualitative interview guide. [DOCX File, 15 KB - mhealth_v11i1e43241_app3.docx ]

Multimedia Appendix 4

Supplement to quantitative results. [DOCX File, 76 KB - mhealth_v11i1e43241_app4.docx ]

Multimedia Appendix 5

Summary and quotes from the thematic analysis. [DOCX File, 23 KB - mhealth_v11i1e43241_app5.docx ]

References


Abbreviations

CONSORT: Consolidated Standards of Reporting Trials
DBCI: digital behavior change interventions
H: hypothesis
ITT: intention-to-treat
MOST: Multiphase Optimization Strategy
REDCap: Research Electronic Data Capture
T1: baseline
T3: follow-up
ZUF: Fragebogen zur Messung der Patientenzufriedenheit

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Associations Between Product Type and Intensity of Tobacco and Cannabis Co-use on the Same Day Among Young Adult Smokers: Smartphone-Based Daily-Diary Study

Nhung Nguyen¹,², PhD; Johannes Thrul³,⁴,⁵, PhD; Torsten B Neilands⁶, PhD; Pamela M Ling¹,², MD, MPH

¹Center for Tobacco Control Research and Education, University of California San Francisco, San Francisco, CA, United States
²Division of General Internal Medicine, University of California San Francisco, San Francisco, CA, United States
³Department of Mental Health, Bloomberg School of Public Health, Johns Hopkins University, Baltimore, MD, United States
⁴Sidney Kimmel Comprehensive Cancer Center at Johns Hopkins, Baltimore, MD, United States
⁵Centre for Alcohol Policy Research, La Trobe University, Melbourne, Australia
⁶Center for AIDS Prevention Studies, Division of Prevention Science, University of California San Francisco, San Francisco, CA, United States

Corresponding Author:
Nhung Nguyen, PhD
Center for Tobacco Control Research and Education
University of California San Francisco
530 Parnassus Ave
San Francisco, CA, 94143
United States
Phone: 1 415 476 2265
Email: Nhung.Nguyen@ucsf.edu

Abstract

Background: Co-use of tobacco and cannabis is highly prevalent among young US adults. Same-day co-use of tobacco and cannabis (ie, use of both substances on the same day) may increase the extent of use and negative health consequences among young adults. However, much remains unknown about same-day co-use of tobacco and cannabis, in part due to challenges in measuring this complex behavior. Nuanced understanding of tobacco and cannabis co-use in terms of specific products and intensity (ie, quantity of tobacco and cannabis use within a day) is critical to inform prevention and intervention efforts.

Objective: We used a daily-diary data collection method via smartphone to capture occurrence of tobacco and cannabis co-use within a day. We examined (1) whether the same route of administration would facilitate co-use of 2 substances on the same day and (2) whether participants would use more tobacco on a day when they use more cannabis.

Methods: This smartphone-based study collected 2891 daily assessments from 147 cigarette smokers (aged 18-26 years, n=76, 51.7% female) during 30 consecutive days. Daily assessments measured type (ie, cigarette, cigarillo, or e-cigarette) and intensity (ie, number of cigarettes or cigarillos smoked or number of times vaping e-cigarettes per day) of tobacco use and type (ie, combustible, vaporized, or edible) and intensity (ie, number of times used per day) of cannabis use. We estimated multilevel models to examine day-level associations between types of cannabis use and each type of tobacco use, as well as day-level associations between intensities of using cannabis and tobacco. All models controlled for demographic covariates, day-level alcohol use, and time effects (ie, study day and weekend vs weekday).

Results: Same-day co-use was reported in 989 of the total 2891 daily assessments (34.2%). Co-use of cigarettes and combustible cannabis (885 of the 2891 daily assessments; 30.6%) was most commonly reported. Participants had higher odds of using cigarettes (adjusted odds ratio [AOR] 1.92, 95% CI 1.31-2.81) and cigarillos (AOR 244.29, 95% CI 35.51-1680.62) on days when they used combustible cannabis. Notably, participants had higher odds of using e-cigarettes on days when they used vaporized cannabis (AOR 23.21, 95% CI 8.66-62.24). Participants reported a greater intensity of using cigarettes (AOR 1.35, 95% CI 1.23-1.48), cigarillos (AOR 2.04, 95% CI 1.70-2.46), and e-cigarettes (AOR 1.48, 95% CI 1.16-1.88) on days when they used more cannabis.

Conclusions: Types and intensities of tobacco and cannabis use within a day among young adult smokers were positively correlated, including co-use of vaporized products. Prevention and intervention efforts should address co-use and pay attention to all forms of use and timeframes of co-use (eg, within a day or at the same time), including co-use of e-cigarettes and vaporized cannabis, to reduce negative health outcomes.
Co-use of tobacco and cannabis is highly prevalent among young US adults. National data indicates that 21% of the general population of young adults has used both tobacco and cannabis in the past 30 days [1]. The use of cannabis is associated with persistent cigarette smoking and may pose a barrier to successful tobacco cessation [2,3]. At the person level, combined use of tobacco and cannabis can increase the risk for addiction and negative health outcomes (eg, mental health and respiratory problems) among people who co-use both products compared to those who use only a single substance [4,5]. This public health impact from co-use underscores the need to prevent this behavior during young adulthood. However, much remains unknown about co-use of tobacco and cannabis at both the personal level (ie, comparing people who co-use to those using a single substance) and at the event level (eg, comparing co-use to single-substance use within a day), in part due to challenges in measuring this complex behavior [6,7].

At the event level, the inherent complexity of co-use behavior includes a variety of products and timeframes, which adds extra burden to assessment and intervention [6]. People can use both substances in any combination of forms across the wide array of tobacco and cannabis products available on the marketplace [8]. While co-use is commonly defined in survey research as the use of both tobacco and cannabis within a month or year, it can also occur in a shorter timeframe (eg, within the same occasion or day). Studies indicate that the extent to which individuals use tobacco and cannabis closely in time is associated with more cigarettes smoked per day, greater nicotine dependence, and worse physical and mental functioning [9-11]. In addition, exposure to toxicants may vary by route of coadministration (eg, smoking vs vaping), posing differential health impacts [5]. Smoking both tobacco and cannabis is a well-known route, including the use of “blunts” (cannabis rolled in a cigar leaf for smoking), “spliffs” (combining cannabis and loose-leaf tobacco in a joint), or “chasing” (smoking cigarettes after smoking cannabis). A newer route of co-use is with vaporized products, in which liquid- or leaf-vaporizing devices are used to deliver both nicotine and tetrahydrocannabinol (THC—the main psychoactive component in cannabis), sometimes with the same device, on the same occasion, or in quick succession [12]. As such, understanding co-use among young adults at the event level, taking into account specific products and timeframes, is critical to inform prevention and intervention efforts [7].

Existing evidence at the event level, however, has predominantly focused on co-use in general (eg, any tobacco and cannabis) or has been limited to only combustible products (eg, blunts). In addition, co-use is mostly measured as any use of both tobacco and cannabis in the past 30 days, and little is known about intensity of co-use (defined in this study as quantity of tobacco and cannabis use within a day). Studies are lacking that address co-use via newer products and in shorter timeframes, yet these patterns of use may result in greater substance use and associated health impacts. Cross-sectional surveys and retrospective behavioral measures used in prior research have asked few questions about the nuances of co-use [6,7]. Newer data collection methods (eg, daily-diary assessments and ecological momentary assessments) have the potential to capture occurrence of tobacco and cannabis co-use within a day or moment and generate a richer picture of the behavior [7]. Using this approach, a few studies have indicated that cannabis use increased the odds of cigarette use on the same day [13] or within 4-hour windows [14,15] and that same-day co-use was more prevalent among young sexual-minority adults than their heterosexual peers [10]. These studies, however, have not examined the intensity of co-use within a day as well as co-use of noncombustible products (eg, e-cigarettes and vaporized cannabis). A better understanding of co-use at the event level, including whether and how types and intensity of cannabis use would drive tobacco use within a day, may be beneficial in developing interventions targeting young adults with problematic use of both substances.

To address the aforementioned gaps in knowledge of co-use of tobacco and cannabis at the day level, we analyzed smartphone-based daily assessment data collected among 147 young adult cigarette smokers during 2016 and 2017. We examined day-level associations between types (ie, combustible, vaporized, and edible) and intensity (ie, number of times) of cannabis use and types of tobacco product use (ie, cigarettes, cigarillos, and e-cigarettes). Based on the aforementioned research [10,13-15], we hypothesized that (1) participants would use more tobacco on a day when they use more cannabis; and (2) the same route of administration would facilitate co-use of 2 substances (eg, participants would smoke/vape tobacco on a day when they smoke/vape cannabis, respectively).

### Methods

#### Study Design

This study analyzed daily assessments from a smartphone-based study conducted in California during 2016 and 2017. The study procedure was described in detail elsewhere [10]. Initially, participants completed a baseline survey on their demographics and substance use history. They were then trained on use of the study app to collect data every day for a 30-day period. Each day, participants were prompted between 10 and 11 AM to complete a daily assessment reporting their use of tobacco and cannabis on the entire previous day, including substance use occurrences late at night. To increase participant study compliance and retention, incentives were contingent on level of data-collection completion.

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NM: This article has an intentional error in the citation of a key study. The correct citation should be: [12] instead of [12].
Ethics Approval

Electronic informed consent was obtained from all participants. The study was approved by the University of California San Francisco Institutional Review Board (15-18033).

Study Participants

Participants were recruited through social media and online advertisements (eg, Facebook and Craigslist). To conduct a nested qualitative substudy, participants were also recruited via the websites of sexual-minority youth organizations, and we oversampled women identifying as a sexual minority. Eligible participants were aged 18 to 26 years, had smoked at least 100 cigarettes in their lifetime, and currently smoked at least one cigarette per day at least 3 days per week. Since the parent study focused on cigarette smoking, cannabis use was not part of the inclusion criteria. Of 184 participants who completed the baseline assessments, 147 who completed at least one daily assessment were included in the analytic sample. There was no statistical difference between the analytic sample (n=147) and those who were excluded from the analysis (n=37) in baseline characteristics (ie, age, sex, educational attainment, race, ethnicity, and past-30-day use of tobacco and cannabis). Baseline characteristics of the study sample are presented in Table 1. The sample had a mean age of 22.7 (SD 2.4) years, 51.7% (76/147) of participants were female, 40.8% (60/147) of participants were non-Hispanic White, and 76.9% (113/147) of participants were currently in college or had a college degree or higher. At baseline, a majority of participants reported past-30-day use of cannabis (96/147, 65.3%) and alcohol (136/147, 92.5%). We included 51 participants who did not report past 30-day use of cannabis at baseline in our sample, since these participants could report co-use during the daily-diary period (and n=7 did), allowing for comparison between co-use and single-substance use within a day.

Table 1. Sample characteristics.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Total (n=147)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years), mean (SD)</td>
<td>22.7 (2.4)</td>
</tr>
<tr>
<td>Sex at birth, n (%)</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>71 (48.3)</td>
</tr>
<tr>
<td>Female</td>
<td>76 (51.7)</td>
</tr>
<tr>
<td>Race, n (%)</td>
<td></td>
</tr>
<tr>
<td>Non-Hispanic White</td>
<td>60 (40.8)</td>
</tr>
<tr>
<td>Non-Hispanic Asian</td>
<td>30 (20.4)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>31 (21.1)</td>
</tr>
<tr>
<td>Other/multiracial</td>
<td>17 (11.6)</td>
</tr>
<tr>
<td>Education, n (%)</td>
<td></td>
</tr>
<tr>
<td>Less than college</td>
<td>33 (22.5)</td>
</tr>
<tr>
<td>College or higher</td>
<td>113 (76.9)</td>
</tr>
<tr>
<td>Past 30-day substance use at baseline, n (%)</td>
<td></td>
</tr>
<tr>
<td>Tobacco use</td>
<td></td>
</tr>
<tr>
<td>Cigarettes</td>
<td>145 (98.6)</td>
</tr>
<tr>
<td>e-Cigarettes</td>
<td>47 (32)</td>
</tr>
<tr>
<td>Cannabis use</td>
<td>96 (65.3)</td>
</tr>
<tr>
<td>Alcohol use</td>
<td>136 (92.5)</td>
</tr>
</tbody>
</table>

Measures

Outcome Variables (Type and Intensity of Tobacco Use)

For each day, participants reported whether they used cigarettes, cigarillos, or e-cigarettes. These binary variables (yes/no) indicated types of tobacco used in each daily assessment. We examined cigarillos rather than other types of cigars since cigarillos are the most common cigar type used by young adults [16]. Regarding intensity of tobacco use, participants were asked, “Yesterday: How many [cigarettes, cigarillos] used?” and “How many times [disposable e-cigarettes, rechargeable e-cigarettes, tanks, or pod-mods] used?” We assessed tobacco products and different types of e-cigarettes separately. These types of devices included 4 generations of e-cigarettes available on the marketplace at the time of the study (eg, the first generation refers to disposable e-cigarettes, the second generation refers to rechargeable e-cigarettes, the third generation refers to tank devices, and the fourth generation refers to pod-mods). A total intensity of e-cigarette use for each day was calculated by summing the intensities of using all 4 types of e-cigarettes. To not overburden participants, response options provided categories of increasing intensity of use of each product (ie, 0, 1, 2-5, 6-10, 11-15, 16-20, 21-30, and ≥31 cigarettes, cigarillos, or times vaping e-cigarettes per day).
Independent Variables (Type and Intensity of Cannabis Use)

For each day, participants were asked, “How many times did you use marijuana or hash?” Answer options ranged continuously from 0 to 7 or more times. Those who reported any cannabis use were then asked, “How did you use marijuana or hash?” with answer options including smoking, vaping, and edibles. While we asked about intensity of use of cannabis in general, we did not ask about intensity of use of each cannabis product separately, to avoid overburdening participants. As such, depending on a participant’s interpretation, a smoking occasion of combustible cannabis, a hit of a cannabis vaporizer, or consuming 1 edible may have been considered as a single occasion of cannabis use in our study.

Covariates

Demographic characteristics were collected at baseline. Age was calculated based on self-reported date of birth. Sex assigned at birth was measured as female or male. Race/ethnicity was categorized into 4 groups: non-Hispanic White, non-Hispanic Asian, Hispanic, and other/multiracial. Educational attainment was dichotomized as “less than college” and “college or higher,” since having a college education is associated with tobacco and cannabis use among young adults [17]. Participants also reported alcohol use (yes/no) in each daily assessment. A dummy variable was created to indicate the study day of each daily assessment, ranging from day 1 to day 30. As use of substances may differ between weekends and weekdays [18], another dummy variable was created to indicate weekend or weekday.

Statistical Analyses

Statistical analyses were performed using Stata (version 15; Stata Corp). Descriptive statistics of sample characteristics at baseline and substance use in daily assessments were summarized. First, to examine associations of type of tobacco and cannabis co-use on the same day, we fitted multilevel logistic regression models examining associations of use of cannabis products (combustible, vaporized, and edible) with each of the binary outcomes (ie, any use of cigarettes, cigarillos, or e-cigarettes on a given day). Second, to examine associations between intensities of tobacco and cannabis use on the same day, we fitted multilevel mixed-effects ordered logistic regression models examining intensity of cannabis use (ie, number of times using cannabis on a given day) with each of the ordinal outcomes (ie, numbers of cigarettes or cigarillos smoked and number of times using e-cigarettes on a given day) [19]. The models also included random intercepts for participants to control for variation in tobacco use intensity attributable to individual participants.

The variable of intensity of cannabis use was decomposed into 2 elements: personal mean (ie, average intensity of cannabis use for each participant, indicating comparisons between participants, in other words, between-person effects), and deviation (ie, the difference between intensity in a particular daily observation and the personal mean, indicating comparisons across study days within a certain participant, that is, within-person effects) [20]. For each ordinal outcome, the proportional odds assumption was checked by fitting a generalized multinomial logit model and comparing its likelihood ratio to that of the ordinal model [19]; this assumption was satisfied for all the models. All models controlled for demographic covariates, day-level alcohol use [21], and time effects (ie, study day and weekend vs weekday). All tests were 2-tailed with a significance level of α<.05. The analyses were not preregistered and thus the results should be considered exploratory.

Results

Daily Assessments of Tobacco and Cannabis Use

During the 30-day study period, 147 participants completed an average of 19.7 (SD 9.6) daily assessments with a completion rate of 65.6% (2891 completed assessments of 4410 prompted assessments). Table 2 describes reports of tobacco and cannabis use among the total of 2891 daily assessments. Co-use was reported in 989 daily assessments (34.2%), while use of tobacco without cannabis was reported in 1501 daily assessments (51.9%). The most common intensity of cigarette use reported in the daily assessments was smoking 2 to 5 cigarettes per day. Not using at all was reported the most in the daily assessments for cigarillos, e-cigarettes, and cannabis. On the days when participants used these products, the common intensities of use were smoking 2 to 5 cigarillos per day, vaping e-cigarettes 2 to 5 times per day and using cannabis once a day.

Table 3 presents same-day co-use in terms of combinations of specific products. The most commonly used tobacco product was cigarettes (2407 of 2891 assessments, 83.3%), while combustible cannabis was the most common type of cannabis use (1040 of 2891 assessments, 36%). The 3 most common product combinations on the same day were cigarettes and combustible cannabis (885 of 2891 assessments, 30.6%), cigarillos and combustible cannabis (197 of 2891 assessments, 6.8%), and cigarettes and vaporized cannabis (147 of 2891 assessments, 5.1%).

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Table 2. Daily assessments of substance use among young adult smokers.

<table>
<thead>
<tr>
<th>Substance use assessments</th>
<th>Assessments (n=2891), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Daily assessments</strong></td>
<td></td>
</tr>
<tr>
<td>Use of tobacco only</td>
<td>1501 (51.9)</td>
</tr>
<tr>
<td>Use of cannabis only</td>
<td>145 (5)</td>
</tr>
<tr>
<td>Use of both substances</td>
<td>989 (34.2)</td>
</tr>
<tr>
<td>No use</td>
<td>251 (8.7)</td>
</tr>
<tr>
<td>Missing data</td>
<td>5 (0.2)</td>
</tr>
<tr>
<td><strong>Number of cigarettes smoked in a day</strong></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>483 (16.7)</td>
</tr>
<tr>
<td>1</td>
<td>303 (10.5)</td>
</tr>
<tr>
<td>2-5</td>
<td>1250 (43.2)</td>
</tr>
<tr>
<td>6-10</td>
<td>644 (22.3)</td>
</tr>
<tr>
<td>11-15</td>
<td>145 (5)</td>
</tr>
<tr>
<td>16-20</td>
<td>61 (2.1)</td>
</tr>
<tr>
<td>21-30</td>
<td>2 (0.1)</td>
</tr>
<tr>
<td>≥31</td>
<td>3 (0.1)</td>
</tr>
<tr>
<td><strong>Number of cigarillos smoked in a day</strong></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>2682 (92.8)</td>
</tr>
<tr>
<td>1</td>
<td>85 (2.9)</td>
</tr>
<tr>
<td>2-5</td>
<td>110 (3.8)</td>
</tr>
<tr>
<td>6-10</td>
<td>11 (0.4)</td>
</tr>
<tr>
<td>11-15</td>
<td>3 (0.1)</td>
</tr>
<tr>
<td><strong>Number of times vaping e-cigarettes in a day</strong></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>2664 (92.2)</td>
</tr>
<tr>
<td>1</td>
<td>17 (0.6)</td>
</tr>
<tr>
<td>2-5</td>
<td>113 (3.9)</td>
</tr>
<tr>
<td>6-10</td>
<td>52 (1.8)</td>
</tr>
<tr>
<td>11-15</td>
<td>22 (0.8)</td>
</tr>
<tr>
<td>16-20</td>
<td>15 (0.5)</td>
</tr>
<tr>
<td>21-30</td>
<td>7 (0.2)</td>
</tr>
<tr>
<td>≥31</td>
<td>1 (&lt;0.1)</td>
</tr>
<tr>
<td><strong>Number of times using cannabis in a day</strong></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>1754 (60.7)</td>
</tr>
<tr>
<td>1</td>
<td>351 (12.1)</td>
</tr>
<tr>
<td>2</td>
<td>255 (8.8)</td>
</tr>
<tr>
<td>3</td>
<td>231 (8)</td>
</tr>
<tr>
<td>4</td>
<td>131 (4.5)</td>
</tr>
<tr>
<td>5</td>
<td>77 (2.7)</td>
</tr>
<tr>
<td>6</td>
<td>17 (0.6)</td>
</tr>
<tr>
<td>≥7</td>
<td>75 (2.6)</td>
</tr>
<tr>
<td><strong>Daily assessments with alcohol use</strong></td>
<td>1032 (35.7)</td>
</tr>
<tr>
<td><strong>Daily assessments on weekend</strong></td>
<td>804 (27.8)</td>
</tr>
<tr>
<td><strong>Daily assessments on weekday</strong></td>
<td>2087 (72.2)</td>
</tr>
</tbody>
</table>

https://mhealth.jmir.org/2023/11/e40736
Table 3. Same-day co-use of specific tobacco and cannabis products among young adult smokers (n=2891 assessments). Proportions were calculated as frequency of a given product combination out of the total daily assessments.

<table>
<thead>
<tr>
<th>Types</th>
<th>Any cannabis (n=1136, 39.3%), n (%)</th>
<th>Combustible cannabis (n=1040, 36%), n (%)</th>
<th>Vaporized cannabis (n=190, 6.6%), n (%)</th>
<th>Edible cannabis (n=36, 1.3%), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Any tobacco (n=2490, 86.1%)</td>
<td>989 (34.2)</td>
<td>915 (31.7)</td>
<td>151 (5.2)</td>
<td>28 (1)</td>
</tr>
<tr>
<td>Cigarette (n=2407, 83.3%)</td>
<td>956 (33.1)</td>
<td>885 (30.6)</td>
<td>147 (5.1)</td>
<td>27 (0.9)</td>
</tr>
<tr>
<td>e-Cigarette (n=240, 8.3%)</td>
<td>101 (3.5)</td>
<td>79 (2.7)</td>
<td>39 (1.4)</td>
<td>4 (0.1)</td>
</tr>
<tr>
<td>Cigarillo (n=209, 7.2%)</td>
<td>197 (6.8)</td>
<td>197 (6.8)</td>
<td>8 (0.3)</td>
<td>5 (0.2)</td>
</tr>
</tbody>
</table>

Associations Between Type of Cannabis and Tobacco Products Used on the Same Day

Results from the mixed-effects models are shown in Table 4. Participants had higher odds of reporting using cigarettes (adjusted odds ratio [AOR] 1.92, 95% CI 1.31-2.81) and cigarillos (AOR 244.29, 95% CI 35.51-1680.62) on days when they used combustible cannabis. Notably, participants had higher odds of using e-cigarettes on days when they used vaporized cannabis (AOR 23.21, 95% CI 8.66-62.24). It should be noted that the CIs for cigarillos and e-cigarettes were quite wide due to the small number of daily assessments with use of these products. In addition, participants had higher odds of smoking cigarettes on days with alcohol use (AOR 2.73, 95% CI 1.99-3.76). The study day was negatively associated with the odds of smoking cigarettes (AOR 0.96, 95% CI 0.95-0.99) and cigarillos (AOR 0.96, 95% CI 0.92-0.99). Older participants (vs younger peers) had higher odds of reporting cigarette smoking (AOR 1.31, 95% CI 1.10-1.57), while Hispanic participants (vs non-Hispanic White peers) had higher odds of reporting cigarillo smoking (AOR 22.93, 95% CI 3.30-159.49); however, this estimate was very wide due to a small number of cigarillo-use reports.

Table 4. Day-level associations between tobacco use product types (outcomes) and cannabis use product types (independent variables) among young adult cigarette smokers (n=2891 assessments), controlled for time-varying covariates (day-level) and demographic covariates (participant-level). The outcomes were binary variables (ie, any use of a tobacco product on a given day). All variables were included in a mixed-effects logistic regression model for each outcome.

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Model 1: cigarette smoking AOR(^a) (95% CI)</th>
<th>(P) value</th>
<th>Model 2: cigarillo smoking AOR (95% CI)</th>
<th>(P) value</th>
<th>Model 3: e-cigarette vaping AOR (95% CI)</th>
<th>(P) value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Type of cannabis use</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Combustible cannabis</td>
<td>1.92 (1.31-2.81)</td>
<td>.001</td>
<td>244.29 (35.51-1680.62)</td>
<td>&lt;.001</td>
<td>1.84 (0.93-3.67)</td>
<td>.08</td>
</tr>
<tr>
<td>Vaporized cannabis</td>
<td>1.58 (0.83-3.03)</td>
<td>.17</td>
<td>0.83 (0.30-2.25)</td>
<td>.71</td>
<td>23.21 (8.66-62.24)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Edible cannabis</td>
<td>0.58 (0.21-1.63)</td>
<td>.30</td>
<td>1.18 (0.28-5.02)</td>
<td>.82</td>
<td>4.90 (0.90-26.58)</td>
<td>.07</td>
</tr>
<tr>
<td><strong>Time-varying covariates</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alcohol use</td>
<td>2.73 (1.99-3.76)</td>
<td>&lt;.001</td>
<td>0.91 (0.51-1.63)</td>
<td>.76</td>
<td>1.63 (0.90-2.93)</td>
<td>.10</td>
</tr>
<tr>
<td>Weekend vs weekday</td>
<td>0.85 (0.65-1.12)</td>
<td>.26</td>
<td>1.02 (0.60-1.72)</td>
<td>.96</td>
<td>0.79 (0.48-1.31)</td>
<td>.36</td>
</tr>
<tr>
<td>Study day</td>
<td>0.96 (0.95-0.98)</td>
<td>&lt;.001</td>
<td>0.96 (0.92-0.99)</td>
<td>.01</td>
<td>1.00 (0.97-1.03)</td>
<td>.84</td>
</tr>
<tr>
<td><strong>Demographic covariates</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>1.31 (1.10-1.57)</td>
<td>.003</td>
<td>1.00 (0.75-1.33)</td>
<td>.98</td>
<td>0.92 (0.69-1.22)</td>
<td>.55</td>
</tr>
<tr>
<td>Female vs male</td>
<td>1.06 (0.48-2.34)</td>
<td>.88</td>
<td>2.32 (0.57-9.44)</td>
<td>.24</td>
<td>0.84 (0.24-2.98)</td>
<td>.78</td>
</tr>
<tr>
<td>Education (college or higher vs less)</td>
<td>0.57 (0.20-1.62)</td>
<td>.29</td>
<td>0.70 (0.11-4.52)</td>
<td>.71</td>
<td>0.49 (0.10-2.52)</td>
<td>.40</td>
</tr>
<tr>
<td>Race (reference non-Hispanic White)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-Hispanic Asian</td>
<td>1.47 (0.51-4.20)</td>
<td>.48</td>
<td>6.84 (0.90-52.23)</td>
<td>.06</td>
<td>2.01 (0.38-10.64)</td>
<td>.41</td>
</tr>
<tr>
<td>Hispanic</td>
<td>2.85 (0.88-9.25)</td>
<td>.08</td>
<td>22.93 (3.30-159.49)</td>
<td>.002</td>
<td>0.82 (0.14-4.94)</td>
<td>.83</td>
</tr>
<tr>
<td>Other/multiracial</td>
<td>1.19 (0.41-3.43)</td>
<td>.75</td>
<td>4.29 (0.65-28.21)</td>
<td>.13</td>
<td>0.77 (0.13-4.56)</td>
<td>.78</td>
</tr>
</tbody>
</table>

\(a\)AOR: adjusted odds ratio.

Associations Between Intensity of Cannabis and Tobacco Use on the Same Day

Results from the multilevel ordinal models are shown in Table 5. Participants had higher odds of reporting a greater intensity of using cigarettes (AOR 1.35, 95% CI 1.23-1.48), cigarillos (AOR 2.04, 95% CI 1.70-2.46), and e-cigarettes (AOR 1.48, 95% CI 1.16-1.88) on days when they used more cannabis. In addition, alcohol use on a given day was positively associated with intensity of cigarette use (AOR 1.41, 95% CI 1.35-1.49).

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Participants with higher average intensity of cannabis use had higher average intensity of cigarillo use (AOR 3.72, 95% CI 2.41-5.73). The study day was negatively associated with intensity of smoking cigarettes (AOR 0.97, 95% CI 0.96-0.98) and cigarillos (AOR 0.94, 95% CI 0.91-0.97), meaning that intensity of smoking cigarettes and cigarillos decreased slightly over the study period. Those with education attainment of college or higher reported lower intensity of cigarette smoking (AOR 0.30, 95% CI 0.09-0.97), while older participants reported higher intensity of cigarette smoking (AOR 1.52, 95% CI 1.22-1.89). Hispanic participants (vs non-Hispanic White peers) had higher odds of reporting higher intensity of cigarillo smoking (AOR 11.46, 95% CI 1.82-72.36); however, this estimate was very wide due to a small number of cigarillo-use reports.

Table 5. Day-level associations between tobacco use intensity for different products (as outcomes) and intensity of cannabis use (as independent variables) among young adult cigarette smokers, controlling for time-varying (day-level) and demographic (participant-level) covariates (n=2891 assessments). The outcomes were categorical variables (ie, 0, 1, 2-5, 6-10, 11-15, 16-20, 21-30, and ≥31 cigarettes, cigarillos, or times vaping e-cigarettes in a given day). All variables were included in a multilevel mixed-effects ordered logistic regression model for each outcome.

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Model 1: cigarette smoking intensity AOR(^a) (95% CI)</th>
<th>P value</th>
<th>Model 2: cigarillo smoking intensity AOR (95% CI)</th>
<th>P value</th>
<th>Model 3: e-cigarette vaping intensity AOR (95% CI)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intensity of cannabis use</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intensity of cannabis use in a given day</td>
<td>1.35 (1.23-1.48)</td>
<td>&lt;.001</td>
<td>2.04 (1.70-2.46)</td>
<td>&lt;.001</td>
<td>1.48 (1.16-1.88)</td>
<td>.001</td>
</tr>
<tr>
<td>Personal mean of cannabis use intensity</td>
<td>1.05 (0.78-1.42)</td>
<td>.75</td>
<td>3.72 (2.41-5.73)</td>
<td>&lt;.001</td>
<td>1.16 (0.75-1.78)</td>
<td>.51</td>
</tr>
<tr>
<td>Time-varying covariates</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intensity of alcohol use in a given day</td>
<td>1.41 (1.35-1.49)</td>
<td>&lt;.001</td>
<td>1.02 (0.90-1.15)</td>
<td>.77</td>
<td>1.04 (0.93-1.16)</td>
<td>.48</td>
</tr>
<tr>
<td>Personal mean of alcohol use intensity</td>
<td>0.95 (0.63-1.43)</td>
<td>.80</td>
<td>0.86 (0.44-1.66)</td>
<td>.65</td>
<td>1.08 (0.59-1.99)</td>
<td>.80</td>
</tr>
<tr>
<td>Weekend vs weekday</td>
<td>0.95 (0.80-1.12)</td>
<td>.52</td>
<td>1.05 (0.67-1.65)</td>
<td>.84</td>
<td>0.86 (0.57-1.30)</td>
<td>.48</td>
</tr>
<tr>
<td>Study day</td>
<td>0.97 (0.96-0.98)</td>
<td>&lt;.001</td>
<td>0.94 (0.91-0.97)</td>
<td>&lt;.001</td>
<td>1.01 (0.99-1.04)</td>
<td>.25</td>
</tr>
<tr>
<td>Demographic covariates</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>1.52 (1.22-1.89)</td>
<td>&lt;.001</td>
<td>1.00 (0.72-1.37)</td>
<td>.98</td>
<td>0.82 (0.60-1.14)</td>
<td>.24</td>
</tr>
<tr>
<td>Female vs male</td>
<td>0.45 (0.18-1.13)</td>
<td>.09</td>
<td>3.89 (0.95-15.91)</td>
<td>.06</td>
<td>1.06 (0.28-4.04)</td>
<td>.94</td>
</tr>
<tr>
<td>Education (college or higher vs less)</td>
<td>0.30 (0.09-0.97)</td>
<td>.045</td>
<td>0.82 (0.15-4.57)</td>
<td>.82</td>
<td>0.67 (0.12-3.81)</td>
<td>.66</td>
</tr>
<tr>
<td>Race (reference: non-Hispanic White)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-Hispanic Asian</td>
<td>1.05 (0.30-3.65)</td>
<td>.94</td>
<td>6.39 (0.90-45.55)</td>
<td>.06</td>
<td>1.35 (0.23-7.82)</td>
<td>.74</td>
</tr>
<tr>
<td>Hispanic</td>
<td>1.58 (0.44-5.61)</td>
<td>.48</td>
<td>11.46 (1.82-72.36)</td>
<td>.01</td>
<td>0.31 (0.04-2.35)</td>
<td>.26</td>
</tr>
<tr>
<td>Other/multiracial</td>
<td>0.72 (0.19-2.73)</td>
<td>.63</td>
<td>2.96 (0.37-23.54)</td>
<td>.31</td>
<td>0.60 (0.09-4.07)</td>
<td>.60</td>
</tr>
</tbody>
</table>

\(^a\)AOR: adjusted odds ratio.

**Discussion**

**Principal Results**

This study is one of very few examining young adult co-use of tobacco and cannabis within shorter timeframes (ie, a day) than the typical survey measure of past-30-day use, and it is among the first to examine same-day co-use of tobacco and cannabis products that are not smoked (ie, e-cigarettes and vaporized cannabis), including day-level intensity of co-use. The main findings were as hypothesized and showed that the more cannabis participants reported using on a given day, the greater the intensity of tobacco product use (cigarettes, cigarillos, and e-cigarettes). Notably, participants reported smoking cigarettes or cigarillos on the days they smoked cannabis, and vaping e-cigarettes on the days they vaped cannabis, indicating the same routes of administration may play a role in facilitating same-day co-use.

**Comparison With Prior Work**

Since traditional measures are insufficient to fully capture and monitor co-use of tobacco and cannabis, recent research called for more accurate measures of this behavior [6] and highlighted the potential of digital health applications for collecting fine-grained data and specifying co-use patterns [7]. As a methodological example, our study used a daily-diary design and smartphone-based data collection to generate intensive longitudinal data on co-use patterns on a daily basis over 30 consecutive days, providing a nuanced understanding of the extent of co-use within a day. Another strength of this study was an examination of use of a variety of tobacco and cannabis products, including co-use of vaporized products (ie, e-cigarettes and vaporized cannabis), for which more evidence is needed. In addition to our smartphone-based daily assessment method, future research should also consider using other mobile-data collection methods (eg, ecological momentary assessments and mobile sensors) that may more comprehensively assess co-use of tobacco and cannabis [6,7]. Furthermore, while there are only a handful of studies, including this study, that have directly
examined co-use as the focal outcome, many prior studies indirectly addressed co-use by adjusting for use of both tobacco and cannabis in the same analytic models. Systematic review or meta-analysis of both direct and indirect evidence may be warranted to provide comprehensive insights on co-use and its effects.

The positive associations between use of the same types of tobacco and cannabis products on the same day indicate that there may be behavioral cues from shared routes of administration that may facilitate co-use of tobacco and cannabis (eg, smoking or vaping one substance triggers smoking or vaping the other) [22]. Indeed, a combination of cigarettes and combustible cannabis was the most common same-day co-use pattern in our sample of young adult cigarette smokers. It was also the most common pattern of past-30-day and past-year co-use found in other samples of young adults [8,11]. In addition to well-documented co-use patterns via smoking (eg, cigarettes/cigarillos and combustible cannabis), we also found that participants reported vaping e-cigarettes more on the days when they vaped cannabis. This finding, coupled with the high prevalence of vaping among young populations, indicates that more attention to emerging co-use patterns via vaping is needed [12,23]. Previous research has reported vaping-related harms among co-users, such as lung impairments [24] and increased odds of having COVID-19 symptoms and diagnoses [25]. Further investigation of tobacco and cannabis coing among young adults and its health consequences is warranted. Moreover, our participants also reported using other product combinations across the spectrum of tobacco and cannabis products, underlining the heterogeneity of co-use patterns. Further exploration of unique reasons and contexts for different patterns of co-use would help to identify targets for tailored prevention and treatment strategies.

While one might expect a potential drug substitution effect, in which people use cannabis as a substitute for tobacco [26], our finding of positive associations between intensity of tobacco and cannabis use on the same day suggests the substitution effect did not occur in our sample of young adult smokers. Instead, as explained by the theory of synergistic effects, individuals may use 2 substances at the same time or use 1 substance under the effect of the other to amplify positive effects or counteract negative effects between nicotinic and endocannabinoid systems [22]. Relatedly, shared contexts (eg, being with friends and socializing) may also facilitate intensity of same-day co-use of tobacco and cannabis [27,28]. In addition, our participants with higher average intensity of cannabis use also reported higher average intensity of cigarillo use. This finding could be due to our participants using cigarillos for blunt smoking. Although we did not directly ask about blunt use in the daily assessments, previous studies indicated that young adults perceived cigarillos were frequently used for blunts [29,30]. We also found that participants smoked more cigarettes on the days when they drank alcohol. This finding could be explained by well-known rewarding effects when cigarettes and alcohol are used together [13,31-33].

In addition, several subgroups in our sample demonstrated greater average intensity of tobacco use. Participants who were older and had less than a college education reported greater intensity of cigarette smoking, whereas Hispanic participants reported a greater intensity of cigarillo use. These findings are consistent with previous research documenting high prevalence of tobacco use in these subgroups [17,34,35]. Interestingly, participants’ use of cigarettes and cigarillos decreased over the study period. This may be due to a Hawthorne effect or other impacts of research participation, as the process of reporting on their own behaviors may induce reflection and influence participants’ behaviors [36]. To our knowledge, this reactivity effect was rarely observed in previous research. Future studies using experience-sampling methods (eg, ecological momentary assessments or daily diaries) should explore reactivity effects and potential impacts on behavioral outcomes.

Study Implications
Collectively, our study has implications for efforts to support smoking cessation among young adults. As co-use of tobacco and cannabis was common, and this may increase harm and addiction, smoking cessation programs may need to address co-use of multiple tobacco products or tobacco and cannabis to improve efficacy with this age group. Most available interventions to reduce tobacco use in young people may not address engaging in co-use [7,37]. A recent study found that when young people reduced their tobacco use, their cannabis use also decreased, suggesting the potential benefits of dual cessation treatment for co-users [38]. In addition, treatment strategies should be expanded to include co-use of nonsmoking products to meet cessation needs of covapers [7,39]. As such, tailored interventions that adapt supports to individuals’ co-use patterns may be more effective for reducing the use of both substances. Moreover, tailored interventions may be needed to reach those with high rates of co-use, such as those without college education or those who identify as Hispanic.

Limitations
Several limitations ought to be considered. The data were collected during 2016 and 2017. Since then, there have been rapid changes in public policy related to both tobacco and cannabis, in patterns of use (eg, increasing use of vaporization devices), in cannabis legalization, and in product availability in the marketplace. As such, more recent data are needed to replicate our findings. The convenience sampling procedure via online recruitment in California and the oversampling of young sexual minority adults limit our study’s generalizability to other young adult samples or geographic regions. While co-use of tobacco and cannabis is common among smokers, our sample included a minority of young adults who did not report past-30-day cannabis use at baseline; further research should examine co-use of tobacco and cannabis among young adults who report recent use of both substances. Although using categories for intensity of use of tobacco products provided a general measure of increasing intensity, this may result in limitations to interpretation of actual effects for each product, given that the increase of using e-cigarettes from, for example, one time per day to 2 to 5 times per day may be different from the increase of smoking from one to 2 to 5 cigarillos per day. Data on cigar use were not collected, and simultaneous use of tobacco and cannabis and their overlapping effects were not directly assessed in our study. Moreover, data on timing or...
ordering in use of tobacco and cannabis were not collected; thus, we could not identify temporal relationships in use of these substances. Likewise, we did not collect data on cannabis concentrations and specific intensity of use by type of cannabis. The use of concentrated cannabis could impact the same-day co-use of tobacco and cannabis in meaningful ways depending on complementing versus supplementing behaviors. In addition, our participants were not trained in defining intensity of cannabis use and the meaning of "times of cannabis use" may vary depending on personal definitions of use sessions and types of cannabis use. Future research should consider collecting these data and developing more accurate measures of daily use of tobacco and cannabis in order to provide a better understanding of co-use. Missing data due to participants’ compliance with daily assessments may impact the study’s internal validity; however, our compliance rate is within the range of previous studies using the same data collection methods [10,13-15] and the models in our analysis are generally robust to missing data under the missing-at-random assumption [40,41].

Conclusion
By using smartphone-based daily assessments, this study identified a substantial correlation of product types and intensities of tobacco and cannabis co-use at the day level, with young adults reporting more tobacco use on days when they used more cannabis, including same-day co-use of e-cigarettes and vaporized cannabis. Future research and interventions should address co-use in all forms, especially co-use via new products and in short timeframes, to better prevent and reduce use of both tobacco and cannabis and related health impacts among young people.

Acknowledgments
This research was supported by the California Tobacco-Related Disease Research Program (grants T31FT1564 and T32KT5071 to NN and 25FT0009 to JT), by the Food and Drug Administration Center for Tobacco Products and the National Heart, Lung, and Blood Institute (grant U54 HL147127 to PML), and by the National Cancer Institute (grants U01 CA154240 to PML and R01 CA246590 to JT). NN is also supported by the University of California San Francisco Clinical and Translational Science Institute (UL1 TR001872-06). The content is solely the responsibility of the authors and does not necessarily represent the official views of the funding agencies. We would like to thank Dr Donald Hedeker at the University of Chicago for his advice on our data analysis.

Authors’ Contributions
NN, JT, TBN, and PML were involved in writing the manuscript. NN conceptualized the study, obtained funding, drafted the initial manuscript, analyzed and interpreted the data, and contributed to all subsequent drafts of the manuscript. JT and TBN analyzed and interpreted the data and reviewed and revised the manuscript. PML supervised and reviewed and revised the manuscript. All authors have read and approved the final manuscript for submission.

Conflicts of Interest
None declared.

References


**Abbreviations**

AOR: adjusted odds ratio
Original Paper

Evaluating the Effects of the Supportive Parenting App on Infant Developmental Outcomes: Longitudinal Study

Shefaly Shorey\(^1\), PhD; Yap Seng Chong\(^2\), MBBS; Luming Shi\(^3\), MBBS; Jing Shi Chua\(^1\), BSocSci; Thilagamangai\(^4\); Jancy Mathews\(^5\), MN; Siew Hoon Lim\(^6\), PhD; Ruochen Du\(^2\), MPH; Yiong Huak Chan\(^2\), PhD; Thiam Chye Tan\(^7\), MMed; Cornelia Chee\(^8\), MMed; Evelyn Law\(^8\), MD

\(^1\)Alice Lee Centre for Nursing Studies, National University of Singapore, Singapore, Singapore
\(^2\)Yong Loo Lin School of Medicine, National University of Singapore, Singapore, Singapore
\(^3\)Singapore Clinical Research Institute, Singapore, Singapore
\(^4\)Division of Nursing, KK Women’s and Children’s Hospital, Singapore, Singapore
\(^5\)National University Polyclinics, Singapore, Singapore
\(^6\)Singapore General Hospital, Singapore, Singapore
\(^7\)Mount Elizabeth Novena Specialist Centre, Singapore, Singapore
\(^8\)National University Hospital, Singapore, Singapore

Corresponding Author:
Shefaly Shorey, PhD
Alice Lee Centre for Nursing Studies
National University of Singapore
Clinical Research Centre, Level 2, Block MD11
10 Medical Drive
Singapore, 117597
Singapore
Phone: 65 66011294
Email: nurssh@nus.edu.sg

Abstract

Background: Previous studies have investigated the various effects of parenting on infant developmental outcomes. In particular, parental stress and social support have been found to significantly affect the growth of the newborn. Although many parents today use mobile apps to obtain more support in parenting and perinatal care, few studies have examined how these apps could affect infant development.

Objective: This study aimed to examine the effectiveness of the Supportive Parenting App (SPA) in improving infant developmental outcomes during the perinatal period.

Methods: This study adopted a 2-group parallel prospective longitudinal design and recruited 200 infants and their parents (N=400 mothers and fathers). The parents were recruited at 24 weeks of gestation for a randomized controlled trial conducted from February 2020 to July 2022. They were randomly allocated to either the intervention or control group. The infant outcome measures included cognition, language, motor skills, and social-emotional development. Data were collected from the infants when they were aged 2, 4, 6, 9, and 12 months. Linear and modified Poisson regressions were used to analyze the data to examine between- and within-group changes.

Results: At 9 and 12 months post partum, the infants in the intervention group were found to have better communication and language skills than those in the control group. An analysis of motor development revealed that a larger proportion of the infants in the control group fell under the at-risk category, where they scored approximately 2 SDs below the normative scores. The control group infants scored higher on the problem solving domain at 6 months post partum. However, at 12 months postpartum, the infants in the intervention group performed better on cognitive tasks than those in the control group. Despite not being statistically significant, the intervention group infants were found to have consistently scored better on the social components of the questionnaires than the control group infants.

Conclusions: Overall, the infants whose parents had received the SPA intervention tended to fare better in most developmental outcome measures than those whose parents had received standard care only. The findings of this study suggest that the SPA intervention exerted positive effects on the communication, cognition, motor, and socioemotional development of the infants.
Further research is needed to improve the content and support provided by the intervention to maximize the benefits gained by infants and their parents.

**Trial Registration:** ClinicalTrials.gov NCT04706442; https://clinicaltrials.gov/ct2/show/NCT04706442

(JMIR Mhealth Uhealth 2023;11:e43885) doi:10.2196/43885

**KEYWORDS**
infant development; parenting; mobile health technology; social support; psychoeducation; peer support; mobile phone

**Introduction**

**Background**

The effects of parenting on infant development are a widely investigated topic. Studies have found that parenting knowledge, parental stress, and parental perceived support have significant impacts on the growth of an infant [1-3]. For example, parents’ knowledge of and participation in their child’s play contribute significantly to the development of the child, as it helps boost executive functioning, encourage prosocial behavior, and enhance creativity [4]. Greater parenting stress and low levels of perceived social support have also been found to be associated with depression among mothers, which is correlated with developmental delays in infants [1].

The lack of social support has been linked to various parental outcomes, such as postnatal depression [5], parental stress [6], and anxiety [7]. Social support is often regarded as a protective factor for parents, especially during the perinatal period. Receiving support from others often helps parents feel less overwhelmed, aiding them with the transition to parenthood or helping them cope with having to care for multiple children. Some studies [8-10] conducted in Singapore found that parents desire more informational and familial support. Specifically, some parents perceived having a lack of knowledge of infant care and wanted to have access to reliable information sources [8]. With the rapid advancements in technology over the last 2 decades, parents today tend to look for information from web-based sources or seek support from web-based parenting communities, as these sources are extremely convenient and accessible [10-12]. They are mostly aware that information found on the web can be fabricated or exaggerated [12]; therefore, they tend to prefer gathering information directly from health care professionals such as obstetricians and neonatologists [8]. This is not always possible, especially during the postnatal period, as parents no longer have regular appointments with their obstetricians or gynecologists. As a result, parents try to obtain accurate information on the web by visiting only reputable sites that disseminate information provided by health care professionals or going to less commercially based websites [13]. Even then, these sites might not be consistent in the information they provide, especially when the information is not contextualized and does not incorporate cultural norms, and this may cause confusion among parents regarding what the right childcare practices are [14]. This justifies the need to create evidence-based programs tailored to the present generation of tech-savvy parents to improve their well-being and aid them in developing competent childcare skills [15].

According to Milgrom et al [5], it is recommended to implement programs to improve parental well-being during the perinatal period, as social support plays a large role in mediating the relationship between postnatal depression and child development during this time. During the perinatal period, low levels of social support such as insufficient partner support [5], lack of reliable information sources [16], and caring for a newborn without aid from others [17] often induce much stress and negative moods in parents. To fulfill the support needs of parents during the perinatal period, a mobile health (mHealth) app known as the Supportive Parenting App (SPA) was developed. The mHealth SPA was developed as a one-stop resource center because past studies have found technology-based interventions to be effective in offering parenting education and support [18,19]. Such remote interventions were found to be helpful specifically for parents who were facing childcare issues but were not always able to seek immediate advice from health care professionals [18,19].

The SPA is a theory- and evidence-based psychoeducational app developed using different theoretical frameworks, such as Singh et al’s [20] mHealth user engagement pyramid, Bandura’s [21] social cognitive theory, and Bowlby’s [22] attachment theory. Through SPA, parents were able to obtain information on childcare and parenting-related topics to aid them in their parenting journey. In addition, unique to SPA, a peer support feature was included to provide parents with emotional support from trained peer volunteers. Although various parenting interventions have been developed and evaluated to improve parental outcomes, a recent review by Adina et al [23] found that few studies have explored how these interventions can indirectly affect infant or child developmental outcomes. This is unexpected, as the improvement of child developmental outcomes is often cited as a reason for developing these parenting programs [1,15]. Therefore, although these interventions are often directed at parents, it is important to examine how the development of infants may be affected as a consequence.

**Aims and Hypotheses**

This study aimed to examine whether the SPA intervention had any indirect effects on the developmental outcomes of the app users’ infants from birth to 12 months of age. The direct effects on parenting outcomes have been reported separately [24]. It was hypothesized that infants in the intervention group would exhibit better language, motor, cognitive, and social skills than their counterparts in the control group.
Methods

Study Design
A 2-group parallel prospective longitudinal design was adopted for this study, which was conducted from February 2020 to July 2022. Expecting parents were recruited from 2 public health care institutions in Singapore. The study was part of a randomized controlled trial (RCT) investigating the effectiveness of SPA in improving perinatal parental outcomes such as postnatal depression and anxiety [24]. Along with their parents, the infants in this study were randomly allocated to either the SPA intervention group or standard care control group.

Eligibility Criteria
Parents were considered eligible for the study if they met the following criteria: (1) both parents were aged ≥21 years; (2) both parents were able to read and speak English; (3) the pregnancy was at low risk with >24 weeks of gestation (age of viability in Singapore); and (4) both parents owned a smartphone with internet access. Parents were excluded from the study if they had high-risk pregnancies (eg, pregnancy-induced hypertension, preeclampsia, and placenta previa major). Infants who were born via a complicated assisted delivery where the mother required prolonged hospitalization and admitted to the neonatal intensive care unit and infants with congenital issues were excluded from the study to minimize confounding influences on the outcome variables.

Sample Size Calculation
As this study was part of an RCT investigating the effectiveness of the SPA intervention on parental outcomes, the parents enrolled in the RCT and their infants were recruited for this study. Considering the medium-sized effect of SPA, a Cohen d of 0.5 (90% power and 0.05 significance), and an attrition rate of 20% (based on another study) [25], 200 couples were recruited for the main RCT. Two couples had twins; therefore, 202 infants were recruited for this study.

Intervention
The control group parents received the standard perinatal care offered by the hospitals they were recruited from, which consisted of antenatal checkups, optional antenatal classes, care during their stay in the ward, and a postnatal review scheduled 6 weeks post partum. Perinatal care was provided to the parents by obstetricians, nurses, neonatologists, and lactation consultants. The intervention group parents received the standard perinatal care as well, but they were also granted access to the mHealth intervention SPA upon recruitment into the study. In addition, they were matched with trained peer volunteers, who were experienced mothers trained by the research team to provide peer support for the parents in the RCT.

SPA included a variety of pregnancy-, childbirth-, postpartum-, and infant care–related information. This included articles, audio files, and videos about birth preparation, bonding and attachment across the perinatal period, breastfeeding, baby care–related tasks (from bathing to safe sleep habits), and involvement of both fathers and mothers in baby care tasks. The information was curated by the health care professionals involved in the study so that parents could conveniently access reliable and accurate information. Expert advice, discussion forums, and frequently asked questions were also features of the mobile app that aimed to resolve any pregnancy- or childcare-related queries that the parents might have. The parents were encouraged to interact with the peer volunteer with whom they were matched if they needed emotional or informational support from experienced mothers who had previously had and recovered from postnatal depression. Detailed features of the SPA mobile app and peer volunteer intervention can be found in the published development study [26]. The SPA intervention was made available to the intervention group parents from the point of recruitment until 6 months post partum.

Procedure
Couples were recruited by a research assistant during their scheduled antenatal checkups at 2 tertiary hospitals in Singapore. They were provided with an explanation of the study, and interested couples were screened for eligibility before giving them an informed consent form where they could indicate their willingness to participate in the study. Subsequently, the couples were randomly allocated to the intervention or control group. The estimated due date of the couples was recorded, and the couples were then contacted shortly after their due date to gather information regarding their childbirth (eg, gender of the baby and whether they attended prenatal classes). The parents also entered this information into SPA so that the app could send them information that is specific and relevant to the infant’s age and respective postpartum time points.

The parents were contacted via SMS text messages to complete the follow-up questionnaires at 1, 2, 4, 6, 9, and 12 months post partum. Mothers tended to be the ones who completed the infant-related questionnaires. A house visit was also scheduled at 6 and 12 months, during which a trained research assistant visited the participants’ homes to assess the infant using the Bayley-4.

Outcome Measures
Conducting research with very young children involves various challenges regarding the accuracy of the data collected, as infants are not verbal, and thus it is difficult to obtain information directly from them. Therefore, the following instruments were used to measure the constructs examined in this study to provide an accurate representation of the infants’ developmental progress.

Ages and Stages Questionnaire—Third Edition
The parent-reported Ages and Stages Questionnaire (ASQ) was used to measure the development of the infants across 5 domains: personal-social, gross motor, fine motor, problem solving, and communication [27]. There are 21 sets of ASQ, each catering to a different developmental time point; these can be used to assess infants or children aged 2 to 66 months. Existing literature has found that Cronbach α for the ASQ ranges from .49 to .87, depending on the domain and time point [28]. In this study, the ASQ sets were administered at 2, 4, 6, 9, and 12 months. Each set of ASQ consisted of 30 items, and the parents were asked to select “yes” (10 points), “sometimes” (5 points), or “not yet” (0 points) to indicate whether their child
Bayley Scales of Infant and Toddler Development—Fourth Edition

The Bayley-4 consists of 5 scales: cognitive, language, motor, social-emotional, and adaptive behavior (ADBE) [29]. The assessment was administered by a research assistant involved in the study and scored based on the research assistant’s observation of the infant’s performance in various tasks. The Bayley-4 assessment was conducted at 6 and 12 months post partum, and the number of items administered varied depending on the infant’s performance. The Bayley-4 items were scored on a 3-point Likert scale ranging from 0 to 2. Points were added to form a total raw score, which could be converted into scaled or standard scores. Cutoff scores were also provided, where standard scores <85 were marked as “at-risk” to indicate possible developmental delay [30]. Prior studies [31,32] that administered Bayley-III assessments have reported Cronbach α ranging from .88 to .96 across all scales. Cronbach α for the newest Bayley-4 assessment has not been reported in the existing literature; in this study, the average Cronbach α of the Bayley-4 was found to be .61.

Brief Infant Toddler Social Emotional Assessment

The 42-item parent-reported Brief Infant Toddler Social Emotional Assessment (BITSEA) was divided into 2 scales: the problem scale (31 items) and the competence scale (11 items) [33]. The BITSEA items were scored on a 3-point Likert scale ranging from 0 to 2. The scores for the items in each scale were added to obtain the respective total score. Higher scores on the problem scale indicated a higher frequency and range of behavioral and emotional problems, whereas higher scores on the competence scale indicated a higher level of social competence. For the competence scale, the cutoff score was 11, whereas for the problem scale, the cutoff score was 13 for girls and 12 for boys. The BITSEA was administered only during the 12-month follow-up, as it is meant to be administered to infants from 12 months onward. The Cronbach α for the BITSEA was .71, similar to that in a previous study [34], where the Cronbach α for the problem and competence scales were .82 and .72, respectively.

Data Analysis

Data analyses were conducted using SPSS (version 27.0; IBM Corp) [35], and statistical significance was set at \( P < .05 \). Descriptive statistics are presented as mean (SD) for continuous variables and as n (%) for categorical variables. Linear regression was used to examine the association between continuous outcome scores and the intervention adjusted for baseline measures and other covariates. Each participant’s score on the 3 instruments was subsequently categorized based on the cutoff scores determined by the respective developers of each instrument. Modified Poisson regression was used to analyze the association between binary outcome scores and the intervention adjusted for baseline measurements and other covariates based on the cutoff scores for each instrument. This was done to compare the proportion of infants in each group who fell into the at-risk category for each domain. Established correlations between the main outcomes and covariates based on previous studies [36,37] were used to determine which covariates were needed to be statistically corrected for.

Ethics Approval

Before the commencement of the study, ethics approval was obtained from the National Health Group Domain Specific Review Board (NHG DSRB:2019/00875). The parents of the infants involved in this study were provided with information on the study and its procedures before they provided their written consent. It was communicated to the parents that participation was voluntary and that they had the right to withdraw anytime without incurring any consequences.

Results

Overview

In total, 200 couples and their infants were recruited for this study. However, owing to the attrition rate of 28.5% that was reported in the main RCT [24], only 79% (158/200) of infants were included in the analysis (the remaining 42/200, 21% parent-infant dyads dropped out of the study). The demographic characteristics of the participants are presented in Table 2. The mean age of the parents was 31.4 (SD 4.93) years, and Malay

Table 1. Cronbach α and cutoff scores for the Ages and Stages Questionnaire.

<table>
<thead>
<tr>
<th>Cutoff scores</th>
<th>2 months</th>
<th>4 months</th>
<th>6 months</th>
<th>9 months</th>
<th>12 months</th>
</tr>
</thead>
<tbody>
<tr>
<td>Communication</td>
<td>.746</td>
<td>.883</td>
<td>.864</td>
<td>.877</td>
<td>.910</td>
</tr>
<tr>
<td>Gross motor</td>
<td>22.77</td>
<td>34.60</td>
<td>29.65</td>
<td>13.97</td>
<td>15.64</td>
</tr>
<tr>
<td>Fine motor</td>
<td>41.84</td>
<td>38.41</td>
<td>22.25</td>
<td>17.82</td>
<td>21.49</td>
</tr>
<tr>
<td>Problem solving</td>
<td>30.16</td>
<td>29.62</td>
<td>25.14</td>
<td>31.32</td>
<td>34.50</td>
</tr>
<tr>
<td>Personal-social</td>
<td>24.62</td>
<td>34.98</td>
<td>27.72</td>
<td>28.72</td>
<td>27.32</td>
</tr>
</tbody>
</table>

αScores below the cutoff indicate that the child could be at risk of neurodevelopmental conditions, and further assessment with a professional might be needed.

https://mhealth.jmir.org/2023/11/e43885

(Shorey et al. JMIR Mhealth Uhealth 2023 | vol. 11 | e43885 | p.638)
(115/316, 36.4%) and Chinese (125/316, 39.6%) were the most common ethnicities. Most (87/316, 55.1%) of the infants were male. Most (257/316, 81.3%) parents did not attend any prenatal courses.

**Table 2.** Demographic characteristics of the parents and their infants.

<table>
<thead>
<tr>
<th>Demographic characteristics</th>
<th>Intervention group</th>
<th>Control group</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age of parents, mean (SD)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mothers</td>
<td>29.9 (4.2)</td>
<td>30.5 (4.2)</td>
</tr>
<tr>
<td>Fathers</td>
<td>32.1 (4.9)</td>
<td>33.3 (5.4)</td>
</tr>
<tr>
<td><strong>Parent’s ethnicity (intervention: n=83; control: n=75), n (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mothers</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chinese</td>
<td>83 (100)</td>
<td>75 (100)</td>
</tr>
<tr>
<td>Malay</td>
<td>31 (37.3)</td>
<td>28 (37.3)</td>
</tr>
<tr>
<td>Indian</td>
<td>14 (16.9)</td>
<td>9 (12)</td>
</tr>
<tr>
<td>Others</td>
<td>6 (7.2)</td>
<td>11 (14.7)</td>
</tr>
<tr>
<td>Fathers</td>
<td>83 (100)</td>
<td>75 (100)</td>
</tr>
<tr>
<td>Chinese</td>
<td>35 (42.2)</td>
<td>31 (41.3)</td>
</tr>
<tr>
<td>Malay</td>
<td>29 (34.9)</td>
<td>27 (36)</td>
</tr>
<tr>
<td>Indian</td>
<td>14 (16.9)</td>
<td>10 (13.3)</td>
</tr>
<tr>
<td>Others</td>
<td>5 (6)</td>
<td>7 (9.3)</td>
</tr>
<tr>
<td><strong>Sex of baby (intervention: n=86; control: n=72), n (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>44 (51.2)</td>
<td>43 (59.7)</td>
</tr>
<tr>
<td>Female</td>
<td>42 (48.8)</td>
<td>29 (40.3)</td>
</tr>
<tr>
<td><strong>The educational level of parents (intervention: n=83; control: n=75), n (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mothers</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Primary school</td>
<td>83 (100)</td>
<td>75 (100)</td>
</tr>
<tr>
<td>Secondary school</td>
<td>11 (13.3)</td>
<td>4 (5.3)</td>
</tr>
<tr>
<td>ITE, polytechnic, or junior college</td>
<td>25 (30.1)</td>
<td>35 (46.7)</td>
</tr>
<tr>
<td>University</td>
<td>47 (56.6)</td>
<td>36 (48)</td>
</tr>
<tr>
<td>Fathers</td>
<td>83 (100)</td>
<td>75 (100)</td>
</tr>
<tr>
<td>Primary school</td>
<td>0 (0)</td>
<td>2 (2.7)</td>
</tr>
<tr>
<td>Secondary school</td>
<td>17 (20.5)</td>
<td>7 (9.3)</td>
</tr>
<tr>
<td>ITE, polytechnic, or junior college</td>
<td>27 (32.5)</td>
<td>34 (45.3)</td>
</tr>
<tr>
<td>University</td>
<td>39 (47)</td>
<td>32 (42.7)</td>
</tr>
<tr>
<td><strong>Monthly household income (SGD $; intervention: n=164; control: n=147), n (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;1000 (&lt;US $761.88)</td>
<td>14 (8.5)</td>
<td>5 (3.4)</td>
</tr>
<tr>
<td>1000-3000 (US $761.88-$2285.64)</td>
<td>34 (20.7)</td>
<td>40 (27.2)</td>
</tr>
<tr>
<td>3000-5000 (US $2285.64-$3809.39)</td>
<td>50 (30.5)</td>
<td>47 (32.0)</td>
</tr>
<tr>
<td>&gt;5000 (&gt;US $3809.39)</td>
<td>66 (40.2)</td>
<td>55 (37.4)</td>
</tr>
<tr>
<td><strong>Attended prenatal courses (intervention: n=166; control: n=150), n (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>33 (19.9)</td>
<td>26 (17.3)</td>
</tr>
<tr>
<td>No</td>
<td>133 (80.1)</td>
<td>124 (82.7)</td>
</tr>
</tbody>
</table>

*aOnly 158 infants (86 in the intervention group and 72 in the control group) were included in the analysis because 42 parent-infant dyads dropped out of the study by 6 months post partum.

bITE: Institute of Technical Education.

cNot all parents provided this information.
Communication
The mean and SD scores for the ASQ and Bayley-4 are presented in Tables 3 and 4, respectively, along with the proportion of infants who scored below the cutoff scores (labeled as “at-risk”). Results from the generalized linear regression model indicated that the infants in the intervention group scored significantly higher on the communication domain of the ASQ at 6 (effect size=3.31, 95% CI 0.10-6.53; \(P=0.04\)) and 9 (effect size=6.14, 95% CI 0.90-11.38; \(P=0.02\)) months post partum. However, this difference was not significant after the Bonferroni adjustment (at 4 months: \(P=0.22\); at 6 months: \(P=0.11\)). The Poisson regression results showed that the intervention group infants were less likely to fall under the at-risk category, but there were only a few at-risk cases (Table 3); therefore, the estimation might not be reliable. Results from the linear (effect size=9.304, 95% CI 5.58-13.13; \(P<0.001\)) regression model of the 12-month Bayley-4 assessment also showed that the infants from the intervention group tended to perform better than those from the control group on the language scale.

Table 3. Ages and Stages Questionnaire scores based on domains.

<table>
<thead>
<tr>
<th></th>
<th>2 months (n=158)</th>
<th>4 months (n=146)</th>
<th>6 months (n=143)</th>
<th>9 months (n=146)</th>
<th>12 months (n=140)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Intervention (n=87)</td>
<td>Control (n=71)</td>
<td>Intervention (n=83)</td>
<td>Control (n=63)</td>
<td>Intervention (n=81)</td>
</tr>
<tr>
<td>Communication</td>
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<tr>
<td>Values, mean (SD)</td>
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<tr>
<td>Gross motor</td>
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<tr>
<td>Fine motor</td>
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<td>Problem solving</td>
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<tr>
<td>Personal-social</td>
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</tbody>
</table>

aThe at-risk group refers to infants who scored below the cutoff scores stated in Table 1.
Table 4. Mean and SD of the Bayley-4 standard scores based on domains.

<table>
<thead>
<tr>
<th></th>
<th>6 months (n=109)</th>
<th>12 months (n=105)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Intervention (n=59)</td>
<td>Control (n=50)</td>
</tr>
<tr>
<td>Cognitive</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Values, mean (SD)</td>
<td>100.76 (9.64)</td>
<td>95.12 (15.59)</td>
</tr>
<tr>
<td>At risk(^a), n (%)</td>
<td>3 (5.1)</td>
<td>6 (12)</td>
</tr>
<tr>
<td>Motor</td>
<td></td>
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<tr>
<td>Values, mean (SD)</td>
<td>—b</td>
<td>—</td>
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<tr>
<td>At risk, n (%)</td>
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<tr>
<td>Language</td>
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<tr>
<td>Values, mean (SD)</td>
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<tr>
<td>At risk, n (%)</td>
<td>—</td>
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<tr>
<td>Social-emotional</td>
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<tr>
<td>Values, mean (SD)</td>
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<tr>
<td>At risk, n (%)</td>
<td>—</td>
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<tr>
<td>Adaptive behavior</td>
<td></td>
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<tr>
<td>Values, mean (SD)</td>
<td>99.88 (9.20)</td>
<td>96.96 (9.43)</td>
</tr>
<tr>
<td>At risk, n (%)</td>
<td>3 (5.1)</td>
<td>4 (8)</td>
</tr>
</tbody>
</table>

\(^a\)The at-risk group refers to infants with standard scores <85.

\(^b\)Data not available.

Figure 1A shows the changes in the ASQ scores in the communication domain from 2 to 12 months post partum in both groups. The infants from both groups showed similar trends: there was an initial increase in communication scores at 2 and 4 months post partum, and, subsequently, there was a steep decrease in communication scores from the 4- to 9-month time points before they increased again at 12 months post partum. From 4 months onward, the infants in the intervention group scored higher in the communication domain than those in the control group. The largest difference was observed at 9 months post partum. Overall, the infants from the intervention group demonstrated better communication skills than those from the control group.
Figure 1. Trend graphs for the changes in the Ages and Stages Questionnaire scores over time: (A) communication domain, assessing speech and language; (B) gross motor domain, assessing ability to produce large movements; (C) fine motor domain, assessing smaller movements; (D) problem solving domain, assessing cognitive and intellectual skills; (E) personal-social domain, assessing emotional and social skills.

Motor Skills

The infants from the control group were significantly more likely to score below the cutoff score of the ASQ gross motor domain at 2 months post partum (risk ratio [RR]=0.417, 95% CI 0.20-0.85; \(P=0.02\)). Although the infants from the intervention group tended to score higher than those from the control group in the gross motor domain (Table 3), this difference was not significant (\(P=0.71\)).

The intervention group infants were found to have better fine motor skills than the control group infants at 6 months post partum, based on the results of the logistic regression model analysis. The infants from the control group were more likely to score below the cutoff score on the ASQ fine motor domain than those from the intervention group (RR=0.25, 95% CI 0.08-0.76; \(P=0.02\)). In addition, the infants from the intervention group had significantly higher scores on the ASQ fine motor domain than those from the control group (effect size=6.02, 95% CI 1.03-11.02; \(P=0.02\)). However, there were no significant differences between both groups in the Bayley-4 motor scale scores at 12 months post partum (effect size=−4.91, 95% CI −12.96 to 3.14; \(P=0.23\)).
Similar to the trend graph of the ASQ communication domain, the ASQ gross motor graph showed that the intervention group scored better than the control group on the gross motor items (Figure 1B). The gross motor scores of both groups slightly increased during the first 2 time points before sharply decreasing at 6 months post partum. There was a steady increase in the gross motor scores of both groups from 9 to 12 months post partum, accompanied by a decreasing difference in gross motor scores. Figure 1C shows the trend graph of the ASQ fine motor scores. The fine motor scores of both groups of infants reduced from 2 to 6 months post partum before gradually increasing again. At 12 months post partum, the infants from the control group had higher scores than those from the intervention group, but this difference was not significant (effect size=-0.98, 95% CI -5.87 to 3.91; \( P=0.69 \)).

**Cognition**

At 6 months post partum, the infants from the control group had a higher chance of being in the at-risk group for the problem solving domain of the ASQ than those from the intervention group (RR=0.34, 95% CI 0.12-0.91; \( P=0.03 \)). However, the linear regression model did not find any significant differences in problem solving scores between the 2 groups (effect size=-16.88, 95% CI -52.34 to 18.59; \( P=0.35 \)). The infants from the intervention group fared significantly better than their control group counterparts on the cognition scale of the Bayley-4 assessment (effect size=9.30, 95% CI 5.48-13.12; \( P<0.001 \)) at 12 months post partum.

According to Figure 1D, the infants from the control group generally scored higher in the problem solving domain than those from the intervention group. There was a sharp increase in the problem solving scores of the control group infants at the 6-month time point. Following this increase, an equally sharp decrease in problem solving scores was found at 9 months post partum, where the control group scores fell below those of the intervention group.

**Social-Emotional Skills**

No significant group differences were found in the scores related to the social-emotional skills of the infants across all time points (at 2 months: \( P=0.28 \); at 4 months: \( P=0.61 \); at 6 months: \( P=0.17 \); at 9 months: \( P=0.06 \); at 12 months: \( P=0.57 \)). This was true for the personal-social domain of the ASQ, the social-emotional scale of the Bayley-4 assessment, and the competence scale of the BITSEA.

Figure 1E shows the changes in the ASQ personal-social scores of the infants from both groups. Scores on the personal-social domain were relatively high during the 2- and 4-month time points but decreased from 4 to 9 months post partum. The personal-social scores increased subsequently at 12 months post partum. Overall, the intervention group appeared to perform better in terms of social-emotional skills than the control group.

**Behavioral Outcomes**

The ADBE scale of the Bayley-4 and the problem scale of the BITSEA assessed the behavioral outcomes of the infants. The BITSEA problem scale covered externalizing behaviors, dysregulating behaviors, and maladaptive behaviors. The infants from the control group were found to have significantly higher scores on the BITSEA problem scale than those from the intervention group (effect size=-5.87, 95% CI -10.44 to -1.70; \( P=0.006 \)). As such, the control group infants tended to exhibit more problem behaviors, as described in the BITSEA. By contrast, the ADBE scale mainly focused on the infants’ ability to engage in functional developmental tasks that are critical to their survival. This included feeding oneself and communicating basic needs. No significant group differences in the ADBE scores were found at both 6 months (effect size=2.05, 95% CI -2.74 to 6.84; \( P=0.40 \)) and 12 months (effect size=0.954, 95% CI -2.53 to 4.44; \( P=0.59 \)) post partum.

**Analysis of Covariates**

Parents attending prenatal courses was found to significantly influence whether their infants’ ASQ scores on the communication (RR=0.13, 95% CI 0.02-0.75; \( P=0.01 \)), gross motor (RR=0.43, 95% CI 0.21-0.90; \( P=0.03 \)), and personal-social (RR=0.28, 95% CI 0.10-0.82; \( P=0.02 \)) domains fell below the cutoff at 2 months post partum. The infants whose parents had attended prenatal courses tended to score better in these domains.

The education level of the parents was also a predictor of the infants’ motor skills. The infants of parents with secondary educational qualifications had a higher chance of being in the at-risk group at 6 months post partum than those of parents who graduated from universities (RR=13.41, 95% CI 2.27-79.09; \( P=0.004 \)). The generalized linear regression model for fine motor skills at 6 months post partum also showed that the infants of parents who received up to secondary-level education scored significantly lower than those of parents who graduated from universities (effect size=-13.55, 95% CI -24.95 to -2.15; \( P=0.02 \)). Thus, the results suggest that the infants of parents with higher educational levels tended to have developed better motor skills at 6 months post partum.

In this study, monthly household income was found to significantly affect the cognition and motor skills of the infants. The infants from households with a monthly income between SGD $3000 (US $2285.64) and SGD $5000 (US $3809.39) were more likely to belong to the at-risk group of the cognition domain of the Bayley-4 assessment than those from households earning > SGD $5000 (US $3809.39) monthly (RR=14.79, 95% CI 15.42 to 44.15; \( P<0.001 \)). Those with higher monthly household income also scored higher on the motor skills domain of the Bayley-4 assessment at 12 months post partum. Those with household income > SGD $5000 (US $3809.39) per month scored significantly higher in the motor skills domain than those with a household income of SGD $3000 (US $2285.64) to SGD $5000 (US $3809.39) per month (effect size=-10.65, 95% CI -15.42 to -5.89; \( P<0.001 \)) and those with a household income < SGD $1000 (US $761.88) per month (effect size=-14.97, 95% CI -22.97 to -5.17; \( P=0.002 \)). The generalized linear regression model also found similar results with the gross motor scale of the ASQ (effect size=-9.91, 95% CI -15.76 to -4.06; \( P<0.001 \)). Nonetheless, the modified Poisson regression model did not find any significant differences in the number of infants at risk for delayed motor skill development based on their income groups (\( P=0.68 \)).
Discussion

Principal Findings

This study examined the effects of the SPA intervention on infants’ developmental outcomes during the first 12 months of life. The infants in the intervention group mostly scored better in domains assessing communication, cognition, and social-emotional development. More infants from the control group fell under the at-risk category for motor skills than those from the intervention group. Findings from the main RCT reported a high attrition rate of 28.5% [24]. The outbreak of the COVID-19 pandemic in early February 2020 may have affected the parents’ and infants’ participation in the study, especially for the home visits. Hence, this led to a smaller-than-expected sample size, which likely affected the statistical power of the study. In general, although the infants from the intervention group tended to exhibit better developmental outcomes than those from the control group, these differences were modest. Therefore, the results of this study are not completely in line with the hypothesis.

Communication

From 2 to 12 months post partum, the infants from the intervention group were found to exhibit better communication skills than their control group counterparts. According to Bortfeld and Gabouer [38], early infant communication lays the groundwork for language. Previous studies [38,39] have emphasized that communication development often begins in the womb, where the fetus receives auditory inputs that enable them to start learning how to distinguish sounds. The SPA knowledge base included content encouraging the intervention group parents to communicate with their newborn and suggested ways to enhance parent-child interactions, even during pregnancy. For example, expecting parents can respond to the kicks made by the fetus during late pregnancy to communicate with them. With newborns, parents can play soothing music or read stories aloud to them to facilitate better communication and language development. According to the SPA traffic data, many parents in the intervention group accessed these materials in the mobile app and thus communicated with their infants more effectively, boosting their communication development. The decrease in communication scores from 4 to 9 months in both groups was unsurprising, as normative scores on the ASQ vary across ages and domains. For communication, the normative scores were approximately 42.5 at 4 months, 34 at 6 months, and only 30 at 9 months. Therefore, the reduction in mean communication scores during this period does not indicate that the infants’ communication abilities did not progress during this period. They mostly performed well above the normative scores.

On the basis of the trend graphs, the difference in the communication scores between the 2 groups increased over time. Topping et al [40] explained that parent interaction during the infant’s preliminary development was important in enhancing the child’s future language abilities. Parenting intervention programs have been found to have a positive impact on children’s language development. It is possible that the intervention group parents acted upon the things that they had read about, such as child play and infant milestones, which enabled them to interact more with their newborns. This, in turn, would have enhanced their child’s future language development. Therefore, the implementation of the SPA intervention might have led to the widening difference in communication scores between the 2 groups from 6 months onward. Future research could investigate in greater detail the relationship between the materials that parents read and what they put into practice.

Motor Skills

Similar to the communication trend graphs, the fluctuations in gross and fine motor skills indicated by the ASQ scores can be attributed to the differences in normative scores. Overall, the motor skills of the intervention group infants developed to a greater extent than those of the control group infants. This might have been because the parents in the intervention group had read the guide on how they could engage in play with their children on SPA. The guide included some toy recommendations that can help improve the motor skills of infants by allowing them to practice movements such as grasping and head turning. Semistructured interviews with some of the parents [10] revealed that the parents enjoyed having access to SPA, as it included various localized information that applied to them, which was unique because other parenting apps were more general. The parents could also anticipate and encourage the growth of their infants, as they read about developmental milestones. Consequently, the infants from the intervention group were exposed to more opportunities to practice and develop their motor skills. Descriptions of developmental milestones were also provided to educate parents on the motor skills that their children should achieve at each stage of development. However, the results suggest that the positive effects of the SPA intervention on the infants’ motor skills did not persist beyond 6 months post partum. As the SPA intervention only lasted up to 6 months post partum, information related to infant motor skill development beyond 6 months was rather scarce. The achievement of various motor-related milestones often drastically changes the subsequent behaviors of infants; thus, the toys or games used to engage them during earlier months might be less relevant in facilitating more advanced motor skill development [2]. Further research is needed to determine whether more age-appropriate information on motor skill development would help improve the motor skills of infants aged ≥6 months.

Cognition

Results from the problem solving domain of the ASQ revealed that the control group infants generally fared better than the intervention group infants during the first 6 months of their lives. However, the results of the 12-month Bayley-4 assessment revealed that the intervention group infants did better on the cognition scale than the control group infants. This finding is contrary to the hypothesis of this study, which proposed that the intervention group infants would perform better on cognition tasks than the control group infants. A reason for this might be that SPA did not include much content on enhancing the cognition and problem-solving skills of infants. Most of the parenting information available was related to childcare tasks...
such as feeding and swaddling or was related to parent-child communication and motor skills. As reported in a published qualitative paper [10] regarding the perspectives of the parents in the study, the control group parents described how they took the initiative to explore web-based resources and installed other parenting mobile apps to obtain more parenting-related information than what the standard care offered [10]. Some mobile apps used by the control group parents might have included information on how to build on the cognitive development of the infants during the first few months post partum. Therefore, more research is needed to obtain greater insight into the parenting resources used by Singaporean parents and how they influence infant development. More importantly, health care providers developing educational programs such as SPA should consider including content focusing on the holistic development of infants and children.

Social-Emotional Skills

Although there were no statistically significant group differences in the personal-social domain of the ASQ and social-emotional scale of the Bayley-4 assessment, the intervention group generally demonstrated greater social-emotional development. This lack of significance could be attributed to the fact that SPA did not include much information regarding the development of social-emotional skills in infants. However, the encouragement provided to parents to engage in age-appropriate parent-child play and increase parent-child interactions might have contributed to the slightly higher social-emotional and personal-social scores [38]. As mentioned, the COVID-19 pandemic hit Singapore in early 2020, immediately after the study began. During this period, various restrictions were set in place to minimize social interactions to prevent the spread of the virus [41]. This included the closure of infant care and prohibition of social gatherings. Hence, there were fewer opportunities for infants to engage in social situations with other infants and foster peer relationships. Existing literature has found that playing with peers is an important activity that allows for better development of prosocial behaviors and the formation of relationships with others [42]. The lack of such interactions owing to the pandemic might have further undermined the significance of the group difference in social-emotional development.

Behavioral Outcomes

The infants from the intervention group were found to engage in more ADBEs than those from the control group. On the basis of the parents’ responses to the BITSEA, the control group infants exhibited more problem behaviors as well. Maternal responsiveness and sensitivity to infant distress are important factors in predicting ADBE in infants. Higher maternal responsiveness is associated with greater emotional regulation and fewer behavioral issues [43]. Lorber et al [44] also found that well-known predictors of externalizing behavior include daily parenting hassles, authoritarian parenting, and poor parent-child bonding. The parents who received the SPA intervention were more educated on how to interact and bond with their newborns, which possibly led to improved parent-child bonding. They were also provided with support from the peer volunteers, which helped reassure them and provide them with an avenue to discuss parenting-related worries [10]. Ultimately, the parents in the intervention group received more informational, appraisal, and emotional support than those in the control group [10,26]. This helped them better adjust to the newborn care tasks that they had to take on after childbirth. Therefore, this study suggests that the SPA intervention was effective in facilitating the development of ADBEs in infants.

Prenatal Courses, Education, and Household Income

This study found that prenatal classes had a positive impact on communication, gross motor, and personal-social scores at 2 months post partum. Prior research [45] has found that prenatal education courses can help reduce anxiety during pregnancy, which can help improve prenatal bonding. This is especially true for first-time parents, who experience greater fear of childbirth and parenting self-efficacy [46]. Improved maternal well-being would then facilitate better infant outcomes, such as fewer maladaptive tendencies and greater levels of social competence [47]. However, most of the parents in this study did not attend prenatal classes. During interviews, the parents revealed that they were unable to attend these classes, as they were canceled because of the COVID-19 pandemic [10]. This left many new parents unprepared for the transition to parenthood, causing them to feel stressed and clueless. The implementation of social distancing restrictions also amplified this problem, as parents were unable to seek instrumental support from their family members or nannies [10]. Therefore, it is crucial for maternal care institutions to prepare and provide parents with sufficient support, especially through remote means at times when the availability of support is affected. This study was unable to examine how the development of children of new parents and that of children of experienced parents differed, as information regarding whether the parents were new or experienced was not collected in the main RCT. Therefore, it is crucial for future research to gather this information to further examine how the intervention impacts the differing needs of these parents.

The infants from families with higher household incomes were found to have more developed cognition. This is supported by previous literature, where it was found that children from families with low socioeconomic status (SES) had lower cognitive flexibility [48]. It was explained that the consequences of living with low SES are less favorable for children’s development. This includes greater exposure to stress, which affects children’s performance on cognitive tasks, and reduces maternal sensitivity and verbal stimulation [48]. Unsafe living conditions and stressors associated with low SES may also result in more negative or authoritarian parenting, which can affect cognitive outcomes.

Both higher parental education and higher monthly household income were significantly associated with stronger motor skills. Freitas et al [49] evaluated the relationship between SES and the availability of resources to promote motor development in infants. This study found that SES is a crucial factor influencing the availability of motor affordances at home. Educational level was also found to significantly affect the provision of toys to infants [49]. Parental education often affects the SES of the family, as higher education levels tend to open up job opportunities for infants and foster peer relationships. Existing literature has included information on how to build on the cognitive development of infants and children.
opportunities that offer higher income. Having more income would then lead to the purchase of more play materials or even the ownership of a larger home that provides more physical space for motor development [49,50]. As a result, infants from low-SES families and infants of parents with lower education levels tend to develop motor skills more slowly. Hence, researchers, health care providers, and policy makers may focus their efforts on developing interventions focusing on family factors that contribute to infant developmental outcomes across SES.

**Strengths and Limitations**

Given that social support has been proven to improve parental well-being and, in turn, promote infant growth in various areas, the SPA intervention was developed. The intervention aimed to meet the support needs of Singaporean parents during the perinatal period, thus helping them adjust to parenting roles and Infant-care tasks. This study found that technology-based parenting interventions such as SPA can lead to benefits beyond enhancing parental well-being. The findings of this study are crucial for the future development of not only mobile apps for parents in Singapore but also those for parents in other countries. Providing parenting education and emotional support can indirectly improve infant developmental outcomes. However, it is important to recognize and consider the cultural beliefs, practices, and support needs of parents from other countries. This would allow app developers to provide a knowledge base and appraisal support that would be respectful of and helpful in meeting their individualized needs.

Another strength of this study is that it used questionnaires that were completed by both parents and trained personnel. Parent-completed measures are advantageous in that parents spend the most time with their infants and are the most knowledgeable about them. However, existing literature [51] has also pointed out that there are biases associated with parent-reported questionnaires. Generally, parents are not trained in evaluating the development of infants, which can make them susceptible to overestimating or underestimating their child’s abilities and thus render their responses less reliable. By contrast, although the Bayley-4 was administered by a trained research assistant and can, therefore, provide a more objective assessment of the infant’s growth, infants tend to behave differently with unfamiliar individuals [51]. As such, Miller et al [51] expressed that a fuller picture of the infant’s development could be obtained if both types of assessments were used.

This study has some limitations. One of its limitations is its high attrition rate. Because of the COVID-19 pandemic, parents were more cautious of physical interactions, as they did not want themselves, their infants, or other family members to contract the virus. Therefore, many parents declined home visits for the Bayley-4 assessment. This may have affected the accuracy of the findings in representing the sample recruited for this study. Moreover, the longitudinal nature of the study might have also contributed to the high attrition rate. Parents tend to become busier post partum owing to the need for them to adjust to parenting responsibilities; in the case of this study, the need to take extra precautions to prevent contracting the COVID-19 virus added to these responsibilities. Therefore, it is paramount to devise strategies to keep parents interested in and willing to participate in the study. For example, research team members can frequently contact parents to build stronger rapport and remind them to access SPA if they have parenting-related concerns. Although the research team originally intended to do so, some technical issues led to the absence of chat notifications, affecting the communication between the team and parents. Furthermore, many of the research team members were also frontline health care workers; therefore, they were unable to meet often and resolve these issues in a timely manner.

Another limitation of this study is the lack of information regarding whether the parents were experienced or new. This is an important limitation, as the struggles and support needs that new and experienced parents encounter may differ widely. Hence, future studies should take note to collect such information from parents to provide deeper perspectives regarding the effectiveness of parenting interventions in new and experienced mothers and fathers. Subsequent research may also investigate parental sensitivity and responsivity to provide further insight into how they may affect infant behavioral outcomes.

**Conclusions**

This study examined the effects of the SPA intervention on infant developmental outcomes. The results showed that the infants from the intervention group generally developed better in terms of communication, motor skills, cognition, and social-emotional skills than those from the control group. The peer support and informational support that the SPA intervention offered to the intervention group parents were thus helpful in indirectly influencing the development of infants. More research is needed to obtain an in-depth understanding of what functions of the intervention influenced the infant outcomes and what information the current generation of parents hopes to see in parenting mobile apps. This would facilitate the creation of more effective mHealth app–based support for parents. In the future, interventions targeting infant growth and development should be created to measure the direct effects of educational interventions. In addition, future parenting interventions should focus on providing more support to families with lower SES to help promote the development of infants and support parents from these families.

**Acknowledgments**

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Conflicts of Interest
None declared.

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Abbreviations

| ADBE | adaptive behavior |
| ASQ | Ages and Stages Questionnaire |
| BITSEA | Brief Infant Toddler Social Emotional Assessment |
| mHealth | mobile health |
| RCT | randomized controlled trial |
| RR | risk ratio |
| SES | socioeconomic status |
| SPA | Supportive Parenting App |

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Effectiveness of a Mobile App to Increase Risk Perception of Tobacco, Alcohol, and Marijuana Use in Mexican High School Students: Quantitative Study

Patricia María del Carmen Fuentes A, PhD; Alberto Jiménez Tapia, MSc; Eunice M Ruiz-Cortés, BSc; Fernando Bolaños-Ceballos, PhD; Julio César Flores Castro, BSc; Rafael Gutiérrez, MSc; Catalina González-Forteza, PhD

1Direction of Epidemiological and Psychosocial Research, National Institute of Psychiatry Ramón de la Fuente Muñiz, Mexico City, Mexico
2Universidad Autónoma del Estado de Hidalgo, Actopan, Hidalgo, Mexico
*all authors contributed equally

Corresponding Author:
Alberto Jiménez Tapia, MSc
Direction of Epidemiological and Psychosocial Research
National Institute of Psychiatry Ramón de la Fuente Muñiz
Calzada Mexico Xochimilco, 101
Mexico City, 14370
Mexico
Phone: 52 5541605154
Email: alberjt1969@gmail.com

Abstract

Background: Young people have the highest rate of drug use worldwide. Recent data from Mexico in this population show that the prevalence of illicit drug use doubled between 2011 and 2016 (2.9%-6.2%), with marijuana being the one with the highest increase (2.4%-5.3%), but also point out that alcohol and tobacco use have remained steady or decreased. Mexican adolescents are at high risk for drug use owing to a low perception of risk and the availability of drugs. Adolescence is an ideal period to reduce or prevent risky behaviors using evidence-based strategies.

Objective: In this study, we aimed to test the short-term effectiveness of a mobile intervention app (“What Happens if you Go Too Far?” [“¿Qué pasa si te pasas?”]) that seeks to increase risk perception of tobacco, alcohol, and marijuana use in a sample of Mexican high school students.

Methods: A nonexperimental evaluation based on pretest-posttest design was used to measure the effectiveness of a preventive intervention using a mobile app, “What Happens If You Go Too Far?” The dimensions analyzed were knowledge of drugs and their effects, life skills, self-esteem, and risk perception. The intervention was conducted on a high school campus with 356 first-year students.

Results: The sample included 359 first-year high school students (mean 15, SD 0.588 years; women: 224/359, 62.4% men: 135/359, 37.6%). The intervention increased the overall risk perception of tobacco ($\chi^2=21.6; P<.001$) and alcohol use ($\chi^2=15.3; P<.001$). There was no significant difference in the perception that it is dangerous to smoke 5 cigarettes, and there was a marginal difference in the perception that it is very dangerous to smoke 1 cigarette or to use alcohol or marijuana. We used a generalized estimating equation method to determine the impact of the variables on risk perception. The results showed that knowledge about smoking increased the risk perception of smoking 1 cigarette (odds ratio [OR] 1.1065, 95% CI 1.013-1.120; $P=.01$), and that knowledge about marijuana use (OR 1.109, 95% CI 1.138-1.185; $P=.002$) and self-esteem (OR 1.102, 95% CI 1.007-1.206; $P=.04$) produced significant increases in the risk perception of consuming 5 cigarettes. Resistance to peer pressure and assertiveness also increased the perceived risk of using alcohol and alcohol.

Conclusions: The intervention has the potential to increase the perception of risk toward drug use in high school students by providing knowledge about the effects and psychosocial risks of drug use and by strengthening life skills that are associated with increased risk perception. The use of mobile technologies in intervention processes may broaden the scope of preventive work for adolescents.
Introduction

Background

Drug use is shaped by the interaction of personal, social, and contextual factors. Lack of knowledge about substance use dynamics (social influence, positive attitudes toward use, peer group use, availability, and inadequate parental supervision) are elements that favor use in adolescents [1,2]. The most recent data in this population not only show that the prevalence of illicit drug use doubled between 2011 and 2016 (2.9%-6.2%), with marijuana being the one with the highest increase (2.4%-5.3%), but also point out that alcohol and tobacco use have remained steady or decreased [3]. The negative consequences of use affect general well-being, academic performance, physical and mental health, family dynamics, and peer relationships, and they increase the likelihood of fatal accidents [4].

Adolescents and young adults have the highest rates of substance use throughout the world [5]. The data show that adolescents are the population group with the highest risk for substance use in Mexico and that they start at increasingly younger ages. Their perception of risk is low, and drug availability is increasing [6,7]. This situation highlights the need for evidence-based early interventions with a public health approach and an ecological perspective.

During adolescence (10-19 years of age), there are important biological, psychological, and social transitions resulting from rapid physical, psychological, sexual, and social development that involves changes in the brain, cognition, and emotions [1,8]. Adolescents are in a vulnerable position that brings them closer to risk behaviors such as drug abuse [9-12], and it has become a public health problem.

Adolescents are exposed to individual, family, and social risks and protective factors that can increase or decrease the probability of drug use. Family risk factors include conflict, lack of parental supervision, and family members who are abusive physically, emotionally, and sexually. Social risk factors include peer pressure to use drugs as a form of socialization, peers who use it, and the availability of drugs. Individual risk factors include inclination toward experimentation, curiosity, rebelliousness, and impulsivity, as well as low self-esteem, lack of emotional regulation, depression, anxiety, behavioral problems, poor school performance, previous experiences with drugs, and low risk perception toward drug use [13-16]. Risk perception may contribute to increasing the odds of drug use in adolescents, and there is evidence that it may act in both ways as a risk or protective factor; that is, when it is low, it increases the risk of drug use and vice versa [13,16].

Health behavior theories such as the Health Belief Model and the Theory of Planned Behavior suggest that risk perception is an important factor in health behavior and that the level of risk perception determines the likelihood of the occurrence of risk behaviors such as adolescent drug use [14,17-19]. Because risk perception is an attitude that represents the evaluation of an object through its favorable and unfavorable attributes [17], levels of risk perception have been considered important determinants of risky behaviors.

There is evidence indicating that the probability of drug use increases as people perceive little or no risk of associated harm. That is, a higher perceived risk can be considered as a protective factor against drug use [13]. A longitudinal study on risk perception toward tobacco, alcohol, and cannabis use with a 10-year follow-up reported that it reduced the probability of consumption in German adolescents aged 14 and 15 years [18]. Other studies in the Latin American population reported a low risk perception associated with drug use [20], which is usually at these levels for tobacco and alcohol and higher for other drugs. However, a reduction in the perception of risk of marijuana use has also been reported between 2000 and 2014, which has been associated with an increase in the use of this drug in the adolescent population [3].

Evidence shows that a lower perception of risk is related to higher rates of use [21] and that protective dynamics can emerge within the perception of negative consequences or health risks [22-24]. Work is necessary in this regard because the perceived risk of regular marijuana use has decreased by 40% between 1995 and 2019, but the potency of the drug and its consumption have increased; therefore, it is important to reduce this gap to lower its impact on public health [25].

Adolescence is an ideal period for interventions designed to reduce or prevent risky behaviors [26]. Life skills, including positive and adaptive social skills, enable adolescents to cope with everyday challenges [27,28]. The life skills approach considers the following: (1) the recognition and evidence of the role of cognitive, interpersonal, and coping skills in psychosocial development; (2) the effect of skills on young people’s ability to protect their health, adopt positive behaviors, and foster healthy relationships; (3) the application of skills in managing education, violence, and human rights; (4) the reinforcement of protective factors such as self-awareness, self-confidence, and self-esteem; and (5) the mastery and application of skills in everyday situations to feel self-confident, self-efficient, and self-worthy [29,30]. The development of life skills is part of the learning, competence, and education that underpin adolescent well-being [31].

Interventions based on life skills training have proven to be effective for the prevention of drug use in adolescents, are easy to adapt and disseminate [29,32-35], and are an effective strategy to promote health care in schools [27,28,36]. However, their design requires providing knowledge and skills to the professionals who perform them, which in turn requires economic, human, and time resources [8].

Schools are effective settings for preventive interventions, given the ease of access to adolescents and because they are spaces
designed to foster learning and socialization [32,37]. Studies on prevention and early intervention based on life skills to address drug use in educational settings have shown excellent results [8]. The COVID-19 pandemic has underscored the importance of measuring the effects of these interventions when they are executed using digital technologies [38].

Mobile apps are effective tools for prevention and intervention in health care. There are various examples of the use of this technology to address depression, anxiety, drug use, and suicide [10,11,39]. Some strategies provide only information and education, and others focus on giving advice, strategies, or skills training, but fewer offer the possibility of self-assessing drug use and providing feedback [11,39]. Additional research is needed to evaluate the effectiveness of apps, and funding is needed to develop apps using evidence-based techniques [40].

Interventions that are designed for the internet or mobile devices using current evidence-based approaches and resources are more likely to be successful in prevention [11,39,41]. The use of these technologies, including life skills training, has the advantages of accessibility, portability, interactivity, feedback, ease of use, and wide reach at low cost; they reach adolescent and young adult populations because of their ubiquity and mobility and because young people know, accept, and integrate them easily into their lifestyle [32,42].

### Objective

There are few studies that have evaluated the characteristics and effectiveness of digital mobile interventions. It is necessary to evaluate their effectiveness and applicability in real-world contexts to verify their potential and usefulness [32,39-41]. Consequently, the objective of this study was to test the short-term effectiveness of a mobile intervention app (“What Happens if you Go Too Far?” [“¿Qué pasa si te pasas?”]). This study aimed to increase risk perception of tobacco, alcohol, and marijuana use in a sample of Mexican high school students.

### Methods

#### Ethics Approval

All participants’ parents signed an informed consent form, and all participants provided written informed consent. The study was approved by the Research Ethics Committee of the Instituto Nacional de Psiquiatría Ramón de la Fuente Muñiz (approval number CEI/C/003/2016).

#### Design and Procedure

##### Overview

This study used a nonexperimental pretest-posttest design, with assessments at baseline and at the end of the intervention. The intervention was performed in a high school campus, as part of the introductory curriculum for the school year, in a classroom with 45 computers using the Android emulator BlueStacks (BlueStacks) to execute the app “What Happens if you Go Too Far?” (“¿Qué pasa si te pasas?”). The intervention evaluation questionnaire (Brief Life Skills Scale for Adolescents) (González-Forzeta et al, unpublished data, August 2022) was administered as a Google Form. The Brief Life Skills Scale for Adolescents was developed using items from several more extensive scales, each including 35 to 65 items that assess the skills separately and have been validated for Mexican adolescents. These skills include planning for the future, assertiveness, expression of emotions, taking responsibility, decision-making, and resistance to peer pressure.

Before its implementation, teachers and psychology interns received training in the management of the intervention, which included modules on the effects and risks of drug use in adolescents and on strengthening 6 life skills and addressing the emotions that occur when these skills are applied.

The intervention was performed during the orientation week for the incoming students. The students were invited to participate in the study voluntarily and anonymously. The school authorities and teachers were informed of the project and granted access to the school. The objectives of the research as well as the risks and benefits of participating in the study were explained to the students; they were informed that their participation was voluntary, their answers would be anonymous, and the results would not affect their activities or evaluation in school.

In total, 10 groups of first-year high school students from the 2019-2020 classes participated. The intervention lasted 10.5 hours: three 90-minute sessions for each group at school, plus 2 hours per day of individual activities at home using the app during the same week the intervention was implemented. In each of the 3 sessions, there was an average of 36 students per group. Participants did not receive any incentives for their involvement in the study.

#### Session 1

The first session aimed to apply the pretest evaluation, present the mobile app, and explain life skills. The evaluation questionnaire took 20 minutes to complete. After the evaluation, participants were instructed to download the “What Happens If you Go Too Far?” apps on mobile devices (iOS and Android). Downloading the app required students to connect to the internet via a mobile network or Wi-Fi, and once the app was installed on their devices, it could be used offline. The session also included a description of the World Health Organization (WHO)–recommended life skills (decision-making, resistance to peer pressure, problem-solving, future planning, and assertiveness), an explanation of basic emotions, and the link between life skills and the absence or presence of emotions. We also showed the objectives and options included in the main menu of the app and the available resources (comics, video games, quizzes, trivia, agendas, and news). Participants were asked to form teams of 5 to 6 members to share their answers as a group in subsequent sessions on the effects and risks of drug use and the use of life skills in different cases. Finally, we assigned the comic resources on the topics of alcohol consumption and women or men as homework.

#### Session 2

The second session was designed to (1) identify the effects and risks of alcohol use in women and men; (2) apply decision-making skills, resistance to peer pressure, problem-solving, and goal achievement skills; and (3) identify the consequences and emotions associated with the application of the skills. Participants were instructed to read the comic
“Alcohol and Women” to understand the risks and immediate effects of alcohol use on women, to use the cases of Mony and Lucy to choose 3 options and their consequences, and to identify the decision-making and resistance to peer pressure involved. Subsequently, they were asked to answer the questions on the “What Happens If You Go Too Far?” app activity form, based on their interaction with the comic to identify the immediate effects of alcohol use and recognize or describe different situations that encourage alcohol use, some of the consequences and emotions involved in using drugs, and some strategies to resist peer pressure. The facilitator asked the teams to answer some questions related to the scenarios described before to reinforce the identification of the immediate social and health effects of alcohol use in women, apply their skills to situations that lead to drug use, associate them with emotions that may occur, and think about the consequences of the characters’ decisions (Lucy and Mony) in the situations they face. Participants then completed the trivia and quiz on alcohol and women to reinforce their knowledge. The second part of the session comprised the same procedure with the comic “Alcohol and Men,” in which problem-solving and goal setting were applied to the cases of the male characters (Beto and Angel). Participants then completed the trivia and quiz on alcohol and men to reinforce their knowledge, and they received orientation on using the comics on tobacco and marijuana to apply negotiation, assertive communication, problem-solving, and resistance to peer pressure.

Session 3

The third session sought to (1) identify the effects and risks of tobacco and marijuana use; (2) apply skills related to negotiation, assertive communication, problem-solving, and resistance to peer pressure; (3) identify consequences and emotions associated with the application of the skills; and (4) administer the posttest evaluation questionnaire. Participants were asked to read the comic about tobacco to review the risks and effects of using it. The characters of the comic (Susy, Alma, and Lizet) were used to model the consequences and identify the negotiations and assertive communication involved. Participants then answered the questions on the “What Happens If You Go Too Far?” app activity form to check their understanding of the steps of negotiation, their ability to identify situations that encourage tobacco use, if they could recognize decision-making options and discuss consequences and emotions involved, and if they could apply the life skills in an everyday situation. The facilitator asked the teams to answer some questions related to the scenarios described before to reinforce the identification of the immediate social and health effects of tobacco and marijuana use, apply their skills to situations that lead to drug use, associate them with emotions that may occur, and think about the consequences of the characters’ decisions in the situations they face. Participants then completed the trivia and quiz on tobacco to reinforce their knowledge. The second part of the session followed the same procedure with the comic “Marijuana” to understand the risks and immediate effects of using drugs, and identify the skills involved in problem-solving and resistance to peer pressure involved. This was applied using the cases of the characters (Agus, Diana, Pedro, and Omar). Participants then completed the trivia and quiz on marijuana to reinforce their knowledge. Finally, we administered the posttest evaluation questionnaire (evaluation questionnaire, 20 minutes).

Intervention to Prevent Addiction: the “What Happens If You Go Too Far?” App

The “What Happens If You Go Too Far?” [43] intervention app seeks to strengthen life skills and increase risk perception of drug use. It is based on the WHO Skills for Health model and Bandura’s Social Learning Theory.

The intervention acts at cognitive and behavioral levels to increase the risk perception of drug use. At the cognitive level, it facilitates the acquisition of specific knowledge of the effects of drugs on the brain and behavior. It contains evidence-based scientific information translated into textual and visual language to generate interactive comics, trivia, quizzes, and games that facilitate understanding and encourage thinking about substance use. At the behavioral level, it strengthens life skills and improves adolescents’ ability to relate with their peers, resist pressure to use substances, solve problems effectively, and make responsible decisions with awareness of consequences. The comics in the app depict and simulate everyday situations related to drug use to apply these skills.

The comics include three elements: (1) information about drugs, their immediate effects, and their risks; (2) situations experienced by young people that are associated with drug use; and (3) skills involved in decision-making, problem-solving, negotiation, assertiveness, and resistance to peer pressure that help to face the challenges of everyday life.

The trivia is a question-and-answer game that facilitates immediate self-assessment of knowledge of the effects of drug use to reinforce the knowledge acquired with the comics. The quiz is a brief, flexible, and self-administered resource based on the WHO alcohol, smoking, and substance involvement screening test, which assesses drug use using 8 questions and indicates low-, moderate-, or high-risk scores [44,45]. It allows participants to identify their individual level of risk and provides them with information to recognize likely consequences and risks.

The video game models situations associated with drug use experienced by the characters Beto and Bety and facilitates the application of skills to making decisions, communicating assertively, negotiating, and resisting peer pressure; it provides automatic reinforcement. The news feature facilitates constant updating of (1) preventive messages or specific events for timely dissemination and (2) links of interest to youth. The agenda feature connects to hotlines that focus on drug use problems.

The Technology Behind the “What Happens If You Go Too Far?” App

The configuration of comics and game resources uses the potential of interactive technology, using stories that model everyday situations associated with drug use in young people, to practice decision-making with various options and their consequences. This serves to reinforce knowledge and encourage thinking about the risks and effects of drug use.

The interactive dynamic favors (1) reinforcing the knowledge of drugs and their effects, (2) thinking about the risks and...
consequences of consumption, (3) interactively applying decision-making and its automatic and immediate feedback in the situations presented, (4) concluding reinforcement with infographics of the different skills in each case, and (5) giving immediate feedback on the trivia and quiz. The app content was developed to be both didactic and informative.

The app is available for free on the 2 most important platforms in the market (Google Android [Google LLC] and Apple iOS [Apple Inc]). It can be installed on a wide range of mobile devices and has a broad reach among young people. A third option is to use an Android emulator that allows the app to be used offline on PCs for students and schools without internet access.

The app was developed using Unity 3D and state-of-the-art web technologies. It is based on the current standards of responsive web design and user experience to generate an accessible and optimized product that is fast and easy to download. The front-end offers interactive content and resources that can be used individually or in groups (the game, trivia, and quiz). The information is complemented by an agenda that facilitates contact with specialized care centers and services, as well as links to relevant news and web content. The back end includes various web tools for web-based editing and updating of content, as well as data consultation and statistical reports for use analysis by the developers, administrators, and researchers in charge of the project.

Data Analysis

In this study, 2 types of analyses were used to identify differences between pre- and posttest measurements. The first was used to measure variations in the perceived risk of using marijuana, alcohol, and tobacco (smoking 1 cigarette and smoking 5 cigarettes) in both measurements. The original categories of risk perception were “not dangerous,” “dangerous,” and “very dangerous.” There was no statistically significant difference between “not dangerous” and “dangerous”; therefore, the former category was excluded from the analysis, and differences in pre- and posttest measurements of risk perception were made between the categories of “dangerous” and “very dangerous.”

Comparisons were performed using McNemar test, with 95% certainty considered statistically significant. This is a nonparametric analysis of the comparison of proportions for 2 related samples whose function is to compare the change in the distribution of proportions between 2 measurements of a dichotomous variable and determine that the difference is not due to chance. In this case, there was no dependent or independent variable, as they were related or paired measurements. The impact of variables on risk perception was calculated using the generalized estimating equation (GEE) method, which extends the generalized linear model to allow for the effect of repeated measurements and other related observations. GEE is a method for modeling longitudinal or pooled data, and is often used with nonnormal data, such as binary or count data. This method uses a set of equations that are solved to obtain parameter estimates. This modeling strategy uses a quasi-likelihood function that assumes only a relationship between μ and Var(Y) rather than a specific distribution for Y. This allows deviation from the usual assumptions, such as overdispersion caused by correlated observations or unobserved explanatory variables. To do this, the quasi-likelihood approach takes the usual formula for variance but multiplies it by a constant that is estimated using the data. GEE is designed for simple clustering or repeated measures; it is not easily adaptable to more complex designs, such as nested or cross-group designs [46].

We took care in the analysis that (1) the mean structure was correctly specified (all relevant variables were included and all irrelevant variables were removed), (2) the observations between clusters were unrelated (there is no higher-level clustering mechanism), (3) the sample size was large enough for asymptotic inference (356 records); (4) the normality of residuals was not assumed with GEE; and (5) the database was restructured to obtain the necessary information. As there is no field called TIME, we used the SAMPLE field, which in our case, expresses the ratio of time between evaluations as a function of TIME. Although it was designed for longitudinal studies, in this case, it was applied to 2 measurements because missing measurements are common in longitudinal designs and are assumed to be caused by chance. Therefore, missing values were imputed using IBM SPSS Modeler (version 18.3; IBM Corp) tool, which has different imputation methods (fixed, random, expression, and algorithm). In this analysis, we used the algorithm method, which replaces a predicted value with a model based on the classification and regression trees algorithm. In each field imputed with this method, there is a separate classification and regression trees model, along with a fill node that replaces empty and null values with the value predicted by the model.

Results

Participants

The sample for the initial evaluation included 359 (90% of the 399 enrolled students) first-year middle-class high school students at the Escuela Superior Actopan, affiliated with the Universidad Autónoma del Estado de Hidalgo. The mean age of the participants was 15 (SD 0.588) years. Of the total sample, 224 (62.4%) of the students were women and 135 (37.6%) were men; 182 (50.7%) participants were in the morning session and 176 (49%) participants were in the afternoon session. Regarding drug use history, 64 (17.8%) participants reported tobacco use sometime in life (women: 36/224, 16.1%; men: 28/135, 20.7%) and 27 (7.5%) in the past 3 months (women: 11/224, 4.9%; men: 16/135, 11.9%); 174 (48.5%) students reported alcohol use sometime in life (women: 99/224, 44.2%; men: 75/135, 55.6%) and 126 (35.1%) in the past 3 months (women: 81/224, 36.2%; men: 45/135, 33.3%); 18 (5%) participants reported marijuana use sometime in life (women: 7/224, 3.1%; men: 11/135, 8.1%) and 6 (1.7%) in the past 3 months (women: 1/224, 0.4%; men: 5/135, 3.7%; Multimedia Appendix 1).

The follow-up evaluations were completed by 356 (99.2%) of the 359 study participants. The mean age of the participants was 15 (SD 0.574) years. Of them, 224 (62.9%) participants were women, 132 (37.1%) were men; 224 (62.9%) were in the morning session, and 132 (37.1%) were in the afternoon session.
The inclusion criterion was enrollment in the first semester of high school at Escuela Superior Actopan.

**Effectiveness of the App**

Of the 356 students, the proportion of those who perceived that it was dangerous to smoke 1 cigarette decreased from 197 (55.3%) to 161 (46%) comparing the pre- and posttest measurements, but the perception that it was very dangerous increased from 85 (23.9%) to 142 (39.9%). Of the 356 students, the proportion perceiving that it was dangerous to smoke 5 cigarettes increased from 62 (17.4%) to 73 (20.5%) comparing the pre- and posttest measurements, and the perception that it was very dangerous decreased from 288 (80.9%) to 271 (76.1%).

The proportion perceiving that it was dangerous to consume alcohol decreased from (193/356, 54.2%) to (131/356, 36.8%) comparing the pre- and posttest measurements, and the perception that it was very dangerous increased from (156/356, 43.8%) to (210/356, 60%).

Similarly, the proportion of the students perceiving that it was dangerous to use marijuana decreased from (141/356, 39.6%) to (111/356, 31.2%) and that it was very dangerous increased from (203/356, 57%) to (235/356, 66%).

The overall risk perception of the use of these drugs showed significant differences only for the use of 1 cigarette ($\chi^2 = 21.6; P < .001$) and the use of alcohol ($\chi^2 = 15.3; P < .001$); there was a marginal difference for the use of marijuana ($\chi^2 = 3.6; P = .057$).

There was no significant difference in the risk perception of smoking the 5 cigarettes.

Tables 1-4 show the GEE models in which gender, drug knowledge, life skills, and self-esteem were included as covariates (Multimedia Appendix 2). The analysis showed that knowledge of smoking was the variable that generated a significant increase in risk perception (odds ratio [OR] 80.060, 95% CI 0.009-0.110; $P = .02$) of smoking 1 cigarette (Table 1).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Exp(B)</th>
<th>95% Wald CI for exp(B)</th>
<th>$P$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intersection)</td>
<td>−6.555</td>
<td>−8.725 to −4.385</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Gender (men)</td>
<td>0.017</td>
<td>−0.323 to 0.357</td>
<td>.92</td>
</tr>
<tr>
<td>Knowledge about tobacco</td>
<td>0.060</td>
<td>0.009 to 0.110</td>
<td>.02</td>
</tr>
<tr>
<td>Knowledge about marijuana</td>
<td>0.038</td>
<td>−0.030 to 0.106</td>
<td>.28</td>
</tr>
<tr>
<td>Knowledge about alcohol</td>
<td>0.002</td>
<td>−0.030 to 0.034</td>
<td>.90</td>
</tr>
<tr>
<td>Planning for the future</td>
<td>−0.015</td>
<td>−0.090 to 0.059</td>
<td>.68</td>
</tr>
<tr>
<td>Assertiveness</td>
<td>0.083</td>
<td>−0.023 to 0.189</td>
<td>.12</td>
</tr>
<tr>
<td>Expression of emotions</td>
<td>0.069</td>
<td>−0.024 to 0.162</td>
<td>.14</td>
</tr>
<tr>
<td>Resistance to peer pressure</td>
<td>0.003</td>
<td>−0.057 to 0.062</td>
<td>.93</td>
</tr>
<tr>
<td>Decision-making</td>
<td>0.023</td>
<td>−0.035 to 0.080</td>
<td>.44</td>
</tr>
<tr>
<td>Taking responsibility</td>
<td>0.015</td>
<td>−0.115 to 0.145</td>
<td>.82</td>
</tr>
<tr>
<td>Self-esteem</td>
<td>0.059</td>
<td>−0.025 to 0.142</td>
<td>.17</td>
</tr>
</tbody>
</table>

Knowledge of marijuana (OR 0.091, 95% CI 0.023-.160; $P = .009$), and self-esteem (OR 0.131, 95% CI 0.046-0.217; $P = .003$), were the variables that produced significant increases in the risk perception of consuming 5 cigarettes (Table 2).

The variables that increased the risk perception of alcohol consumption were knowledge of smoking (OR 0.089, 95% CI 0.043-0.135; $P < .001$), assertiveness (OR 0.102, 95% CI 0.004-0.200; $P = .04$), resistance to peer pressure (OR 0.078, 95% CI 0.023-0.134; $P = .006$), and self-esteem (OR 0.140, 95% CI 0.063-0.216; $P < .001$; Table 3).

For perceived risk of marijuana use, the variables that significantly increased risk perception were knowledge of tobacco (OR 0.074, 95% CI 0.026-0.121; $P = .002$), knowledge of marijuana (OR 0.110, 95% CI 0.047-0.174; $P = .001$), resistance to peer pressure (OR 0.117, 95% CI 0.060-0.174; $P < .001$), and self-esteem (OR 0.165, 95% CI 0.085-0.244; $P < .001$) (Table 4).
### Table 2. Generalized estimating equation model for the risk perception of smoking 5 cigarettes.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Exp(B)</th>
<th>95% Wald CI for exp(B)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intersection)</td>
<td>−3.265</td>
<td>−5.452 to −1.078</td>
<td>.003</td>
</tr>
<tr>
<td>Gender (men)</td>
<td>0.132</td>
<td>−0.255 to 0.518</td>
<td>.50</td>
</tr>
<tr>
<td>Knowledge of tobacco</td>
<td>0.023</td>
<td>−0.029 to 0.075</td>
<td>.39</td>
</tr>
<tr>
<td>Knowledge of marijuana</td>
<td>0.091</td>
<td>0.023 to 0.160</td>
<td>.009</td>
</tr>
<tr>
<td>Knowledge of alcohol</td>
<td>−0.006</td>
<td>−0.042 to 0.031</td>
<td>.77</td>
</tr>
<tr>
<td>Planning for the future</td>
<td>−0.062</td>
<td>−0.157 to 0.032</td>
<td>.20</td>
</tr>
<tr>
<td>Assertiveness</td>
<td>0.077</td>
<td>−0.039 to 0.193</td>
<td>.20</td>
</tr>
<tr>
<td>Expression of emotions</td>
<td>0.007</td>
<td>−0.096 to 0.110</td>
<td>.89</td>
</tr>
<tr>
<td>Resistance to peer pressure</td>
<td>0.027</td>
<td>−0.035 to 0.090</td>
<td>.39</td>
</tr>
<tr>
<td>Decision-making</td>
<td>−0.024</td>
<td>−0.087 to 0.039</td>
<td>.46</td>
</tr>
<tr>
<td>Taking responsibility</td>
<td>−0.028</td>
<td>−0.175 to 0.118</td>
<td>.70</td>
</tr>
<tr>
<td>Self-esteem</td>
<td>0.131</td>
<td>0.046 to 0.217</td>
<td>.003</td>
</tr>
</tbody>
</table>

### Table 3. Generalized estimating equation model for the risk perception of frequent alcohol use.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Exp(B)</th>
<th>95% Wald CI for exp(B)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intersection)</td>
<td>−8.326</td>
<td>−10.404 to −6.248</td>
<td>&lt;.001</td>
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<tr>
<td>Gender (men)</td>
<td>0.087</td>
<td>−0.238 to 0.412</td>
<td>.60</td>
</tr>
<tr>
<td>Knowledge of tobacco</td>
<td>0.089</td>
<td>0.043 to 0.135</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Knowledge of marijuana</td>
<td>0.005</td>
<td>−0.056 to 0.066</td>
<td>.87</td>
</tr>
<tr>
<td>Knowledge of alcohol</td>
<td>0.010</td>
<td>−0.020 to 0.041</td>
<td>.50</td>
</tr>
<tr>
<td>Planning for the future</td>
<td>−0.047</td>
<td>−0.143 to 0.049</td>
<td>.34</td>
</tr>
<tr>
<td>Assertiveness</td>
<td>0.102</td>
<td>0.004 to 0.200</td>
<td>.04</td>
</tr>
<tr>
<td>Expression of emotions</td>
<td>0.019</td>
<td>−0.068 to 0.106</td>
<td>.66</td>
</tr>
<tr>
<td>Resistance to peer pressure</td>
<td>0.078</td>
<td>0.023 to 0.134</td>
<td>.006</td>
</tr>
<tr>
<td>Decision-making</td>
<td>0.020</td>
<td>−0.033 to 0.073</td>
<td>.46</td>
</tr>
<tr>
<td>Taking responsibility</td>
<td>0.062</td>
<td>−0.060 to 0.183</td>
<td>.32</td>
</tr>
<tr>
<td>Self-esteem</td>
<td>0.140</td>
<td>0.063 to 0.216</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

### Table 4. Generalized estimating equation model for the risk perception of marijuana use.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Exp(B)</th>
<th>95% Wald CI for exp(B)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intersection)</td>
<td>−9.428</td>
<td>−11.611 to −7.246</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Gender (men)</td>
<td>0.314</td>
<td>−0.030 to 0.658</td>
<td>.07</td>
</tr>
<tr>
<td>Knowledge of tobacco</td>
<td>0.074</td>
<td>0.026 to 0.121</td>
<td>.002</td>
</tr>
<tr>
<td>Knowledge of marijuana</td>
<td>0.110</td>
<td>0.047 to 0.174</td>
<td>.001</td>
</tr>
<tr>
<td>Knowledge of alcohol</td>
<td>−0.011</td>
<td>−0.044 to 0.022</td>
<td>.51</td>
</tr>
<tr>
<td>Planning for the future</td>
<td>−0.040</td>
<td>−0.106 to 0.026</td>
<td>.23</td>
</tr>
<tr>
<td>Assertiveness</td>
<td>0.045</td>
<td>−0.059 to 0.149</td>
<td>.40</td>
</tr>
<tr>
<td>Expression of emotions</td>
<td>−0.033</td>
<td>−0.126 to 0.061</td>
<td>.49</td>
</tr>
<tr>
<td>Resistance to peer pressure</td>
<td>0.117</td>
<td>0.060 to 0.174</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Decision-making</td>
<td>0.049</td>
<td>−0.007 to 0.105</td>
<td>.08</td>
</tr>
<tr>
<td>Taking responsibility</td>
<td>−0.025</td>
<td>−0.153 to 0.104</td>
<td>.71</td>
</tr>
<tr>
<td>Self-esteem</td>
<td>0.165</td>
<td>0.085 to 0.244</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>
Principal Findings

The objective of this study was to evaluate the effectiveness of a mobile app in increasing the risk perception of tobacco, alcohol, and marijuana use based on life skills and self-esteem training components in a sample of Mexican high school students. The results of the study showed four main findings regarding the intervention: (1) it increased the overall risk perception of tobacco and alcohol use, (2) it increased the perception that it was dangerous to smoke 5 cigarettes, (3) it increased the perception that it was very dangerous to smoke 1 cigarette or to use alcohol or marijuana, and (4) the variables that significantly increased the risk perception of using these drugs were knowledge of tobacco, knowledge of marijuana, resistance to peer pressure, assertiveness, and self-esteem.

Risk perception of the possible consequences of drug use is usually low in adolescents and young adults [47], and evidence has shown that this low perception of risk can increase the likelihood of using drugs [48]. Risk perception is also associated with the type and knowledge of drugs [49]. For example, the recreational use of marijuana in Mexico is still not legal. Although the Supreme Court voted in favor of personal possession and consumption for recreational purposes in 2022, the stigma surrounding the use of this substance is still considerable, which could have an important impact on the perception of risk toward its use.

Interventions that are designed to increase risk perception have the potential to be useful tools in developing strategies to address drug use in this population. Interventions involving life skills training have shown satisfactory effects in reducing drug use and on attitudes and beliefs toward drug use [38]. It is therefore plausible to think that life skills education could also have a positive effect on risk perception and help reduce the likelihood of drug use.

Evidence shows that life skills education helps modify the risk perception of potentially harmful behaviors [50] and drug use [51].

Our results showed that the self-esteem component of the intervention significantly increased the risk perception of tobacco, alcohol, and marijuana use. This finding should be viewed with caution, given that the evidence on the relationship between self-esteem and the perception and display of risky behaviors is inconsistent. Some studies have reported weak to moderate relationships, while others have reported no correlation between these constructs [52]. However, there is also evidence that self-esteem is a protective element against potentially dangerous behaviors [53-57]. Despite the controversy in the data and in the conceptualization of self-esteem, we believe that its inclusion in intervention programs that seek to reduce substance use could be an important way to improve the results because it has been found to be relevant in improving life skills that contribute to reducing exposure to risk factors and improving the ability to protect themselves from situations that adolescents experience daily [58,59].

Limitations

The results of this study should be considered in light of its limitations. It is necessary to explore the reasons why there was no significant difference in the perception of risk between not dangerous and dangerous and to design strategies to achieve change in these categories. Another limitation is that no variables that could moderate the effect of the modification of risk perception were identified; therefore, the impact of these variables is unknown. We are not unaware of the possible influence of threats to the internal validity of this study. For example, it is possible that there were some events between the 2 measurements that could have influenced the results and of which we had no record. In addition, the selection of the participants could have had some effect, that is, because they were new students to a prestigious school, they could have responded oriented by social desirability and by certain knowledge of or familiarity with the measurement instrument. These threats can be minimized in future studies using quasi-experimental or true experimental designs. It is also important to consider the conditions for the implementation of the intervention, for example, the optimal institutional conditions of technological infrastructure, the selection and training of personnel to administer the intervention, and its incorporation into the school program as a support tool in the curriculum. Another limitation is that given the sample selection strategy, the results are not generalizable to the entire adolescent population. We also acknowledge that our intervention is very brief and this may pose a threat for effectiveness, but our results provide evidence of the potential of this intervention to become a cost-effective tool for prevention strategies and for continuing work on the impact of life skills in modifying risk perception and for the evaluation of this type of intervention in longitudinal studies. Another important element to consider is that it would be very enriching to include more detailed measures of risk perception that would allow an exhaustive taxonomy for the analysis, for example, the perception of risk of possible harm and of sanctions or the risk related to stigma and the emotional risk associated with drug use.

Conclusions and Perspectives

The development of the “What Happens If You Go Too Far?” app focused on increasing the risk perception of substance use in adolescents, based on the evidence that this perception may reduce the probability of use [16] and that the perception of negative health consequences can generate protective dynamics [6,22,24,48]. It is important to note that more research using more robust designs and sampling strategies is necessary. Our results show that the app has the potential to increase the risk perception of alcohol, tobacco, and marijuana use in high school students, and by providing evidence-based content on the psychosocial effects and risks of the use of each of these drugs and strengthening of life skills (assertiveness and resistance to peer pressure), which were significantly associated with increased risk perception, it would be plausible to improve the effectiveness of interventions aimed at preventing drug use in adolescents and youth.

The app is an accessible resource that can be included in intervention strategies for prevention, as it strengthens life skills.
that are useful as self-care strategies for adolescents and favors prevention with different social actors, such as educational and health centers that interact with this population, using basic technological resources. The app may also become popular in a youth population that has accepted and integrated mobile technologies into its lifestyle [8,42], thanks to their accessibility, usability, portability, interactivity, and ease of use. It provides a broad reach at low cost, with the likelihood of expansion among the adolescent population.

The incorporation of mobile technologies as tools to reduce drug use or delay the onset of drug use can be fundamental in reaching larger numbers of people with knowledge of the most commonly used drugs that are considered gateway substances to more serious drugs [8,25,41].

Acknowledgments

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Substance use history pre-intervention.

[PDF File (Adobe PDF File), 75 KB - mhealth_v11i1e37873_app1.pdf ]

Multimedia Appendix 2

Code for the analyses.

[DOC File , 23 KB - mhealth_v11i1e37873_app2.doc ]

References


42. Birrell L, Deen H, Champion KE, Newton NC, Stapinski LA, Kay-Lambkin F, et al. A mobile app to provide evidence-based information about crystal methamphetamine (ice) to the community (cracks in the ice); co-design and beta testing. JMIR Mhealth Uhealth 2018 Dec 20;6(12):e11107 [FREE Full text] [doi: 10.2196/11107] [Medline: 30573434]


Abbreviations

GEE: generalized estimating equation
OR: odds ratio
WHO: World Health Organization

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The Relationship Between How Participants Articulate Their Goals and Accomplishments and Weight Loss Outcomes: Secondary Analysis of a Pilot of a Web-Based Weight Loss Intervention

Danielle E Jake-Schoffman, PhD; Molly E Waring, PhD; Joseph DiVito, BS; Jared M Goetz, BA; Cindy Pan, BA, BS; Sherry L Pagoto, PhD

1Department of Health Education and Behavior, College of Health and Human Performance, University of Florida, Gainesville, FL, United States
2Center for Integrative Cardiovascular and Metabolic Disease, University of Florida, Gainesville, FL, United States
3Department of Allied Health Sciences, University of Connecticut, Storrs, CT, United States
4UConn Center for mHealth & Social Media, University of Connecticut, Storrs, CT, United States

Corresponding Author:
Danielle E Jake-Schoffman, PhD
Department of Health Education and Behavior
College of Health and Human Performance
University of Florida
PO Box 118210
Gainesville, FL, 32611
United States
Phone: 1 352 294 1046
Fax: 1 352 392 1909
Email: djakeschoffman@ufl.edu

Abstract

Background: In behavioral weight loss interventions, participants are asked to set weekly goals to support long-term habits that lead to weight loss. Although participants are asked to set and accomplish weekly goals, we do not know how often they do this and whether doing so is associated with weight loss. Web-based weight loss interventions allow for the analysis of participant engagement data, including how participants articulate their goals and accomplishments. Two independent coders classified participants’ posts that articulated goals or accomplishments as measurable and repeating.

Objective: Using engagement data from a web-based weight loss intervention, we examined whether participants articulating their goals and accomplishments in measurable and repeating terms were associated with greater weight loss.

Methods: Adults with overweight or obesity received a 12-week Facebook-delivered weight loss intervention based on the Diabetes Prevention Program Lifestyle Intervention. Participants replied to conversation threads that queried about their goals and accomplishments. Two independent coders classified participants’ posts that articulated goals or accomplishments as measurable or repeating. Crude and age-adjusted linear regression models were used to examine the relationship between the frequency of post type and percent weight loss.

Results: Participants (N=53; n=48, 91% female; n=48, 91% non-Hispanic White) were on average 46.2 (SD 10.5) years old with a mean BMI of 32.4 (SD 4.8) kg/m². Over 12 weeks, participants shared a median of 4 (IQR 1-8) posts that reported goals and 10 (IQR 4-24) posts that reported accomplishments. Most participants shared ≥1 post with a goal (n=43, 81%) and ≥1 post with an accomplishment (n=47, 89%). Each post reporting a goal was associated with 0.2% greater weight loss (95% CI −0.3% to 0.0%). Sharing ≥1 post with a repeating goal was associated with an average of 2.2% greater weight loss (95% CI −3.9% to −0.4%). Each post with a repeating goal was associated with an average of 0.5% greater weight loss (95% CI −1.0% to 0.0%). Sharing ≥1 post with measurable and repeating goals was associated with an average of 1.9% greater weight loss (95% CI −3.7% to −0.2%). Sharing each post with an accomplishment was associated with an average of 0.1% greater weight loss (95% CI −0.1% to 0.0%). Every post with an accomplishment that was repeating was associated with an average of 0.2% greater weight loss (95% CI −0.3% to 0.0%). Sharing other types of goals and accomplishments was not associated with weight loss.

Conclusions: In a web-based weight loss intervention, stating goals in repeating or both measurable and repeating terms was associated with greater weight loss, but simply stating them in measurable terms was not. For accomplishments, only those articulated in repeating terms were associated with greater weight loss. Posts about one-time goals and accomplishments represent...
an opportunity to encourage planning for future behaviors. Future research should examine if stating goals and accomplishments in repeating terms signals habit formation.

*(JMIR Mhealth Uhealth 2023;11:e41275)* doi:10.2196/41275

**KEYWORDS**

weight loss; social media; goal setting; web-based program; behavior change; habit formation; diabetes; Facebook; lifestyle

**Introduction**

Nearly 40% of US adults have obesity [1], putting them at risk for chronic diseases including diabetes [2], heart disease [3], and some cancers [4]. Behavioral interventions are effective at reducing these risks. For example, the Diabetes Prevention Program (DPP) Lifestyle Intervention [5] has been shown to produce significant weight loss and reduce the risk of diabetes [6]. However, behavioral interventions have not been widely disseminated in part due to the high cost [7] and barriers such as scheduling and transportation issues [8,9]. Technology tools have the potential to expand the reach of behavioral interventions through increased accessibility and access.

Behavioral weight loss programs that have traditionally been delivered in-person have now been adapted for web-based delivery [10] through novel platforms, including commercial social media platforms [11]. A recent systematic review of 21 studies of technology-delivered interventions based on the DPP Lifestyle Intervention found promising weight loss efficacy [10]. Engagement in web-based interventions entails participant actions like viewing content, commenting on posts, posting, and reacting to posts (eg, hitting a like button). In general, engagement in web-based weight loss interventions is variable, ranging from <1 to >100 mean posts made per participant [12]. However, greater participant engagement is generally associated with more weight loss [12-15]. Less is known about the type and quality of engagement that has the most impact on weight loss. As a first step in this line of inquiry, the relationship between overall participant post counts and broad categories of posts with weight loss was examined [16] in a Facebook-delivered weight loss intervention. We found that while the overall volume of participant posts was associated with weight loss, not all types of participant posts were predictive of weight loss [16]. Specifically, participant posts that mentioned a goal or an accomplishment were associated with weight loss, but posts reporting problems losing weight or that simply served to support other group members were not [16].

Posting more about goals and accomplishments, which are predictive of weight loss, is not surprising because goal setting is an effective behavioral strategy. Participants in the DPP are coached on setting weekly “SMART” (Specific, Measurable, Action-oriented, Relevant, and Time-bound) goals, which are goals that are specific, measurable, attainable, relevant, and time-bound [17] and following up on them effectively [5,18]. SMART goals may more effectively lead to habit formation than goals without these parameters. A goal is considered measurable if it is articulated in a way that can be quantified. For example, an exercise goal that mentions frequency, duration, or intensity would be considered measurable. A goal is considered time-bound if it specifies when the action is going to occur. Ideally, time-bound goals specify a repeating habit as opposed to a one-time action. For example, an exercise goal that mentions a frequency greater than 1 episode is more likely to develop into a habit than an exercise goal that mentions a frequency of 1 episode (eg, “I am going to work out 3 days this week” vs “I am going to work out today”) [19]. Habit formation theory suggests that bridging the intention-translation gap, or the disconnect between the desire to routinize new healthy behaviors and actually doing so, might be overcome in part with goal setting that involves careful planning and tracking progress [18]. Thus, the articulation of goals in measurable and repeating ways is likely to be associated with better outcomes. Similarly, the articulation of accomplishments in measurable and repeating ways may also be associated with better outcomes because this would also seem to be evidence of habit formation. Articulation of accomplishments in specific terms may also be related to successful feedback loops in the goal-setting process, whereby participants are effectively receiving information about their progress in relation to a goal and are able to use that information to reflect on whether they also need to recalibrate their goals [20]. However, behavioral interventions do not coach participants on how to articulate their accomplishments per se, so we know little about how accomplishments are articulated and whether how people articulate their accomplishments is associated with better outcomes.

In this study, we examined how participants articulated both their goals and accomplishments in a web-based behavioral weight loss intervention in which all communication occurred in written discussion threads. All participant-reported goals and accomplishments were coded as measurable, repeating, both, or neither. The relationship between the frequency with which participants articulated their goals and accomplishments in these ways and their percent weight loss at 12 weeks was then examined. It was hypothesized that greater sharing goals and accomplishments that were measurable or repeating, particularly those that were both measurable and repeating, would be associated with greater percent weight loss than sharing of goals and accomplishments that were neither measurable nor repeating.

**Methods**

**Sample**

This study is a secondary analysis of data from a previously described randomized feasibility pilot trial of a Facebook-delivered weight loss intervention [21]. Participants were recruited from the Worcester, MA community and were eligible if they used a smartphone, used Facebook, were interested in losing weight, and had a BMI of 25-45 kg/m².
Participants were ineligible if they had type 1 or 2 diabetes, were unable to attend assessment visits, had participated in a previous weight loss study with our team, were in a concurrent weight loss program, were taking certain medications, had bariatric surgery, had plans to move during the study period, had a medical condition that would limit their physical activity or diet, did not have clearance from their primary care provider, were pregnant or breastfeeding, did not have a body weight scale at home, or did not speak English.

Eligible participants (N=56) were randomized to 1 of 2 conditions, both of which received a 12-week Facebook-delivered weight loss intervention. However, in 1 group, 3 participants received financial compensation to post in the group daily to be a role model for engagement and social support. The results of the overall trial have been reported previously [16,21]. The 3 participants who received financial incentives were excluded from the present analyses because the content of their posts could have been influenced by the incentives, yielding an analytic sample of 53 participants. As conditions did not differ in weight loss or frequency of participant posts [21], we combined the conditions for the present analyses. The sample size for the parent study was based on the necessities for examining feasibility and acceptability.

**Intervention**

All participants received a 12-week Facebook-delivered weight loss intervention based on the DPP Lifestyle Intervention [5]. Two weight loss counselors were responsible for providing counseling to each participant, invitation-only Facebook group. Intervention posts were prescheduled to occur twice daily from the counselors’ accounts, and then counselors logged in twice a day to generate discussion, field questions, and provide support and problem-solving to participants [21]. The program was delivered asynchronously, meaning no meeting time was required to participate but rather participants could participate whenever convenient, any time of the day or night. Participants were given a calorie goal to help them lose 1-2 pounds per week and an exercise goal of acquiring at least 175 minutes of moderate-intensity physical activity per week. However, participants were also asked to set small weekly goals for behaviors to work on, report their progress, discuss challenges, and problem solve with the counselors. They were encouraged to set SMART goals and were given instructions on what a SMART goal is. The weight loss counselors were trained to provide corrective feedback, and often participants clarified or specified their goals in a follow-up reply.

**Measures**

**Weight Loss**

Baseline and follow-up weights were measured in the lab by research staff using a calibrated balance beam scale. For participants missing weight at follow-up (n=2), we assumed no weight change (baseline value carried forward). The percent weight loss was calculated by dividing the pounds lost between baseline and follow-up by the baseline weight and multiplying by 100.

**Demographics**

At baseline, participants reported demographics on a survey, including age, sex, marital status, and educational attainment.

**Facebook Posts**

Participants’ posts, including original posts and replies to other posts, were extracted from Facebook using Facebook’s application programming interface with a program developed for this purpose.

**Analytic Plan**

**Content Analysis**

We previously conducted a directed content analysis of all original posts and replies shared by participants [16]. In the original analysis, all posts were classified as 1 of 10 types (eg, goal and accomplishment) to describe the overall intent of the post. In our original content analysis, posts that included a report of a goal or accomplishment could have been coded as another post type. For example, a post in which a participant shared an accomplishment and a challenge or slip was coded as a challenge or slip post. For this analysis, we re-reviewed participant posts and replies that were originally coded in other categories for the purpose of the previous study. This analysis includes all participant posts with content classified as a goal (ie, reported an intention or plan to make a healthy lifestyle change) or an accomplishment (ie, reported that they completed an action toward a goal). A subset of posts was independently reviewed by a second coder (n=113, 35% of goal posts and n=394, 50% of accomplishment posts). Codes were compared, and discrepancies were resolved through team discussion. Interrater reliability was examined by calculating percent agreement and k statistics.

**Goals**

Coders classified whether the goals were measurable (ie, specified a particular behavior and how often it will happen; see Table 1). An example of a measurable physical activity goal is “I’m going to walk 3 times this week,” and an example of a specific calorie goal is “I’m going to stay under 1,500 calories each day this week.” Examples of nonmeasurable goals include “I will try harder to eat healthy this week,” “I will increase my willpower,” “I will do my best to stay active,” or any other language that does not specify a specific behavior and how often it will happen. Agreement for measurable goal codes was 81.5% (κ=0.62, 95% CI 0.49-0.78). The 2 coders also determined if a goal was repeating (eg, “I will walk three times a week”) versus a one-time goal (eg, “I will eat a light salad for lunch today”); Table 1). The agreement for repeating codes was 89.7% (κ=0.62, 95% CI 0.49-0.75).

<table>
<thead>
<tr>
<th>Goals</th>
<th>Content</th>
<th>Language</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measurable</td>
<td>“I will walk 3 times this week.”</td>
<td>Language that specifies a behavior</td>
<td>Yes</td>
</tr>
<tr>
<td>Nonmeasurable</td>
<td>“I will try harder to eat healthy this week.”</td>
<td>Language that does not specify a specific behavior and how often it will happen</td>
<td>No</td>
</tr>
</tbody>
</table>

**Table 1**
Table 1. Participant posts sharing goals and accomplishments in a Facebook-delivered lifestyle intervention by whether posts were phrased in measurable or repeating terms.

<table>
<thead>
<tr>
<th>Type of post</th>
<th>All posts, n (%)</th>
<th>Participants with any posts, n (%)</th>
<th>Number of posts per participant, median (IQR; range)</th>
<th>Example post</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Goal posts</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All goal posts</td>
<td>322 (100.0)</td>
<td>43 (81.1)</td>
<td>4 (1-8; 0-24)</td>
<td>N/A³</td>
</tr>
<tr>
<td>Measurable and repeating</td>
<td>64 (19.9)</td>
<td>28 (52.8)</td>
<td>1 (0-2; 0-8)</td>
<td>“My first exercise goal is to walk for at least fifteen minutes a day this week.”</td>
</tr>
<tr>
<td>Measurable, not repeating</td>
<td>162 (50.3)</td>
<td>41 (77.4)</td>
<td>2 (1-5; 0-14)</td>
<td>“I’m putting together a shopping list now so that I can get meals prepped this weekend for my lunches and dinners after work.”</td>
</tr>
<tr>
<td>Not measurable, repeating</td>
<td>16 (5.0)</td>
<td>11 (20.8)</td>
<td>0 (0-0; 0-3)</td>
<td>“...stay away from junk food and hitting the gym more”</td>
</tr>
<tr>
<td>Not measurable, not repeating</td>
<td>80 (24.8)</td>
<td>34 (64.2)</td>
<td>1 (0-2; 0-9)</td>
<td>“I simply want to feel better mentally and physically. I hope to learn more about nutrition.”</td>
</tr>
<tr>
<td><strong>Accomplishment posts</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All accomplishment posts</td>
<td>789 (100.0)</td>
<td>47 (88.7)</td>
<td>10 (4-24; 0-62)</td>
<td>N/A</td>
</tr>
<tr>
<td>Measurable and repeating</td>
<td>146 (18.5)</td>
<td>39 (73.6)</td>
<td>2 (0-4; 0-11)</td>
<td>“…I did everything right this week. I walked a lot every day. I [swam] laps one day and took that zumba class. I drank water like it was my job and stayed within my calorie range every day except yesterday.”</td>
</tr>
<tr>
<td>Measurable, not repeating</td>
<td>287 (36.4)</td>
<td>43 (81.1)</td>
<td>3 (1-6; 0-36)</td>
<td>“I did a mile without stopping. Took about 20 minutes. It’s a start.”</td>
</tr>
<tr>
<td>Not measurable, repeating</td>
<td>146 (18.5)</td>
<td>36 (67.9)</td>
<td>2 (0-4; 0-11)</td>
<td>“I have been following my plan with healthy eating and walking. Slow and steady wins the race!”</td>
</tr>
<tr>
<td>Not measurable, not repeating</td>
<td>210 (26.6)</td>
<td>39 (73.6)</td>
<td>3 (0-6; 0-14)</td>
<td>“I’m like a little kid and being told no makes the treat all the more desirable. So that is why I will do a bite or two as a cheat and then walk away!”</td>
</tr>
</tbody>
</table>

³N/A: not applicable.

Accomplishments

Coders classified accomplishments as measurable or repeating. Measurable accomplishments specified a particular behavior and how often it occurred. An example of a measurable accomplishment is reporting a daily step total (eg, “Got 10K steps today”), a healthy food selection (eg, “Chose the grilled chicken sandwich for lunch”), or eliminating an unhealthy habit (eg, “Cut out my after dinner snack today”; see Table 1). Agreement for measurable codes was 82.4% (κ=0.65; 95% CI 0.58-0.72). An example of a nonmeasurable accomplishment is “I choose to not get down on myself about bad days” or “I have been going out for walks.” The 2 coders also determined if an accomplishment was repeating (eg, “I was under my calorie goal on five days this week”) or a one-time accomplishment (eg, “I was under my calorie goal today”). Agreement for repeating codes was 86.3% (κ=0.70; 95% CI 0.63-0.76).

Analytic Plan

Because the number of each type of goal and accomplishment per participant was not normally distributed, we reported medians, IQRs, and ranges. The relationship between frequency of each post type and percent weight loss with crude and age-adjusted linear regression models was assessed. Because the total number of posts sharing goals or accomplishments of different types was small for some post types (eg, repeating but not measurable goals), the association between posting one or more of each type versus none and percent weight loss was first examined. The association between the number of posts of each type and percent weight loss was then examined. Together, these analyses describe if sharing just 1 goal or accomplishment post of each type (ie, measurable and repeating) is associated with weight loss, as well as specifically how much weight loss is associated with each post of a specific type. Similar to other studies examining the relationship between engagement in a web-based intervention and weight loss [13], we planned to also adjust for gender and race or ethnicity; however, we did not have an adequate distribution in our sample to do so, and thus our adjusted regression model includes only age. All regression models were checked to ensure they met the assumptions of linear modeling. Scatter plots of any posts and
number of posts and percent weight loss (ie, a linear relationship) were reviewed. Diagnostic plots were examined to assess the distribution of residuals (ie, normally distributed and homogeneity of variance), and Shapiro-Wilk tests were used to additionally assess whether residuals were normally distributed. We also assessed for the presence of outlying or potentially influential observations. Results from these analyses indicated no clear violations of the model assumptions and adequate model fit. Analyses were conducted using SAS 9.4 (SAS Institute, Inc).

Ethics Approval
The University of Massachusetts Medical School Institutional Review Board approved this study (H00001484). As this was a pilot trial, with data collection initiated before 2017, it did not meet the Applicable Clinical Trial final rule for ClinicalTrials.gov and was not preregistered.

Results
Demographics and General Result
Participants (N=53) were predominantly female (n=48, 91%), non-Hispanic White (n=48, 91%), married (n=35, 66%), and college educated (n=30, 57%). On average, participants were 46.2 (SD 10.5) years old with a baseline BMI of 32.4 (SD 4.8) kg/m$^2$. As previously reported, during the 12-week program, participants lost an average of 2.6% ±3.5% (range -12.5% to 5.4%) of their body weight, with 26% (n=14) losing 5% or more of their baseline body weight [19]. Overall, participants made 2918 posts to the Facebook group, with a median of 37 (IQR 16-76; range 0-262) posts per participant. Higher post frequency in general was significantly associated with greater percent weight loss (r=-0.38; P=.005) [16].

Goal Posts
Overview
During the 12-week intervention, participants posted 322 posts that included a goal, of which 19.9% (n=64) were measurable and repeating, 50.3% (n=162) were measurable but not repeating, 5% (n=16) were not measurable but were repeating, and 24.8% (n=80) were not measurable or repeating. The majority (n=43, 81%) of participants posted at least 1 goal, and participants shared a median of 4 (IQR 1-8; range 0-24) posts that included goals (Table 1). In adjusted models, the frequency of sharing goal posts was associated with weight loss, and each goal post shared was associated with an average of 0.2% greater weight loss (95% CI -0.3% to 0.0%; Table 2).
More than half of the participants (n=28, 53%) shared at least 1 post that included a measurable and repeating goal. In adjusted models, sharing at least 1 post that included a measurable and repeating goal was associated with an average of 1.9% greater weight loss (95% CI −3.7% to −0.2%; Table 2); sharing each post that mentioned a goal that was measurable and repeating was not associated with greater weight loss.

**Accomplishment Posts**

**Overview**

During the 12-week intervention, participants posted 789 posts that included an accomplishment, of which 18.5% (n=146) were measurable and repeating, 36.4% (n=287) were measurable but not repeating, 18.5% (n=146) were not measurable but were repeating, and 26.6% (n=210) were neither measurable nor repeating (Table 1). The majority of participants (n=47, 88%) posted at least 1 accomplishment, and participants shared a median of 10 (IQR 4-24; range 0-62) posts that included accomplishments (Table 1). In adjusted models, the frequency of sharing accomplishment posts was associated with weight loss, where each accomplishment post was associated with an average of 1.9% greater weight loss (95% CI −3.7% to −0.2%; Table 2).

**Table 3.** Distribution of participant posts sharing measurable or repeating goals and percent weight loss in a Facebook-delivered lifestyle intervention.

<table>
<thead>
<tr>
<th>Type of goal post</th>
<th>All goal posts, n (%)</th>
<th>Shared 1+ goal postsa</th>
<th>Number of goal postsb</th>
<th>Crude β (95% CI)</th>
<th>Adjustedβ (95% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Participants with any goal posts, n (%)</td>
<td>Adjustedβ (95% CI)</td>
<td>Number of goal posts per participant, median (IQR; range)</td>
<td>Crude β (95% CI)</td>
<td>Adjustedβ (95% CI)</td>
</tr>
<tr>
<td>All goal posts</td>
<td>322 (100.0)</td>
<td>43 (81.1)</td>
<td>-1.5 (-4.0 to 0.9)</td>
<td>-0.7 (-3.0 to 1.7)</td>
<td>4 (1-8; 0-24)</td>
</tr>
<tr>
<td>Measurable</td>
<td>226 (70.2)</td>
<td>42 (79.3)</td>
<td>-2.1 (-4.4 to 0.2)</td>
<td>-1.3 (-3.5 to 0.9)</td>
<td>3 (1-7; 0-17)</td>
</tr>
<tr>
<td>Not measurable</td>
<td>96 (29.8)</td>
<td>34 (64.2)</td>
<td>-1.6 (-3.6 to 0.3)</td>
<td>-1.1 (-2.9 to 0.7)</td>
<td>1 (0-2; 0-10)</td>
</tr>
<tr>
<td>Repeating</td>
<td>80 (24.8)</td>
<td>30 (56.6)</td>
<td>-2.8 (-4.5 to -1.0)</td>
<td>-2.2 (-3.9 to -0.4)</td>
<td>1 (0-2; 0-8)</td>
</tr>
<tr>
<td>Not repeating</td>
<td>242 (75.2)</td>
<td>43 (81.1)</td>
<td>-1.5 (-4.0 to 0.9)</td>
<td>-0.7 (-3.0 to 1.7)</td>
<td>3 (1-7; 0-20)</td>
</tr>
<tr>
<td>Measurable and repeating</td>
<td>64 (19.9)</td>
<td>28 (52.8)</td>
<td>-2.6 (-4.4 to -0.8)</td>
<td>-1.9 (-3.7 to -0.2)</td>
<td>1 (0-2; 0-8)</td>
</tr>
<tr>
<td>Measurable, not repeating</td>
<td>162 (50.3)</td>
<td>41 (77.4)</td>
<td>-1.7 (-4.0 to 0.5)</td>
<td>-0.8 (-3.0 to 1.4)</td>
<td>2 (1-5; 0-14)</td>
</tr>
<tr>
<td>Not measurable, repeating</td>
<td>16 (5.0)</td>
<td>11 (20.8)</td>
<td>-3.1 (-5.3 to -0.9)</td>
<td>-2.5 (-4.6 to -0.5)</td>
<td>0 (0-0; 0-3)</td>
</tr>
<tr>
<td>Not measurable, not repeating</td>
<td>80 (24.8)</td>
<td>34 (64.2)</td>
<td>-1.6 (-3.6 to 0.3)</td>
<td>-1.1 (-2.9 to 0.7)</td>
<td>1 (0-2; 0-9)</td>
</tr>
</tbody>
</table>

Aβ represents the difference in mean percent weight loss for participants who shared 1+ goal post versus those who did not share any goal posts.

Bβ represents the difference in mean percent weight loss for each goal post shared.

CAdjusted for age.

DItalicized entries indicate statistical significance (P<.05).

EDue to the small sample size, this type of post did not meet the assumptions for the regression model.

**Measurable Goals**

Most participants (n=42, 79%) shared at least 1 post that included a measurable goal. In adjusted models, sharing posts that included measurable goals was not associated with greater weight loss (Table 2).

**Repeating Goals**

More than half of the participants (n=30, 57%) shared at least 1 post that included a repeating goal. In adjusted models, sharing at least 1 post that included a repeating goal was associated with an average of 2.2% greater weight loss (95% CI −3.9% to −0.4%), and each post that mentioned a repeating goal was associated with an average of 0.5% greater weight loss (95% CI −1.0% to 0.0%).

**Measurable and Repeating Goals**

More than half of the participants (n=28, 53%) shared at least 1 post that included a goal that was both measurable and repeating (Table 1). In adjusted models, sharing at least 1 post that included a measurable and repeating goal was associated with an average of 1.9% greater weight loss (95% CI −3.7% to −0.2%; Table 2); sharing each post that mentioned a goal that was measurable and repeating was not associated with greater weight loss.
Table 3. Distribution of participant posts sharing measurable or repeating accomplishments and percent weight loss in a Facebook-delivered lifestyle intervention.

<table>
<thead>
<tr>
<th>Type of accomplishment post</th>
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<th>Shared 1+ accomplishment postsa</th>
<th>Number of accomplishment postsb</th>
<th>Crude β (95% CI)</th>
<th>Adjustedβ (95% CI)</th>
<th>Number of accomplishment posts per participant, median (IQR; range)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All accomplishment posts</td>
<td>789 (100.0)</td>
<td>47 (88.7)</td>
<td>0.0 (−3.0 to 3.0)</td>
<td>10 (4-24; 0-62)</td>
<td>−0.1 (−0.2 to 0.0)d</td>
<td>−0.1 (−0.1 to 0.0)</td>
</tr>
<tr>
<td>Measurable</td>
<td>433 (54.9)</td>
<td>46 (86.8)</td>
<td>0.1 (−2.7 to 2.9)</td>
<td>6 (2-9; 0-49)</td>
<td>−0.1 (−0.2 to 0.0)</td>
<td>−0.1 (−0.2 to 0.0)</td>
</tr>
<tr>
<td>Not measurable</td>
<td>356 (45.1)</td>
<td>42 (79.3)</td>
<td>−1.7 (−4.1 to 0.6)</td>
<td>4 (2-9; 0-25)</td>
<td>−0.2 (−0.4 to −0.1)</td>
<td>−0.2 (−0.3 to 0.0)</td>
</tr>
<tr>
<td>Repeating</td>
<td>292 (37.0)</td>
<td>41 (77.4)</td>
<td>−1.8 (−4.1 to 0.4)</td>
<td>4 (1-9; 0-23)</td>
<td>−0.3 (−0.4 to −0.1)</td>
<td>−0.2 (−0.3 to 0.0)</td>
</tr>
<tr>
<td>Not repeating</td>
<td>497 (63.0)</td>
<td>46 (86.8)</td>
<td>−1.3 (−4.1 to 1.6)</td>
<td>6 (3-13; 0-42)</td>
<td>−0.1 (−0.2 to 0.0)</td>
<td>−0.1 (−0.2 to 0.0)</td>
</tr>
<tr>
<td>Measurable and repeating</td>
<td>146 (18.5)</td>
<td>39 (73.6)</td>
<td>−1.4 (−3.5 to 0.8)</td>
<td>2 (0-4; 0-11)</td>
<td>−0.3 (−0.6 to 0.0)</td>
<td>−0.2 (−0.5 to 0.1)</td>
</tr>
<tr>
<td>Measurable, not repeating</td>
<td>287 (36.4)</td>
<td>43 (81.1)</td>
<td>−1.7 (−4.1 to 0.7)</td>
<td>3 (1-6; 0-36)</td>
<td>−0.1 (−0.3 to 0.0)</td>
<td>−0.1 (−0.2 to 0.0)</td>
</tr>
<tr>
<td>Not measurable, repeating</td>
<td>146 (18.5)</td>
<td>36 (67.9)</td>
<td>−2.0 (−4.0 to 0.0)</td>
<td>2 (0-4; 0-11)</td>
<td>−0.5 (−0.8 to −0.3)</td>
<td>−0.4 (−0.7 to −0.2)</td>
</tr>
<tr>
<td>Not measurable, not repeating</td>
<td>210 (26.6)</td>
<td>39 (73.6)</td>
<td>−1.3 (−3.5 to 0.8)</td>
<td>3 (0-6; 0-14)</td>
<td>−0.3 (−0.5 to 0.0)</td>
<td>−0.2 (−0.4 to 0.1)</td>
</tr>
</tbody>
</table>

aβ represents the difference in mean percent weight loss for participants who shared 1+ goal post versus those who did not share any goal posts.
bβ represents the difference in mean percent weight loss for each goal post shared.
cAdjusted for age.
dItalicized entries indicate statistical significance (P<.05).

### Measurable Accomplishments

Most participants (n=46, 87%) shared at least 1 post that included a measurable accomplishment. In adjusted models, sharing posts that included measurable goals was not associated with greater weight loss (Table 3).

### Repeating Accomplishments

Most participants (n=41, 77%) shared at least 1 post that included a repeating accomplishment. While sharing at least 1 post that included a repeating accomplishment was not associated with greater weight loss overall, sharing each post that included an accomplishment that was repeating was associated with an average of 0.2% greater weight loss (95% CI −0.3% to 0.0%; Table 3).

### Measurable and Repeating Accomplishments

Most participants (n=39, 74%) shared at least 1 post that mentioned an accomplishment that was both measurable and repeating (Table 1). In adjusted models, sharing such posts was not associated with greater weight loss (Table 3).

### Discussion

#### Principal Findings

Engagement data from web-based weight loss programs that rely on text-based interactions allows us to study how participants discuss their goals and accomplishments. This study provides insights into the specific ways people articulate their goals and accomplishments that may signal the development of habits that promote weight loss. A greater frequency of sharing goals and accomplishments were both independently related to weight loss. In particular, goals that were articulated in either repeating or both measurable and repeating terms were associated with greater weight loss, but for accomplishments, only those articulated in repeating terms were associated with greater weight loss.

In the DPP Lifestyle Intervention, participants are taught to set SMART goals each week [5,18], but variability exists in the extent to which they actually do so. In this study, we found that setting SMART goals and doing so frequently were associated with greater weight loss. Participants who specified parameters about their goals may have been more likely to have had a
specific plan in place, which is an important element of goal setting. Goal setting, and specifically setting the context, frequency, duration, or intensity of a goal, has been defined within the Behavior Change Taxonomy as encompassing action planning as well [22]. Indeed, setting specific parameters around a goal is associated with improved outcomes in behavioral interventions. Our findings regarding goals are in line with past research that showed that participants who set physical activity goals that specified the time a goal would be enacted were more likely to follow through with the goal [23]. This may be particularly important for participants with ambitious weight-loss goals. One study found that among people who set large weight loss goals, those with more specific diet and exercise goals lost more weight [24].

These findings suggest several areas for additional research. First, research is needed about how best to support participants in a web-based setting to set SMART goals and how to provide corrective feedback when goals are stated in a way that is neither measurable nor repeating. The weight loss counselors provided corrective feedback; however, participants did not always modify their goal in a reply, though it is possible they may have changed their plan without sharing this in the group. Further, little is known about why participants do not set SMART goals when they are coached to do so. Research is needed to understand reluctance to articulate specific targets in a goal (eg, frequency or duration), as it may be related to low self-efficacy, poor planning skills (eg, executive function deficits), or barriers to accomplishing the goal. As an example of the latter, a participant who feels little control over their schedule may be reluctant to publicly share a measurable and repeating exercise goal because they are not confident that they will be able to accomplish the goal. It may also be that participants set SMART goals but do not share them in the group in a way that articulates the features of SMART. Web-based behavioral interventions (where participants engage in conversation threads) provide an opportunity to flag and intervene upon goals that are not expressed in measurable or repeating terms. Digital tools that assist participants in setting SMART goals also may be useful in web-based behavioral weight-loss programs. Additional content on the merits of SMART goals and research supporting their efficacy may be useful.

In regards to accomplishments, findings revealed that more frequent sharing of accomplishments in general was predictive of weight loss in general, as was sharing of accomplishments expressed in repeating terms (eg, went for a walk every day at lunch last week). This suggests that the expression of repeating accomplishments may signal habit formation [25], an important behavioral milestone associated with long-term weight loss maintenance [26]. Indeed, a growing number of recent studies find that habit, as opposed to intentional choices, contributes more to behaviors affecting energy balance, such as physical activity, diet, and sedentary time [25,27,28]. Further, sharing repeating accomplishments may also be associated with participants more effectively applying feedback when reflecting on their goal progress [20]. This reflection could then lead to a recalibration of goals when necessary [20].

Contrary to our hypothesis, participant posts sharing accomplishments in measurable terms were not predictive of weight loss. In fact, posts sharing accomplishments in nonmeasurable terms were predictive of weight loss. We did not coach participants on how to apply the SMART framework to accomplishments in the same way that we did goals. For example, a participant might have accomplished their goal to stay under their daily calorie goal but reported successful execution of this goal more succinctly as “I did well with my eating this week!” Further research should explore how people prefer to articulate their accomplishments in a web-based group setting and the barriers to doing so. Perhaps people who accomplish ambitious goals avoid being overly descriptive of their accomplishments so as not to come off as braggingadics in the group, or it may simply feel like providing all the details of their accomplishment in their post is too time-consuming to type out. People are likely to post their accomplishments to solicit positive reinforcement from the counselor and the group. Thus, great detail about the accomplishment may be felt unnecessary to produce such a response.

In this study, goals and accomplishments were solicited through a variety of posts at different times, so they were not necessarily linked to each other in a way that would show reliably whether a goal was reported later as an accomplishment. On Sunday mornings, participants were asked to report on how they did on their goals each week, and some responded, but others shared at different times or not at all, and this varied from week to week. Future studies could more directly link specific goals to associated accomplishments to examine the extent to which setting a goal and reporting on the outcome are more predictive of weight loss than how goals and accomplishments are articulated.

**Limitations and Strengths**

This study has several limitations. First, it is possible that how participants articulated their goals and accomplishments was not exactly how they thought of their goals and accomplishments. For example, a participant could have set SMART goals for themselves but articulated them in the group in a way that was neither measurable nor repeating. However, we did find a relationship between how goals and accomplishments were articulated in the group and weight loss that suggests that what is shared in the group may be a proxy for how they were thinking about their goals and accomplishments. Second, our sample was predominantly female and non-Hispanic White, similar to many behavioral weight loss intervention trials [29,30], and the analyses conducted here were planned post hoc and therefore not taken into account in the original sample size estimation. Combined with our modest sample size, this homogenous sample limited our ability to control for additional variables in our analyses, such as gender and race or ethnicity. Research is needed with larger and more diverse (eg, racially or ethnically, educationally, and by gender) samples to explore if similar traits of goals and accomplishments are associated with weight loss. Finally, the parent study excluded participants who did not have a body weight scale at home or did not speak English, which reduced the generalizability of the results.

This study also has several strengths. A major strength of this study is the use of objective engagement data to define goals.
and accomplishments. Content analysis of micro-level engagement data from web-based weight loss programs provides the opportunity to dive deeply into participation in ways that have not previously been available to researchers [31]. While participation and engagement have traditionally been conceptualized as session attendance [32-34], web-based programs that allow people to engage via written exchanges offer a transcript of every conversation that occurred during the intervention. These data can be used to study the nuances of how specific types of engagement impact weight loss. While we focus here on using these data to the specifics of setting goals and reporting accomplishments that are related to weight loss, this method has the potential to be adapted to better understand a range of discussions and post types and their relationships with behavioral and clinical outcomes.

Conclusions
Much remains to be explored to fully understand not just how much engagement but what types of engagement are associated with better outcomes in web-based behavioral weight loss programs [31]. A deeper understanding of what types of engagement are associated with greater weight loss can help us refine intervention content in ways that solicit these types of engagement from participants. This type of data may also offer guidance to participants on how to engage in ways that may increase their success in web-based lifestyle interventions.

Acknowledgments
This work was supported by K24HL124366 (to SLP). We would like to thank the research participants and counselors for their support of this research.

Conflicts of Interest
None declared.

References


The Relationship Between How Participants Articulate Their Goals and Accomplishments and Weight Loss Outcomes: Secondary Analysis of a Pilot of a Web-Based Weight Loss Intervention

 Jake-Schoffman DE, Waring ME, DiVito J, Goetz JM, Pan C, Pagoto SL

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Characterization of Self-reported Improvements in Knowledge and Health Among Users of Flo Period Tracking App: Cross-sectional Survey

Liudmila Zhaunova¹, PhD; Ryan Bamford², MSc; Tara Radovic²,³, MSc; Aidan Wickham², PhD; Kimberly Pevn²,⁴, PhD; Jazz Croft³, PhD; Anna Klepchukova², MD; Sonia Ponzo²,⁵, PhD

¹Flo Health LTU, Vilnius, Lithuania
²Flo Health UK Limited, London, United Kingdom
³Department of Psychology and Ergonomics, Technische Universitaet Berlin, Berlin, Germany
⁴Maternal, Adolescent, Reproductive & Child Health Centre, London School of Hygiene & Tropical Medicine, London, United Kingdom
⁵Institute of Health Informatics, University College London, London, United Kingdom

Corresponding Author:
Liudmila Zhaunova, PhD
Flo Health LTU
Saltoniškių g. 2
Vilnius, LT-01109
Lithuania
Phone: 370 60396823
Email: l_zhaunova@flo.health

Abstract

Background: Research shows that poor knowledge and awareness of menstrual and pregnancy health among women are associated with adverse reproductive health and pregnancy outcomes. Menstrual cycle- and pregnancy-tracking mobile apps are promising tools for improving women’s awareness of and attitudes toward their reproductive health; however, there is little information about subscribers’ perceptions of app functionality and its impact on their knowledge and health.

Objective: This study aimed to explore knowledge and health improvements related to menstrual cycle and pregnancy, as well as improvements in general health among Flo app users. We also investigated what components of the Flo app were associated with the abovementioned improvements and evaluated whether those improvements differed based on education level, country of residence (low- and middle-income vs high-income countries), free or premium subscription to the app, short- or long-term use of the app, and frequency of use.

Methods: Flo subscribers who had been using the app for no less than 30 days, completed a web-based survey. A total of 2212 complete survey responses were collected. The survey included demographic questions and questions about motivations guiding the use of the Flo app and which components of the app improved their knowledge and health, as well as to what extent.

Results: Most study participants reported improvements in menstrual cycle (1292/1452, 88.98%) and pregnancy (698/824, 84.7%) knowledge from Flo app use. Participants with higher levels of education and those from high-income countries reported using the app predominantly for getting pregnant ($\chi^2_1=4.2, P=0.04$; $\chi^2_1=52.3, P<0.001$, respectively) and pregnancy tracking ($\chi^2_1=19.3, P<0.001$; $\chi^2_1=20.9, P=.001$, respectively). Participants with less education reported using the app to avoid pregnancy ($\chi^2_1=4.2; P=.04$) and to learn more about their body ($\chi^2_1=10.8; P=.001$) and sexual health ($\chi^2_1=6.3; P=.01$), while participants from low- and middle-income countries intended to mainly learn more about their sexual health ($\chi^2_1=18.2; P<0.001$). Importantly, the intended use of the app across education levels and country income levels matched areas in which they had gained knowledge and achieved their health goals upon use of the Flo app. Period, fertile days, and ovulation predictions as well as symptom tracking were consistently the top 3 components in the app that helped users with their cycle knowledge and general health. Reading articles or watching videos helped with users’ education regarding their pregnancy. Finally, the strongest improvements in knowledge and health were observed in premium, frequent, and long-term users.

Conclusions: This study suggests that menstrual health apps, such as Flo, could present revolutionary tools to promote consumer health education and empowerment on a global scale.
Introduction

Background

Women’s health has long been understudied and underfunded, compromising the amount of health information available to women as well as the quality of health care they receive [1]. Recently, more efforts have been made to include women in clinical trials, and more policies have been introduced to enhance and promote women’s health globally [2–4]. However, many cultures still hold different myths and taboos regarding the reproductive health and menstrual cycle, specifically. Studies have shown that there is a large knowledge gap among adolescent girls and adult women, especially in low- and middle-income countries (LMICs), about menstrual cycle health [5,6], fertility [5,7], healthy pregnancy [8,9], and overall women’s health and well-being [10,11]. For example, a North Indian study found that only 31% of respondents reported the right definition of the menstrual cycle [6], whereas an extremely high prevalence of inadequate knowledge of symptoms, risk factors, and complications of preeclampsia (88.4%) was found among pregnant women in Ghana [9].

In high-income countries (HICs), despite an increase in growing social and governmental momentum to improve reproductive health education [12–16], there is still a knowledge gap and misconceptions about reproductive and fertility health as well as reluctance to seek medical treatment for some health issues [17,18]. A Chicago-based study reported that one of the main reasons for a delayed fibroid diagnosis was the belief among women that heavy menstrual bleeding was normal [17]. Another study conducted on American women of reproductive age found that almost 60% of all surveyed women did not know when they had higher chances of conception during the menstrual cycle, while more than two-thirds were unaware that pain during menstruation (eg, owing to conditions such as endometriosis) may correlate with a woman’s ability to get pregnant [18]. A study conducted in England found that 30% of adolescent girls were unaware if their periods were regular; furthermore, most of them were considerably less aware of endometriosis than of other chronic diseases such as diabetes or epilepsy [19]. Another study found that only 42% of pregnant women in Italy knew of all the main risk factors in pregnancy such as alcohol consumption, smoking, passive smoking, and obesity [20]. Thus, low menstrual cycle and pregnancy health awareness among women and people who menstruate might cause adverse effects on women’s and newborn health and well-being and can restrict women from their daily sociocultural activities and impact their quality of life [21,22]. In addition, poor knowledge and misconceptions about reproductive health might delay the time to diagnosis and increase medical costs associated with treatment [17,23].

Given the lack of reproductive health knowledge among women, identifying medically credible, easy-to-access and understand sources of reproductive health–related information is crucial.

On the basis of survey data, women’s health care providers (HCPs) are one of the main sources of trustworthy reproductive health–related knowledge; however, more than one-third of survey respondents reported visiting their reproductive HCP less than once per year or having never visited one [18]. Furthermore, the use of medical jargon or more dense language by HCPs can confuse patients and result in inability to recall the information that they received during medical consultations [24–27]. Health-related internet websites are another source of education and empowerment for women [18,28,29]. Nevertheless, web-based health sources vary in quality, accuracy, and reliability, and incorrect information or advice from websites may affect health-related behavior and decisions [30].

In the past few years, the rapid growth and acceptance of mobile health apps specifically designed to address women’s health needs have made substantial progress in the area of reproductive and pregnancy knowledge improvements [31–33]. Female health apps are often perceived as helpful by their users, as they provide easy-to-access information that helps them feel more knowledgeable and supported [34,35]. In addition to the educational component, apps for women’s health often provide their users with tracking functionality for their self-knowledge, monitoring, and recording [35,36]. Such functionality includes menstrual cycle and pregnancy tracking or tracking of cycle-related symptoms, for example, hormone-triggered migraines or mood swings [33,37–39]. Previous studies have shown that health mobile apps also facilitate good habit formation and health promotion by providing a number of functions to map behavior patterns across time, including, but not limited to, sleep, diet, physical activity, and mental health practices etc [40,41]. Despite the prevalence and apparent popularity of women health–tracking apps, there remains a knowledge gap regarding the accuracy and safety of the medical advice provided as well as the effectiveness of digital health products in changing health behaviors. Researchers, clinicians, and patient groups have recently advocated for more rigorous requirements regarding the validation and evaluation of digital health solutions, with scientists highlighting the need for a unified evidence generation framework [42–45]. As such, there is a need for health app developers to conduct and publish research assessing the effectiveness of products at both pre- and postmarket time points, so that end users and clinicians are provided with sufficient evidence to make an informed decision [46,47].

One of the mobile apps dedicated to women’s health and well-being is the Flo app (by Flo Health Inc). Flo offers its users artificial intelligence–based period and ovulation predictions and allows them to track their periods, fertile window, ovulation, and symptoms while trying to get pregnant or avoid pregnancy, as well as to track pregnancy symptoms and fetal development. In addition to the tracking functionality, Flo provides its users with evidence-based and expert-reviewed educational content
available through the in-app library. Flo app content creation and validation are based on a peer-reviewed practice in which Flo’s in-house medical doctors and external medical and science experts review each piece of content before it is published in the Flo application or on the website. Each content unit (article, graphics, courses, etc) within the app has references to peer-reviewed articles, medical guidelines, and links to internationally recognized health advocacy organizations and academic institutions. Moreover, each article has a link to the profile of the medical expert or organization who reviewed it. To check for symptoms against an array of conditions, Flo also has interactive questions available via so-called “health assistants” or “chatbots” [38]. Finally, Flo has a secure place called “Secret Chats” where women can discuss intimate topics, ask questions anonymously, and obtain support from millions of women worldwide, thus reducing perceived taboos and stigma surrounding topics such as menstrual health and sexual life [48-50].

**Objective**

Although the Flo app provides a range of functionalities, there is an open question as to whether the Flo users obtain any improvements in knowledge and health by using the app. Hence, the aim of this study was to describe the demographic and app use characteristics of a self-enrolled sample of Flo subscribers and explore the relationship between app use and self-reported improvements in knowledge and health related to the menstrual cycle and pregnancy, as well as improvements in general health in Flo users. We hypothesized that subscribers who use Flo Premium instead of a free version, as well as those who used the app more frequently and for a longer period, would be more likely to report increased health benefits with a greater improvement in their knowledge and understanding across different areas. We also aimed to evaluate the components of the Flo app that were associated with the aforementioned improvements.

**Methods**

**Participants**

Users of the Flo app who had the app installed in English for at least 30 days and were >18 years old were eligible to participate in this study. Recruitment took place within the Flo app between December 5, 2021, and January 16, 2022. We collected 5015 partial responses and 2212 complete survey responses. Only responses from the participants who fully completed the survey were used for the analysis (Table 1 provides the sample’s demographics).
Table 1. Demographics of study participants (N=2212).

<table>
<thead>
<tr>
<th>Category</th>
<th>Frequency, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Country (top 10)</strong></td>
<td></td>
</tr>
<tr>
<td>The United States</td>
<td>758 (34.3)</td>
</tr>
<tr>
<td>The United Kingdom</td>
<td>217 (9.8)</td>
</tr>
<tr>
<td>Canada</td>
<td>121 (5.5)</td>
</tr>
<tr>
<td>India</td>
<td>108 (4.9)</td>
</tr>
<tr>
<td>Australia</td>
<td>92 (4.2)</td>
</tr>
<tr>
<td>South Africa</td>
<td>86 (3.9)</td>
</tr>
<tr>
<td>Nigeria</td>
<td>82 (3.7)</td>
</tr>
<tr>
<td>Ghana</td>
<td>63 (2.8)</td>
</tr>
<tr>
<td>Philippines</td>
<td>43 (1.9)</td>
</tr>
<tr>
<td>Netherlands</td>
<td>32 (1.4)</td>
</tr>
<tr>
<td><strong>Age (years)</strong></td>
<td></td>
</tr>
<tr>
<td>18-24</td>
<td>544 (24.6)</td>
</tr>
<tr>
<td>25-34</td>
<td>1264 (57.1)</td>
</tr>
<tr>
<td>35-44</td>
<td>370 (16.7)</td>
</tr>
<tr>
<td>45-54</td>
<td>34 (1.5)</td>
</tr>
<tr>
<td><strong>Race</strong></td>
<td></td>
</tr>
<tr>
<td>White, European-American, or Caucasian</td>
<td>1041 (47)</td>
</tr>
<tr>
<td>Black or African American</td>
<td>397 (17.9)</td>
</tr>
<tr>
<td>Asian or Asian-American</td>
<td>223 (10.1)</td>
</tr>
<tr>
<td>Hispanic, Latino, Spanish origin</td>
<td>116 (5.2)</td>
</tr>
<tr>
<td>Biracial or multiracial</td>
<td>88 (4)</td>
</tr>
<tr>
<td>American Indian or Alaskan</td>
<td>12 (0.5)</td>
</tr>
<tr>
<td>Native Hawaiian or Pacific Islander</td>
<td>3 (0.1)</td>
</tr>
<tr>
<td>Other</td>
<td>225 (10.2)</td>
</tr>
<tr>
<td>Prefer not to say</td>
<td>107 (4.8)</td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td></td>
</tr>
<tr>
<td>Woman</td>
<td>2181 (96.7)</td>
</tr>
<tr>
<td>Nonbinary</td>
<td>22 (1)</td>
</tr>
<tr>
<td>Genderqueer or gender fluid</td>
<td>19 (0.8)</td>
</tr>
<tr>
<td>Questioning or unsure</td>
<td>10 (0.4)</td>
</tr>
<tr>
<td>Man</td>
<td>5 (0.2)</td>
</tr>
<tr>
<td>Trans man</td>
<td>3 (0.1)</td>
</tr>
<tr>
<td>Trans woman</td>
<td>1 (0.1)</td>
</tr>
<tr>
<td>Agender</td>
<td>3 (0.1)</td>
</tr>
<tr>
<td>I prefer not to say</td>
<td>11 (0.5)</td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td></td>
</tr>
<tr>
<td>Doctorate degree</td>
<td>43 (1.9)</td>
</tr>
<tr>
<td>Master’s degree</td>
<td>373 (16.9)</td>
</tr>
<tr>
<td>Bachelor’s degree</td>
<td>759 (34.3)</td>
</tr>
<tr>
<td>Associate’s degree</td>
<td>139 (6.3)</td>
</tr>
<tr>
<td>High school graduate or diploma</td>
<td>600 (27.1)</td>
</tr>
</tbody>
</table>
Materials
Participants completed a demographic questionnaire followed by an investigator-developed quantitative survey (Multimedia Appendix 1 provides the full list of survey questions). The survey included questions addressing the aim, frequency, and duration of the app use, as well as whether and what components of the Flo app (and to what extent) helped users to improve their knowledge and health. Specifically, the survey included questions addressing improvements in knowledge and health across 5 different areas: menstrual health and education, irregular cycle and related conditions, getting pregnant and pregnancy health, general health (mental, sexual, physical health, and health behaviors), and communication with an HCP.

Overall, the survey contained 70 questions. Not every question was available for every participant, as questions were presented only if they were relevant to the participant based on their previous responses. For example, those who reported that they downloaded the app to track their pregnancy were not asked menstrual cycle–related questions. The survey was created using SurveyMonkey software (Momentive Inc).

Procedure
Participants were notified of the possibility of participating in a survey via an in-app notification. Upon clicking on the survey button, the participants were redirected to SurveyMonkey and asked to provide electronic informed consent. Those who consented proceeded to complete the survey on their electronic devices, which took an average of 8 minutes.

Ethical Considerations
The study was reviewed by the Independent Ethical Review Board (WIRB-Copernicus Group Institutional Review Board), which deemed the study exempt (IRB tracking number: 20216374).

Defining Categories
To describe app use patterns among Flo users, the following categories were defined: a short-term user was any participant who had been using the Flo app for <1 year, whereas a long-term user was anyone using the Flo app for ≥1 year. A frequent user was defined as a participant who used the app several times a day to several times a week, whereas an infrequent user was a participant who used the app once a week or less. Premium app users are those who use the paid version of the Flo app, while free app users are those who use the free version of the app. Compared with the free version, the paid app version provides users with full access to all in-app content materials (including text and video materials), all symptom- and cycle-related chats with Flo’s health assistant, and all community discussion chats with an additional opportunity to ask for support and advice from a medical professional (“Ask an Expert”). Multimedia Appendix 2 lists the complete app use characteristics.

Users with higher education were defined as those who had either a bachelor’s, master’s, or doctorate degree, whereas users with less education included those with any education below a completed bachelor’s degree. In terms of age, a younger user was anyone between the ages of 18 and 34 years, whereas older users were defined as anyone between the ages of 35 and 54 years (Table 1).

Country income level was defined based on the World Bank Country Income classification [51]. In this study, 62.4% (78/125) of countries were defined as LMICs, whereas the remaining 37.6% (47/125) of countries were classified as HICs. Multimedia Appendices 3 and 4 provide a complete breakdown of HICs and LMICs, respectively.

Statistical Analysis
Data were analyzed using Python Jupyter Notebook (version 6.0.1; Project Jupyter). All variables in the survey were categorical. Throughout the survey, participants had options to answer questions as binary categorical variables (yes or no), nominal categorical variables (eg, symptoms they believe Flo has helped with) and ordinal categorical variables (eg, 5 categories from “Not at all” to “A great deal”). Throughout the survey, depending on the participants’ choices, the users were directed to answer different questions. Consequently, the number of participants who answered each question differed. Ordinal categorical variables were recoded as dichotomous variables (not at all—a little vs a moderate amount—a great deal).

Chi-squared tests compared participant responses for the association between user app subscription status (free vs premium), frequency of app use (frequent vs infrequent), and duration of use (short term vs long term). Chi-squared tests were also used to assess whether the country of residence and education level had a relationship with the reasons why they used the app, the areas in which users’ knowledge was improved, and to what extent knowledge was improved. To confirm the relationship between demographic factors (age and education) and the reasons for using the app, we fitted univariate logistic regression models.

Results
Overall Knowledge and Health Improvements Upon Flo App Use
Most respondents reported that the Flo app had improved how educated they feel about their overall cycle (1292/1452, 88.98%; Table S1 in Multimedia Appendix 5, question 46) and pregnancy health (698/824, 84.7%; Table S2 in Multimedia Appendix 5, question 34). Users who had tracked their cycle with Flo felt improvements in the following top 3 menstrual health areas: they knew whether their cycle was regular (1085/1292, 84.0%), whether their cycle length was normal (978/1292, 75.7%), and...
whether it was normal to have certain symptoms during their cycle (755/1292, 58.4%; Table S1 in Multimedia Appendix 5, question 47). Users also reported that they believed Flo had helped them understand how to use their cycle to know when they were most fertile (780/1292, 60.4%) and how their cycle affected their physical (776/1292, 60.1%) and mental health (765/1292, 59.2%; Table S1 in Multimedia Appendix 5, question 51). In addition, 77.3% (1270/1642) of participants reported that Flo had helped them manage their menstrual symptoms, with the top 3 symptoms being “ovulation” (668/1270, 52.6%); “bad mood” (including feeling sad, guilty, irritated, obsessive thoughts, and confused or self-critical; 641/1270, 50.5%); and “cramps” (618/1270, 48.7%; Table S1 in Multimedia Appendix 5; questions 16 and 17). Finally, 65.1% (309/475) of users said that the app had helped them manage their irregular cycles and related conditions (Table S1 in Multimedia Appendix 5, question 21).

Most of the study cohort (627/824, 76.1%) who used the app to track their pregnancy reported getting pregnant while using Flo (Table S2 in Multimedia Appendix 5, question 29). Of those who became pregnant, 73.5% (461/627) of believed that using Flo had helped them become pregnant (Table S1 in Multimedia Appendix 5, question 30). More than 8 in 10 participants (530/627, 84.5%) said that Flo had helped them to prepare for a healthy pregnancy (Table S2 in Multimedia Appendix 5, question 32). Pregnancy-tracking users reported that Flo had improved their knowledge about their body during pregnancy (589/698, 84.4%); their baby’s development (577/698, 82.7%); and which symptoms did not require medical attention and which did during pregnancy (505/698, 72.3%; Table S2 in Multimedia Appendix 5, question 36). The study participants also reported that Flo had improved their understanding of how pregnancy affected their physical health (509/698, 72.9%); how to manage their pregnancy symptoms (403/698, 57.7%); and how to optimize their life around their pregnancy (393/698, 56.3%; Table S2 in Multimedia Appendix 5, question 39).

A smaller number of respondents reported improvements in mental (843/2212, 38.1%), sexual (835/2212, 37.7%), and physical health (589/2212, 26.6%); health behaviors (621/2212, 28.1%); and communication with an HCP (587/2212, 26.5%; Table S3 in Multimedia Appendix 5, question 53).

Period predictions, fertile days and ovulation predictions, and symptom tracking were the top 3 components of the app that have helped users with all the abovementioned areas (Tables S1 and S3 in Multimedia Appendix 5) except pregnancy education where “reading articles or watching video sources” in the app was rated the highest (503/698; 72.1%; Table S2 in Multimedia Appendix 5, question 38). Complete responses regarding knowledge and health improvements in cycle, pregnancy, and general health are shown in Tables S1, S2, and S3 in Multimedia Appendix 5, respectively.

### Knowledge and Health Improvements in Relation to Education Level

Study participants with less education were more likely to use the Flo app to track irregular cycles and related conditions to learn more about their body and sexual health and to help them not become pregnant ($\chi^2_1=10.9, P<.001; \chi^2_1=10.8, P=.001; \chi^2_1=6.3, P=.01; \chi^2_1=4.2, P=.04$, respectively), while higher-educated users were more likely to use the app to help them become pregnant and for pregnancy tracking ($\chi^2_1=4.2, P=.04; \chi^2_1=19.3, P<.001$, respectively; Table 2). Complete statistics on the reasons for using the app in relation to age are shown in Table S1 in Multimedia Appendix 6.

#### Table 2. Education versus reasons for using the app (N=2212).

<table>
<thead>
<tr>
<th>Reasons for using the app</th>
<th>HEa, n (%)</th>
<th>LEb, n (%)</th>
<th>Chi-square (df)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Menstrual cycle and symptom tracking</td>
<td>943 (80.3)</td>
<td>851 (82.1)</td>
<td>1.1 (1)</td>
<td>.01</td>
</tr>
<tr>
<td>Irregular cycles and related conditions</td>
<td>219 (18.6)</td>
<td>254 (24.5)</td>
<td>10.9 (1)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Pregnancy tracking</td>
<td>487 (41.4)</td>
<td>335 (32.3)</td>
<td>19.3 (1)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>To help me get pregnant</td>
<td>657 (55.9)</td>
<td>537 (51.5)</td>
<td>4.2 (1)</td>
<td>.04</td>
</tr>
<tr>
<td>To help me not get pregnant</td>
<td>117 (10)</td>
<td>133 (12.8)</td>
<td>4.2 (1)</td>
<td>.04</td>
</tr>
<tr>
<td>Pregnancy loss</td>
<td>73 (6.2)</td>
<td>78 (7.5)</td>
<td>1.3 (1)</td>
<td>.26</td>
</tr>
<tr>
<td>Sexual health</td>
<td>305 (26)</td>
<td>320 (30.9)</td>
<td>6.3 (1)</td>
<td>.01</td>
</tr>
<tr>
<td>Get tailored health information</td>
<td>390 (33.2)</td>
<td>343 (33.1)</td>
<td>0.0(1)</td>
<td>.99</td>
</tr>
<tr>
<td>To learn more about my body</td>
<td>444 (38)</td>
<td>467 (45)</td>
<td>10.8 (1)</td>
<td>.001</td>
</tr>
</tbody>
</table>

aHE: higher education.  
bLE: lower education.

Univariate logistic regression models confirmed the results of the chi-squared tests. Participants with a higher educational background, for example, master’s degree, had significantly higher odds (odds ratio 1.80, 95% CI 1.15-2.86) of using the app for pregnancy tracking and significantly lower odds (odds ratio 0.59, 95% CI 0.39-0.91) of using the app to learn more about their body compared with users with “Some High School, no Diploma.” Tables S2 and S3 in Multimedia Appendix 6 show full logistic regression results for education and age, respectively.

Furthermore, we examined whether both lower- and higher-educated users achieved health and knowledge improvements in the intended areas of app use. Users with less
education were more likely to report that Flo had helped them improve their understanding of how to manage their menstrual symptoms ($\chi^2 = 4.7; P = .03$; Table S1 in Multimedia Appendix 7, question 51) and helped them identify issues related to endometriosis ($\chi^2 = 8.0; P = .004$; Table S1 in Multimedia Appendix 7, question 47). In addition, they were more likely to report that Flo had improved their sexual health knowledge ($\chi^2 = 9.5; P = .002$), such as sexually transmitted infections (STIs) and how to avoid them ($\chi^2 = 13.1; P < .001$); the signs and symptoms of STIs ($\chi^2 = 19.3; P < .001$); safe sex ($\chi^2 = 11.7; P < .001$); contraception options ($\chi^2 = 11.1; P < .001$); the signs and symptoms during sex that were indicative of a health issue ($\chi^2 = 10.6; P < .001$); and how to have more pleasure during sex ($\chi^2 = 6.7; P = .009$; Table S2 in Multimedia Appendix 7, questions 53, 61, and 62).

Finally, users with less education were more likely to self-report that Flo had helped them improve their skin ($\chi^2 = 4.8; P = .03$) or fitness ($\chi^2 = 5.4; P = .02$) from a moderate to a great deal (Table S2 in Multimedia Appendix 7, question 57). In addition, they reported that Flo had helped them reduce harmful habits ($\chi^2 = 12.1; P < .001$; Table S2 in Multimedia Appendix 7, question 59) and made them more confident about asking their HCPs for resources that they thought they needed (eg, stress relief, birth control, and support: $\chi^2 = 4.5; P = .03$; Table S2 in Multimedia Appendix 7, question 64).

In contrast, users with higher education mainly reported improvements in pregnancy health education (Table S3 in Multimedia Appendix 7, questions 34, 36, and 39). In addition, they were more likely to report that they conceived while using Flo ($\chi^2 = 17.8; P < .001$; Table S3 in Multimedia Appendix 7, question 29). Complete responses regarding knowledge and health improvements in cycle health, general health, and pregnancy health in relation to education level are shown in Tables S1, S2, and S3, respectively, in Multimedia Appendix 7.

### Knowledge and Health Improvements in Relation to Country of Residence (LMICs vs HICs)

The study included participants from both HICs (1513/2212, 68.4%) and LMICs (699/2212, 31.6%), with participants from LMICs having a statistically lower level of education compared with those from HICs ($\chi^2 = 11.0; P < .001$). Table 3 shows that participants from HICs were more likely to use the app for menstrual cycle and symptom tracking, for pregnancy tracking, to get help with getting pregnant, and for pregnancy loss ($\chi^2 = 11.8; P < .001$; $\chi^2 = 20.9; P < .001$; $\chi^2 = 52.3; P < .001$; $\chi^2 = 22.6; P < .001$, respectively), while participants from LMICs were more likely to use the app to improve their sexual health ($\chi^2 = 18.2; P < .001$).

#### Table 3. Low- and middle-income countries (LMICs) and high-income countries (HICs) versus reasons for using the app (N=2212).

<table>
<thead>
<tr>
<th>Reasons for using the app</th>
<th>HIC, n (%)</th>
<th>LMIC, n (%)</th>
<th>Chi-square (df)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Menstrual cycle and symptom tracking</td>
<td>1257 (83.1)</td>
<td>537 (76.9)</td>
<td>11.8 (1)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Irregular cycles and related conditions</td>
<td>324 (21.4)</td>
<td>149 (21.3)</td>
<td>0.0 (1)</td>
<td>.99</td>
</tr>
<tr>
<td>Pregnancy tracking</td>
<td>611 (40.4)</td>
<td>211 (30.2)</td>
<td>20.9 (1)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>To help me get pregnant</td>
<td>894 (59.1)</td>
<td>297 (42.5)</td>
<td>52.3 (1)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>To help me not get pregnant</td>
<td>172 (11.4)</td>
<td>78 (11.2)</td>
<td>0.0 (1)</td>
<td>.94</td>
</tr>
<tr>
<td>Pregnancy loss</td>
<td>130 (8.6)</td>
<td>21 (3)</td>
<td>22.6 (1)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Sexual health</td>
<td>385 (25.4)</td>
<td>240 (34.4)</td>
<td>18.2 (1)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Get tailored health information</td>
<td>502 (33.2)</td>
<td>231 (33)</td>
<td>0.0 (1)</td>
<td>.99</td>
</tr>
<tr>
<td>To learn more about my body</td>
<td>611 (40.4)</td>
<td>303 (43.4)</td>
<td>1.6 (1)</td>
<td>.20</td>
</tr>
</tbody>
</table>

We further tested whether users from LMICs and HICs achieved their health and knowledge improvement in their intended areas of app use. We found that users from HICs were significantly more likely to report that they became pregnant while using the Flo app ($\chi^2 = 17.0; P < .001$; Table S1 in Multimedia Appendix 8, question 29), as well as know more about their baby’s development ($\chi^2 = 4.2; P = .04$; Table S1 in Multimedia Appendix 8, question 36) and communicate better with their HCPs ($\chi^2 = 6.2; P = .01$; Table S2 in Multimedia Appendix 8, question 53) and partners about their cycle ($\chi^2 = 5.7; P = .02$; Table S3 in Multimedia Appendix 8, question 47).

Users from LMICs were significantly more likely to self-report that using Flo had helped them improve their understanding of sexual health ($\chi^2 = 17.7; P < .001$; Table S2 in Multimedia Appendix 8, question 53)—more specifically, their understanding of STIs and how to avoid them ($\chi^2 = 8.1; P = .004$; Table S2 in Multimedia Appendix 8, question 61) and how to have safe sex ($\chi^2 = 17.6; P < .001$; Table S2 in Multimedia Appendix 8, question 61), as well as their understanding of their sexuality ($\chi^2 = 14.7; P < .001$; Table S2 in Multimedia Appendix 8, question 62) and how to get more pleasure during sex ($\chi^2 = 5.0; P = .03$; Table S2 in Multimedia Appendix 8, question 62). In addition to improving their sexual health, users from LMICs also reported improvements in understanding of whether...
their period flow was normal or not ($\chi^2 = 6.3; P = .01$; Table S3 in Multimedia Appendix 8, question 47); how to identify issues related to polycystic ovary syndrome (PCOS; $\chi^2 = 6.7; P = .001$; Table S3 in Multimedia Appendix 8, question 47); and how to manage menstrual symptoms ($\chi^2 = 23.8; P < .001$; Table S3 in Multimedia Appendix 8, question 51) and postpartum symptoms ($\chi^2 = 8.9; P = .002$; Table S1 in Multimedia Appendix 8, question 39). Finally, users from LMICs also reported improvements in physical ($\chi^2 = 25.1; P < .001$; Table S2 in Multimedia Appendix 8) and mental health ($\chi^2 = 4.7; P = .03$; Table S2 in Multimedia Appendix 8, question 53), including having more energy ($\chi^2 = 4.5; P = .03$; Table S2 in Multimedia Appendix 8, question 57); sleeping better ($\chi^2 = 6.0; P = .01$; Table S2 in Multimedia Appendix 8, question 57); having better stress management skills ($\chi^2 = 5.0; P = .03$; Table S2 in Multimedia Appendix 8, question 59); and reducing harmful habits ($\chi^2 = 5.0; P < .001$; Table S2 in Multimedia Appendix 8, question 59).

Complete results regarding knowledge and health improvements in the pregnancy, general health, and cycle health between HICs and LMICs are shown in Tables S1, S2, and S3, respectively, in Multimedia Appendix 8.

### Knowledge and Health Improvements in Relation to Paid Versus Free App Use

Similar to users with higher education, Flo Premium users reported using the app mainly for pregnancy-related issues (pregnancy tracking: $\chi^2 = 109.8, P < .001$; to help get pregnant: $\chi^2 = 21.4, P < .001$) as well as to obtain tailored health information relevant to them ($\chi^2 = 16.7; P < .001$; Table 4).

#### Table 4. Reasons for using the app versus app use characteristics (N=2212).

<table>
<thead>
<tr>
<th>Reasons for using the app</th>
<th>Fr vs II</th>
<th>Fr vs P</th>
<th>LT vs ST</th>
<th>ST vs Fr</th>
<th>Chi-square (df)</th>
<th>P value</th>
<th>Chi-square (df)</th>
<th>P value</th>
<th>Chi-square (df)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Menstrual cycle and symptom tracking</td>
<td>484 (84.9)</td>
<td>674 (80.8)</td>
<td>3.7 (.06)</td>
<td>719 (43.9)</td>
<td>&lt;.001</td>
<td>46.5 (74.3)</td>
<td>889 (1.0)</td>
<td>.001</td>
<td>267 (.12)</td>
<td>389 (.17)</td>
</tr>
<tr>
<td>Irregular cycles and related conditions</td>
<td>132 (23.2)</td>
<td>170 (20.4)</td>
<td>.24 (1)</td>
<td>194 (108)</td>
<td>.01</td>
<td>6.0 (18.3)</td>
<td>217 (20.1)</td>
<td>.004</td>
<td>85 (26.3)</td>
<td>109 (.04)</td>
</tr>
<tr>
<td>Pregnancy tracking</td>
<td>137 (24)</td>
<td>435 (52.2)</td>
<td>109.8 (.001)</td>
<td>338 (234)</td>
<td>.49</td>
<td>0.5 (39.6)</td>
<td>481 (44.5)</td>
<td>.001</td>
<td>91 (28.2)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>To help me get pregnant</td>
<td>273 (47.9)</td>
<td>505 (60.6)</td>
<td>21.4 (.001)</td>
<td>403 (375)</td>
<td>&lt;.001</td>
<td>26.1 (63.5)</td>
<td>643 (59.5)</td>
<td>.001</td>
<td>135 (41.8)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>To help me not get pregnant</td>
<td>69 (12.1)</td>
<td>84 (10.1)</td>
<td>.27 (1)</td>
<td>121 (32)</td>
<td>&lt;.001</td>
<td>30.6 (5.4)</td>
<td>114 (10.5)</td>
<td>.001</td>
<td>39 (12.1)</td>
<td>43 (.0)</td>
</tr>
<tr>
<td>Pregnancy loss</td>
<td>23 (4)</td>
<td>75 (9)</td>
<td>12.1 (.001)</td>
<td>61 (37)</td>
<td>.43</td>
<td>0.6 (6.3)</td>
<td>85 (7.9)</td>
<td>.004</td>
<td>13 (4)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Sexual health</td>
<td>175 (28.1)</td>
<td>234 (30.7)</td>
<td>1.0 .31</td>
<td>273 (136)</td>
<td>&lt;.001</td>
<td>18.0 (23)</td>
<td>315 (29.1)</td>
<td>.004</td>
<td>94 (29.1)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Get tailored health information</td>
<td>163 (28.6)</td>
<td>328 (39.3)</td>
<td>16.7 .001</td>
<td>310 (181)</td>
<td>.004</td>
<td>8.1 (30.6)</td>
<td>389 (36)</td>
<td>.16</td>
<td>102 (31.6)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Learn more about my body</td>
<td>233 (40.9)</td>
<td>351 (42.1)</td>
<td>0.2 .69</td>
<td>368 (216)</td>
<td>.001</td>
<td>10.3 (36.5)</td>
<td>456 (34)</td>
<td>.45</td>
<td>128 (39.6)</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

**aP:** premium app user.

**bP:** free app user.

**cLT:** long-term app user.

**dST:** short-term app user.

**eFr:** frequent user of the app.

**fI:** infrequent user of the app.

We investigated whether Flo Premium users achieved health and knowledge improvements in their intended areas of the app use. First, we found that premium users of Flo were more likely to report knowledge improvements in almost all areas of pregnancy health (Table S1 in Multimedia Appendix 9, Table 4, and questions 29, 32, 34, 36, and 39). In addition, premium users were more likely to report knowledge and health improvements regarding their menstrual health (Table S2 in Multimedia Appendix 9, questions 17, 46, 47, and 51). Finally, Flo Premium users were more likely to report that Flo had helped them...
improve all aspects of general health (except sexual health), as well as improve communication with HCPs; specifically, Flo Premium users felt more confident in sharing what was going on in their body when communicating with their HCPs (Table S3 in Multimedia Appendix 9, questions 53 and 64).

Complete responses regarding knowledge and health improvements in pregnancy, cycle, and general health in relation to paid versus free app use are shown in Tables S1, S2, and S3, respectively, in Multimedia Appendix 9.

Knowledge and Health Improvements in Relation to Frequency of the App Use

Similar to users with higher education and Flo Premium users, participants who used the app frequently reported using the app mainly for pregnancy-related issues (pregnancy tracking: $\chi^2_P=26.8; P<.001$; to get help with becoming pregnant: $\chi^2_P=30.8; P<.001$), whereas infrequent app users were more likely to report using the app to track irregular cycles and related conditions ($\chi^2_P=5.4; P=.02$; Table 4).

We examined whether frequent users of Flo achieved pregnancy health and knowledge improvements from app use. As shown in Table S1 in Multimedia Appendix 10, frequent Flo app users were more likely to report that Flo app had helped them become pregnant ($\chi^2_F=4.5; P=.03$; question 30); prepare for a healthy pregnancy ($\chi^2_F=4.9; P=.03$; question 32); and improve their pregnancy health knowledge ($\chi^2_F=16.2; P<.001$; question 34). For example, frequent Flo app users reported that Flo had helped them to know more about their baby’s development ($\chi^2_F=6.6; P=.01$); their body during pregnancy ($\chi^2_F=6.7; P=.01$); basic do’s and don’ts during pregnancy ($\chi^2_F=4.5; P=.03$; Table S1 in Multimedia Appendix 10, question 36); and how pregnancy affects their physical health ($\chi^2_F=4.4; P=.04$; Table S1 in Multimedia Appendix 10, question 39).

In addition to improvements in pregnancy health and knowledge, study participants who used the Flo app frequently were more likely to report improvements in menstrual health knowledge (Table S2 in Multimedia Appendix 10) such as when symptoms were normal throughout the cycle ($\chi^2_F=6.1; P=.01$; question 47) and how to estimate the most fertile period by using cycle-related knowledge ($\chi^2_F=32.7; P<.001$; question 51). Frequent app users were also more likely to say that Flo had helped them to identify issues related to endometriosis ($\chi^2_F=3.9; P=.047$) and improved communication with their partners about their cycle ($\chi^2_F=30.6; P<.001$; Table S2 in Multimedia Appendix 10, question 47). Finally, frequent app users were more likely to report improvements in communication with a HCPs ($\chi^2_F=13.1; P<.001$; Table S3 in Multimedia Appendix 10, question 53), that is, they became more confident in asking questions about their health and body ($\chi^2_F=6.4; P=.01$) and they became more confident in understanding their reproductive health ($\chi^2_F=9.1; P=.003$; Table S3 in Multimedia Appendix 10, question 64).

We found that short-term Flo users were more likely to report that Flo had helped them to know how to use their cycle to know when they were most fertile ($\chi^2_F=8.1; P=.008$; Table S1 in Multimedia Appendix 11, question 51). At the same time, long-term users were more likely to report improvements across multiple areas of cycle, pregnancy, and general health. Long-term Flo app users were more likely to report that Flo had improved their menstrual health knowledge such as knowing whether their cycle was regular ($\chi^2_F=10.0; P=.002$); cycle length was normal ($\chi^2_F=5.4; P=.02$); and period flow was normal ($\chi^2_F=10.3; P=.001$). In addition, they were more likely to say that Flo had helped them to identify issues related to PCOS ($\chi^2_F=6.9; P=.009$) and helped them to reduce premenstrual syndrome symptoms ($\chi^2_F=14.4; P<.001$; Table S1 in Multimedia Appendix 11, question 47). In addition, long-term users were more likely to say that Flo had helped them to better understand how their cycle affected their mental ($\chi^2_F=12.3; P<.001$) and physical health ($\chi^2_F=14.7; P<.001$) and reactions to situations (lack of patience, sadness, etc; $\chi^2_F=9.3; P=.002$), as well as how to optimize their life around their cycle ($\chi^2_F=4.8; P=.03$; Table S1 in Multimedia Appendix 11, question 51). In addition, long-term users of Flo reported that had Flo helped them to improve their knowledge of fetal development ($\chi^2_F=5.0; P=.03$) and the management of pregnancy symptoms ($\chi^2_F=10.0; P=.002$) and postpartum symptoms ($\chi^2_F=26.0; P<.001$) as well as the reduction of risk of preterm labor ($\chi^2_F=6.1; P=.01$; Table S2 in Multimedia Appendix 11, question 36 and 39). Finally, long-term users were more likely to report improvements in sexual ($\chi^2_F=11.7; P<.001$); mental ($\chi^2_F=12.2; P<.001$); and physical health ($\chi^2_F=13.2; P<.001$) and health behaviors ($\chi^2_F=10.9; P<.001$; Table S3 in Multimedia Appendix 11, question 53). Most improvements were reported in sexual health knowledge such as STIs and how to avoid them ($\chi^2_F=20.9; P<.001$);
safe sex ($\chi^2 = 14.0; P < .001$); contraception options ($\chi^2 = 12.3; P < .001$); and the signs and symptoms during sex that were indicative of a health issue ($\chi^2 = 8.7; P < .003$; Table S3 in Multimedia Appendix 11, question 61).

Complete responses regarding knowledge and health improvements in cycle, pregnancy, and general health in relation to short-term versus long-term app use are shown in Tables S1, S2, and S3, respectively, in Multimedia Appendix 11.

**Discussion**

**Summary**

The aim of this study was to investigate the effects of the Flo app on health and knowledge improvements, with a specific focus on menstrual cycle and pregnancy health. In addition, we aimed to explore whether such effects differed based on education level, country of residence, and app use characteristics (ie, free or paid subscription, frequent or infrequent app use, and short- or long-term app use). We found that most participants reported menstrual cycle and pregnancy knowledge and health improvements upon using the Flo app. These improvements were mostly associated with the use of period and fertile day predictions, symptom-tracking features, and the consumption of relevant in-app health content (articles and videos). Users with different levels of education, countries of residence, and app use patterns differed in their selected health goals. The strongest improvements in knowledge and health were observed in premium, frequent, and long-term users.

**Benefits of Using Menstrual Cycle– and Pregnancy-Tracking Apps**

Our study is the first to date examining the effect of the mobile app Flo in improving menstrual and pregnancy knowledge and health as self-reported by its users. Most users who tracked their menstrual cycle with Flo reported that the app had helped them understand whether their menstrual cycle was normal or not; specifically, whether their cycle was regular, whether their cycle length was within the norms, and whether it was typical to have certain symptoms during their cycle. Menstrual cycle is a vital indicator of women’s health, and cycle abnormalities might be a sign of an underlying health issue [52]. For example, prolonged cycle length and cycle irregularity, in combination with other symptoms such as excessive body hair and acne, might be signs of PCOS [38], while painful and heavy periods or bleeding between periods might be indicative of endometriosis [53]. By improving the understanding of what a normal menstrual cycle is and what body symptoms and signs are associated with it, individuals are equipped with tools to make informed decisions as to whether symptoms they experience may require medical attention. Studies show that increased self-awareness promotes successful health behavior changes and makes individuals more proactive about seeking appropriate care when needed [31,54]. This is of vital importance given that the diagnosis of certain conditions such as endometriosis can be delayed for 8 to 12 years [53]. Prevention or early detection of reproductive conditions can improve women’s quality of life as well as decrease the time to diagnosis and medical costs associated with treatment, thereby reducing the economic burden on health care systems [55,56].

One in 3 participants in our sample reported that the Flo app had helped them to improve communication with an HCP. This is not surprising considering that better self-awareness and understanding of one’s own menstrual cycle and body were shown to be important for improving provider-patient communication [31]. According to the UK Women’s Health Strategy Survey, 1 in 4 women do not feel comfortable talking to health care professionals about their menstrual cycle, while most women do not feel heard by their physician [57]. Our results suggest that women’s health apps could improve the education and self-awareness of one’s menstrual health and facilitate patient-physician conversations.

Our survey respondents also reported that the use of the Flo app had helped them manage their menstrual symptoms such as bad mood or cramps. Symptoms that women experience during their menstrual cycle can negatively impact their quality of life, work productivity, and increase health care costs [58]. Dysmenorrhea (a commonly reported cramp-like pain occurring before or during periods) can affect approximately 45% to 95% of women and is associated with productivity loss and absenteeism (ie, absence from work) [59-62]. Furthermore, symptoms of endometriosis such as painful periods or chronic pelvic pain can also negatively impact work performance and can lead to 10.8 hours of lost work per week with an annual total productivity loss of $6298 (US $6838) per woman [55,63], in addition to the profound effects on psychological and social well-being [64,65]. In addition, 65.1% (309/475) of the Flo users reported that the app had helped them manage their irregular cycles and related conditions, with 1 in 3 participants reporting improvements in their mental health. Perceived improvements in cycle symptom management were largely associated with period predictions (935/1276, 73.3%) and reading and watching articles and video sources in the app (787/1276, 61.7%). Given that menstrual cycle symptoms have an impact on several aspects of women’s lives, cycle-tracking apps can help with being mentally prepared for upcoming periods (eg, via period predictions) and can provide insights into how to manage cycle symptoms (eg, via educational content).

Most participants who had used Flo to track their pregnancy reported improvements in pregnancy and postnatal health knowledge (eg, knowing how to manage pregnancy symptoms and which symptoms require medical attention) and well-being (eg, body image issues associated with pregnancy). Women’s health during pregnancy has profound effects on subsequent generations [66]. Poor maternal health can lead to low neonatal weight and reduced chances of survival, congenital abnormalities, problems with child behavior, poor school performance, and adult health and productivity [67-69]. Furthermore, maternal behaviors such as smoking or alcohol consumption during pregnancy may be significant drivers of infant health issues [70,71]. Therefore, health apps that allow pregnancy tracking are promising tools for improving knowledge about maternal and newborn health, thus decreasing the chances of pregnancy-related complications and child health issues.
Benefits of Using Menstrual Cycle–Tracking Apps for LMICs and HICs

Although participants from LMICs (699/2212, 32.6% of the sample) intended to use the Flo app to improve their sexual health (eg, gaining knowledge of STIs and how to avoid them, safe sex, etc), they also reported significantly higher improvements in multiple areas of their health (menstrual cycle, mental and physical health, and improved healthy behaviors). Compared with HICs, where reproductive and sexual education is mandatory in many schools and menstrual health has started to gain increasing attention from governmental and health care authorities (eg, Women’s Health Strategy in England in 2021) [72], LMICs often lack formal menstrual health education, resulting in high levels of stigma and shame surrounding menstruation and sex [73]. Poor period education results in a lack of knowledge about menstrual cycle norms; menstrual hygiene; gynecological conditions and their symptoms; and sexual health (eg, contraception and STIs). Specifically, according to the World Bank classification, LMICs have the highest prevalence of STIs (eg, gonorrhea, trichomoniasis, and syphilis), and the awareness of STIs other than HIV in those countries is very low [74-76]. Therefore, menstrual and sexual health apps, together with systemic governmental and societal education efforts, can mitigate long-term repercussions of poor health literacy, thereby decreasing unfavorable health outcomes such as infertility, abortions, preterm delivery, and perinatal and neonatal morbidities and helping with cutting health care costs associated with STI treatment [77-80].

Flo app users from HICs reported using the app to help them get pregnant and for pregnancy and menstrual cycle tracking. We found that users from HICs were statistically more likely to report that they became pregnant while using the Flo app, while 97.6% (451/462) acknowledged that fertile days and ovulation predictions made by the Flo app helped them become pregnant. Despite an increase in social and governmental momentum to improve menstrual and sexual health literacy in HICs, topics such as fertility and healthy pregnancy have not received the attention they deserve. A survey conducted on a sample of 1000 American participants showed that younger women (aged 18-24 years) demonstrated a low level of knowledge about conception, ovulation, and the effect of age on the length of time to conception and miscarriage risks. Women aged 25 to 40 years were more likely to believe in common myths around fertility and conception. Finally, more than one-quarter of all survey participants were unaware of factors impacting fertility such as STIs or obesity [18]. Therefore, health apps might help to save costs associated with infertility treatments by educating users on factors impacting fertility and providing fertile window- and ovulation-tracking functionalities to optimize conception strategies.

Menstrual cycle– and pregnancy-tracking apps might represent promising tools for improving reproductive health knowledge and health among women globally. This is largely owing to the anonymity, scalability, and accessibility of such digital solutions. According to a 2019 survey by the Kaiser Family Foundation, 1 in 3 women of reproductive age in the United States used a menstrual cycle–tracking app [81]. At the same time, an increasing adoption of mobile health apps is also observed in LMICs [82]. Thus, app developers and governmental and health authorities should collaborate to promote HCPs encouraging the adoption of menstrual cycle–tracking apps by the target group and facilitate the distribution of health apps in LMICs.

Modes (Free vs Paid), Frequency, and Length of App Use

We found that participants who used a paid version of the app, as well as those who used the app more frequently and for a longer period, were more likely to report improvements in knowledge and health compared with free app users and infrequent or short-term users. These results are not surprising, as studies show that health interventions that are used consistently for prolonged periods are more likely to positively impact behavior, thus leading to better health outcomes [83]. For example, a study conducted by Huberty et al [84] found that more frequent use of the meditation app Calm was associated with an increase in the likelihood of noticing changes in mental health, sleep, and stress levels. Another study by Han and Rhee [85] showed that users who frequently monitored their weight, food consumption, and exercise via a weight loss app, Noom, had more efficient weight loss over time. Therefore, health app developers should consider designing user-friendly, easy-to-navigate, and evidence-based technologies to encourage higher and consistent engagement with the app to achieve better health outcomes for the users.

Limitations

Although this study is the first to provide insights into the benefits of using Flo app for women’s health and education, it has several limitations. First, most of the study cohort consisted of highly engaged (1650/2212, 74.6% use the Flo app several times a day to several times a week) and loyal (1305/2212, 59% use the Flo app for >1 year) users of the Flo app who may have more favorable opinions about the app and have benefited more from using it. Those who did not find Flo helpful may have elected not to participate.

Another limitation is that this was a cross-sectional, nonexperimental study that does not allow us to infer causality with regard to the impact of Flo app on user knowledge, health, and well-being. Future randomized controlled trials assessing the efficacy of the Flo app with baseline and follow-up measures should explore these relationships prospectively to determine the extent to which changes can be attributed to Flo app use. Furthermore, systematic exploration of the health benefits of available women’s health apps is needed to allow clinicians and end users to make informed decisions about effective, safe, and trustworthy solutions. To this end, app developers should conduct and make publicly available pre- and postmarket research assessing the effectiveness and efficacy of their health products. Simultaneously, external organizations should conduct rigorous comparisons of such products to facilitate end users’ understanding of benefits and risks. As mentioned in the Introduction section, despite the call for more rigorous evidence generation, research on this topic is scarce, and a more systematic effort is needed across the board.

Finally, the survey questions were specifically designed for this study; thus, they had not been previously validated in scientific
research. This study used self-reported statements about perceived health knowledge and health behaviors. Although perceived health knowledge and behaviors do not equate to actual improvements in health literacy and health outcomes, they provide useful preliminary insights into the awareness of one’s own health. Future studies should extend the findings of this report by using validated questionnaires to assess changes in menstrual and pregnancy health literacy, as well as knowledge assessment quizzes over time.

Conclusions
This study provides the first insights into the effectiveness of the menstrual cycle and women’s health app, Flo, in improving user knowledge and health, and it builds toward a much-needed body of evidence in digital health. Our results highlight the opportunity for menstrual health apps to become useful tools for promoting reproductive health education and empowerment among users globally.

Acknowledgments
The authors thank the Flo users who took part in the study.

Conflicts of Interest
LZ, RB, TR, AW, KP, JC, AK, and SP were employees of Flo Health.

Multimedia Appendix 1
Survey questions.
[PDF File (Adobe PDF File), 150 KB - mhealth_v11i1e40427_app1.pdf]

Multimedia Appendix 2
Flo users’ app use characteristics.
[PDF File (Adobe PDF File), 52 KB - mhealth_v11i1e40427_app2.pdf]

Multimedia Appendix 3
List of high-income countries and total number of users.
[PDF File (Adobe PDF File), 47 KB - mhealth_v11i1e40427_app3.pdf]

Multimedia Appendix 4
List of low- and middle-income countries and total number of users.
[PDF File (Adobe PDF File), 48 KB - mhealth_v11i1e40427_app4.pdf]

Multimedia Appendix 5
Cycle, pregnancy, and general health responses.
[PDF File (Adobe PDF File), 76 KB - mhealth_v11i1e40427_app5.pdf]

Multimedia Appendix 6
Reasons for using the app versus age and education.
[PDF File (Adobe PDF File), 82 KB - mhealth_v11i1e40427_app6.pdf]

Multimedia Appendix 7
Education level versus cycle, pregnancy, and general health questions.
[PDF File (Adobe PDF File), 84 KB - mhealth_v11i1e40427_app7.pdf]

Multimedia Appendix 8
High-income and low- and middle-income countries versus cycle, pregnancy, and general health questions.
[PDF File (Adobe PDF File), 76 KB - mhealth_v11i1e40427_app8.pdf]

Multimedia Appendix 9
Premium and free users versus cycle, pregnancy, and general health questions.
[PDF File (Adobe PDF File), 83 KB - mhealth_v11i1e40427_app9.pdf]

Multimedia Appendix 10
Frequent and infrequent app use versus cycle, pregnancy, and general health questions.
References


85. Han M, Rhee SY. Effect of adherence to smartphone app use on the long-term effectiveness of weight loss in developing and OECD countries: retrospective cohort study. JMIR Mhealth Uhealth 2021 Jul 12;9(7):e13496 [FREE Full text] [doi: 10.2196/13496] [Medline: 34255708]

Abbreviations

- **HCP**: health care provider
- **HIC**: high-income country
- **LMIC**: low- and middle-income country
- **PCOS**: polycystic ovary syndrome
- **STI**: sexually transmitted infection

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Delivering a Postpartum Weight Loss Intervention via Facebook or In-Person Groups: Results From a Randomized Pilot Feasibility Trial

Molly E Waring1,2, PhD; Sherry L Pagoto1,2, PhD; Tiffany A Moore Simas3,4,5,6, MEd, MPH, MD; Loneke T Blackman Carr2,7, RD, PhD; Madison L Eamiello1, MA; Brooke A Libby1, MPH, MS; Lauren R Rudin1, BS; Grace E Heersping1, BS

1Department of Allied Health Sciences, University of Connecticut, Storrs, CT, United States
2UConn Center for mHealth & Social Media, University of Connecticut, Storrs, CT, United States
3Department of Obstetrics & Gynecology, University of Massachusetts Chan Medical School/UMass Memorial Health, Worcester, MA, United States
4Department of Pediatrics, University of Massachusetts Chan Medical School/UMass Memorial Health, Worcester, MA, United States
5Department of Psychiatry, University of Massachusetts Chan Medical School/UMass Memorial Health, Worcester, MA, United States
6Department of Population & Quantitative Health Sciences, University of Massachusetts Chan Medical School/UMass Memorial Health, Worcester, MA, United States
7Department of Nutritional Sciences, University of Connecticut, Storrs, CT, United States

Corresponding Author:
Molly E Waring, PhD
Department of Allied Health Sciences
University of Connecticut
358 Mansfield Rd
Unit 1101
Storrs, CT, 06269
United States
Phone: 1 8604861446
Email: molly.waring@uconn.edu

Abstract

Background: Postpartum weight retention contributes to weight gain and obesity. Remotely delivered lifestyle interventions may be able to overcome barriers to attending in-person programs during this life phase.

Objective: This study aimed to conduct a randomized feasibility pilot trial of a 6-month postpartum weight loss intervention delivered via Facebook or in-person groups. Feasibility outcomes were recruitment, sustained participation, contamination, retention, and feasibility of study procedures. Percent weight loss at 6 and 12 months were exploratory outcomes.

Methods: Women with overweight or obesity who were 8 weeks to 12 months post partum were randomized to receive a 6-month behavioral weight loss intervention based on the Diabetes Prevention Program lifestyle intervention via Facebook or in-person groups. Participants completed assessments at baseline, 6 months, and 12 months. Sustained participation was defined by intervention meeting attendance or visible engagement in the Facebook group. We calculated percent weight change for participants who provided weight at each follow-up.

Results: Among individuals not interested in the study, 68.6% (72/105) were not interested in or could not attend in-person meetings and 2.9% (3/105) were not interested in the Facebook condition. Among individuals excluded at screening, 18.5% (36/195) were ineligible owing to reasons related to the in-person condition, 12.3% (24/195) related to the Facebook condition, and 2.6% (5/195) were unwilling to be randomized. Randomized participants (n=62) were a median of 6.1 (IQR 3.1-8.3) months post partum, with a median BMI of 31.7 (IQR 28.2-37.4) kg/m². Retention was 92% (57/62) at 6 months and 94% (58/62) at 12 months. The majority (21/30, 70%) of Facebook and 31% (10/32) of in-person participants participated in the last intervention module. Half (13/26, 50%) of Facebook and 58% (15/26) of in-person participants would be likely or very likely to participate again if they had another baby, and 54% (14/26) and 70% (19/27), respectively, would be likely or very likely to recommend the program to a friend. In total, 96% (25/26) of Facebook participants reported that it was convenient or very convenient to log into the Facebook group daily compared with 7% (2/27) of in-person participants who said it was convenient or very convenient to...
attend group meetings each week. Average weight loss was 3.0% (SD 7.2%) in the Facebook condition and 5.4% (SD 6.8%) in the in-person condition at 6 months, and 2.8% (SD 7.4%) in the Facebook condition and 4.8% (SD 7.6%) in the in-person condition at 12 months.

Conclusions: Barriers to attending in-person meetings hampered recruitment efforts and intervention participation. Although women found the Facebook group convenient and stayed engaged in the group, weight loss appeared lower. Research is needed to further develop care models for postpartum weight loss that balance accessibility with efficacy.

Trial Registration: ClinicalTrials.gov, NCT03700736; https://clinicaltrials.gov/ct2/show/NCT03700736

(JMIR Mhealth Uhealth 2023;11:e41545) doi:10.2196/41545

KEYWORDS
postpartum weight loss; Facebook; social media; pilot study; feasibility; mobile phone

Introduction

Background

Postpartum weight retention contributes to long-term weight gain and obesity among childbearing persons [1-4]. Among women in the multicenter Community Child Health Network study, a third of women with a normal weight BMI prepregnancy had overweight or obesity at 1 year post partum, and 44% of women with overweight prepregnancy transitioned to obesity by 1 year post partum [1]. Among women enrolled in the 2016 Los Angeles Mommy and Baby (LAMB) follow-up study, 35% of women with normal weight BMI prepregnancy had transitioned to overweight or obesity by 2 years after giving birth [5]. Postpartum weight retention varies, and although many women return to their prepregnancy weight by 1 year post partum, a substantial proportion retain substantial amounts of weight [2,6]. In a cohort of women delivering their first child from Pennsylvania, 24% had retained 1-9 pounds (0.5-4 kg) and 24% had retained ≥10 pounds (4.5 kg) at 1 year post partum [6]. In the LAMB cohort, 35% had retained ≥10 pounds at 2 years post partum [5].

Although systematic reviews and meta-analyses have demonstrated the efficacy of lifestyle interventions targeting dietary intake and physical activity for weight loss during the postpartum period [7-10], interventions with numerous in-person sessions are not a good logistical match for the busy lives of many postpartum women [11-14]. Indeed, high attrition from treatment has plagued many postpartum weight loss intervention studies [7,8]. Remotely delivered lifestyle interventions can overcome some of the barriers to attending in-person meetings during the postpartum period (eg, work schedules, childcare, and transportation challenges) [11-14], challenges that have only increased during the COVID-19 pandemic [15]. In addition, remotely delivered lifestyle interventions may be more cost-effective to deliver, especially when accounting for participant costs [16]. Establishing noninferiority of remote versus in-person postpartum weight loss intervention models would advance the science by identifying a potentially more convenient and less costly model of care delivery.

Facebook may be an effective platform for remotely delivering evidence-based weight loss programming to postpartum women. Currently, 70% of US adults aged 18-29 years and 77% of adults aged 30-49 years use Facebook [17], with higher rates of use among mothers (87%) and women aged 18-39 years (84%) [18]. Many mothers turn to Facebook for support and information about parenting issues [19,20], and 80% of parents who use Facebook engage on the platform daily [18]. Using this popular commercial social media platform for intervention delivery allows us to leverage women’s daily routines to engage them in behavior change.

Lifestyle interventions that deliver at least some content via Facebook are efficacious for adults generally [21], and pilot studies conducted by our team and others have demonstrated feasibility and acceptability of leveraging Facebook for lifestyle intervention delivery among postpartum women specifically [22-25]. However, our approach is to deliver all the didactic intervention content via Facebook, whereas others have leveraged Facebook along with other treatment modalities (eg, telephone or in-person counseling sessions, text messaging, or an in-person orientation meeting) [23-25]. We previously developed a postpartum weight loss intervention [22] by adapting the Diabetes Prevention Program (DPP) lifestyle intervention [26] to address the needs of postpartum women and for delivery by a trained weight loss counselor via a private Facebook group [27]. In our earlier work, we conducted a 1-arm pilot study of our intervention with 19 postpartum women with overweight or obesity (ie, BMI ≥25 kg/m² but <45 kg/m²) [22]. We were able to retain participants (95% retention) and keep them engaged over the 12-week intervention period [22]. The majority of participants said they would be likely or very likely to participate again if they had another baby, more than 80% would recommend the program to a postpartum friend, and participants lost an average of 4.8% of their baseline weight [22]. Although the results of this 1-arm pilot study are promising, this study did not provide information on the feasibility of recruitment of women able and willing to be randomized to either the Facebook or in-person intervention nor information about sustained participation in the Facebook-delivered intervention beyond 12 weeks. We conducted a randomized pilot trial to answer these feasibility questions (ie, feasibility of recruitment under conditions of randomization, sustained participation through the entire 6-month intervention, and retention at 6- and 12-month assessments) before conducting a large-scale trial to evaluate whether delivery via Facebook groups is noninferior to delivery via in-person group meetings.

https://mhealth.jmir.org/2023/1/e41545 JMIR Mhealth Uhealth 2023 | vol. 11 | e41545 p.691 (page number not for citation purposes)
**Objective**

This study aimed to conduct a randomized feasibility pilot trial of a 6-month postpartum weight loss intervention delivered via Facebook versus in-person groups with postpartum women with overweight or obesity. We examined the feasibility of recruitment, sustained participation, contamination, retention, and assessment procedures in both conditions. We also described intervention acceptability. We described percent weight loss at 6 and 12 months in both treatment groups as an exploratory outcome.

**Methods**

**Study Design**

We conducted a randomized feasibility pilot trial to compare the delivery of a 6-month postpartum weight loss intervention via Facebook versus in-person groups among women with overweight or obesity. The design of this trial has been described in detail elsewhere [28].

**Ethics Approval**

The University of Connecticut Institutional Review Board approved this study (protocol #H17-206). The trial was registered on clinicaltrials.gov (NCT03700736).

**Recruitment and Eligibility**

Participants were recruited in 2 waves starting in August 2018 through October 2019. We recruited women from the Hartford, Connecticut area community by posting recruitment messages on Facebook, Instagram, Twitter, ResearchMatch [29], Craigslist, and University of Connecticut and UConn Health employee email digests, and by posting study flyers in the community. Additional details on recruitment are described elsewhere [28]. Research staff conducted eligibility screenings of interested individuals via phone.

Inclusion criteria were being aged ≥18 years; being at least 8 weeks but <12 months post partum at time of enrollment; having a BMI ≥25 kg/m² per measured height and weight at baseline; either owning a scale or being willing to be provided one if needed; being comfortable reading and writing in English; owning an Android or iPhone smartphone; being an active Facebook user defined as accessing Facebook daily and posting or commenting at least weekly over the past 4 weeks; having clearance from their primary care provider or obstetrician or gynecologist; being willing to participate in either treatment condition (Facebook or in-person); being available to attend in-person meetings over the 6-month study period in Hartford, Connecticut; taking <45 minutes to travel to intervention meetings; and being willing and able to provide informed consent.

Women were excluded if they met any of the following criteria: currently pregnant; plan to become pregnant during the study period; current participation in an in-person or web-based clinical weight loss program; diagnosed with type 1 or type 2 diabetes as self-reported or reported by their health care provider; medical conditions or medications affecting weight; incapable of walking a quarter mile unaided without stopping; pain that prevents engagement in exercise; previous bariatric surgery; planned surgery during the study period; plans to move out of the area during the study period; high depressive symptoms or suicidal ideation (a score of ≥12 or positive on question #10 on the Edinburgh Postnatal Depression Scale [EPDS] [30]); positive screen for binge eating disorder [31]; failure to complete any baseline procedures (eg, baseline survey, orientation webinar, or prerandomization survey); or University of Connecticut student or employee supervised or taught by study investigators.

Eligible participants were all biologically female owing to the inclusion criteria of having given birth; we did not ask participants their gender identity. Although not all persons who become pregnant identify as women [32] as recruitment materials included the phase, “we are recruiting women who had a baby in the past year;” it is likely that all participants identified as women, and we refer to participants in this study as “women” or “mothers.”

**Assessments**

Participants completed assessments at baseline, 6 months (postintervention), and 12 months, and filled out brief weekly surveys during the intervention period, as described in detail elsewhere [28]. Participants were provided gift cards to thank them for completing study assessments at baseline (US $20), 6 months (US $40), and 12 months (US $40). For wave 1, the intervention occurred from February to August 2019, with follow-up assessments in August 2019 and February 2020. For wave 2, the intervention occurred from October 2019 to April 2020, with follow-up assessments in April 2020 and October 2020.

At baseline, participants completed an in-person study visit that included providing informed consent, height and weight measurement, and screenings for elevated depressive symptoms and binge eating disorder. Study staff also provided instructions for downloading and using the MyFitnessPal app and instructions for using the battery settings to report Facebook app use (iPhone users) or a free app to track time on Facebook (Android users). Following this visit, participants completed a 30-minute web-based survey that included demographic and clinical characteristics (including prepregnancy weight for calculation of postpartum weight retention at baseline) and other baseline measures. Next, research staff contacted participants’ primary care provider or obstetrician or gynecologist for medical clearance. After completing their baseline visit and survey, participants completed a 60-minute webinar with other participants to orient them to the scientific process, review study procedures, and discuss the barriers and advantages of each study condition [33]. Following the orientation webinar but before randomization, participants completed a 5-minute web-based survey composed of a randomization agreement, report of app-tracked time on Facebook over the past 7 days, and their Facebook use habits [34]. Weekly during the intervention period, participants in both treatment conditions reported their weight, past 7-day app-tracked time on Facebook, and Facebook use habits [34] via a brief, 5-minute web-based survey.

At the end of the 6-month intervention, participants attended a focus group with other members of their weight loss group to...
provide qualitative feedback on their experiences in the study. The focus groups started out by asking general questions about participants’ experiences in the intervention (eg, “Overall, what do you think of this program?”, “What about this program did you find most helpful?”, and “How could we improve this weight loss program?”), transitioned to asking questions specific to each treatment modality (eg, “What influenced whether you commented on a post or comment?” in the Facebook condition and “How difficult was it for you to attend the sessions?” in the in-person condition), and finally prompted any additional feedback (ie, “Do you have any other feedback about this program?”). Participants also completed a 30- to 45-minute web-based survey that included questions about contamination, acceptability, depressive symptoms (EPDS [30]), quality of life (PROMIS-Preference [PROP] [35,36]), Facebook use habits including time spent on Facebook [17,34], and incident pregnancies. Research staff measured participants’ weight at the focus group visit. Participants who could not attend the focus group completed an individual interview and weight measurement at an individual visit. For wave 2, the 6-month focus groups were conducted via video conferencing software owing to the COVID-19 pandemic, and participants self-reported their current weight on the survey.

At 12 months, participants in wave 1 completed an in-person visit to measure weight and completed a 30-minute web-based survey that included measures of depressive symptoms (EPDS [30]), quality of life (PROP [35,36]), Facebook use habits including time spent on Facebook [17,34], and incident pregnancies. Owing to the COVID-19 pandemic, participants in wave 2 did not attend in-person follow-up visits; follow-up weights were self-reported in the follow-up surveys.

Randomization

Eligible participants who completed all screening and baseline procedures were randomized 1:1 to the Facebook and in-person conditions in randomly permuted blocks of size 4 and 6. Randomization was stratified by months post partum at enrollment (8 weeks to <6 months vs 6-12 months) and type of smartphone (iPhone vs Android). We stratified randomization by months post partum because weight change varies across the postpartum period in the absence of formal intervention [37,38]. We stratified randomization by smartphone type to balance any differences related to methods for measuring time spent on Facebook, as the procedures for collecting these data differed by phone operating system.

Treatment Conditions

Participants in both treatment conditions received a 6-month weight loss intervention based on the DPP lifestyle intervention [26]. As described elsewhere [28], we adapted the intervention content to meet the needs and challenges of the postpartum period [11,39-42]. In the materials for both the in-person and Facebook-delivered interventions (eg, participant handouts and Facebook posts), we included stock images of women with larger bodies with a variety of skin tones, racial or ethnic phenotypes, and family configurations. Weight loss counselors had backgrounds in nutrition and dietetics and completed the National DPP training and training by a licensed clinical psychologist with extensive experience using the DPP in our specific intervention protocols [22,43,44]. The weight loss counselor for wave 1 identified as non-Hispanic White, and the weight loss counselor for wave 2 identified as Hispanic. The intervention goals were 5% to 10% weight loss and increasing physical activity to 150 minutes per week of moderate intensity physical activity. Calorie and physical activity goals were set to facilitate weekly weight loss of 1 to 2 pounds. For women who reported breastfeeding at baseline, initial calorie goals accounted for lactation [45], and calorie goals were adjusted during the intervention, as participants reported changes in breastfeeding. Participants were encouraged to use the free MyFitnessPal app to track their diet, exercise, and weight, and weight loss counselors emailed or messaged participants’ feedback on diet and activity records weekly or every 2 weeks (corresponding to the frequency of meetings in the in-person condition). Participants were withdrawn from the intervention if they reported becoming pregnant to the weight loss counselor or study staff. The 2 treatment conditions received the same intervention content; the difference between conditions was the delivery modality: in-person groups versus Facebook groups.

In the in-person condition, the weight loss counselor facilitated 90-minute group discussions, which were held weekly for the first 15 weeks and every other week during weeks 16-25, for a total of 20 meetings. The intervention materials were provided via paper handouts. Participants were reimbursed up to US $5 for parking or bus fare for each intervention meeting attended. Owing to the COVID-19 pandemic, the last 2 meetings of wave 2 were conducted via synchronous videoconferencing software.

In the Facebook condition, the weight loss counselor facilitated discussion about weekly topics via posts and comments in a private (“secret”) Facebook group [46]. The counselor posted 2 posts per day during weeks 1-15 and 1 post per day during weeks 16-25, corresponding to the intensity of contact in the in-person condition. We used the Facebook post scheduling tool to schedule daily intervention posts from the weight loss counselor’s account. We developed posts covering the intervention content of each module of the DPP lifestyle intervention based on our previous work with postpartum women [22] and adults generally [43,44,47]. Posts provided information and resources related to the topic of the week or asked participants to share their thoughts, experiences, or challenges related to the topic of the week; set goals (Mondays); report their progress toward these goals (Sundays); or report their weekly weight change (Fridays). Additional logistic details about the Facebook group and sample intervention posts are described elsewhere [28].

Participation in both interventions was monitored by the research team. The weight loss counselor recorded attendance at in-person intervention meetings. Research staff reviewed the Facebook group and recorded the date of each participant’s latest post or reply (each Monday during weeks 1-15 and every other Monday during weeks 16-25, corresponding to the frequency of in-person intervention meetings). The weight loss counselor emailed participants who did not participate (ie, did not attend in-person meetings or did not post or reply in the Facebook group) in a given week or 2-week period to encourage them to participate during the following week. After 2 consecutive weeks of no participation, the weight loss counselor
called the participant, and after 3 consecutive weeks, the research coordinator called the participant. After 4 consecutive weeks without participation, the weight loss counselor sent a final email encouraging participation.

Measures

Primary Outcomes: Feasibility

The feasibility outcomes were recruitment, retention, sustained participation, contamination, and feasibility of the assessment procedures. We also report participant feedback regarding the acceptability of the interventions.

Recruitment

We tracked participants through eligibility screening and study procedures and calculated recruitment rates from the number of individuals contacted, screened, consented, and randomized, overall and by recruitment source. We recorded the reasons for ineligibility and nonparticipation, including unwillingness to be randomized to either the Facebook or in-person condition.

Retention

We calculated retention as the proportion of participants who completed the 6- and 12-month follow-up assessments (ie, provided weight or completed the follow-up survey) in each condition.

Sustained Participation

We assessed sustained participation in the intervention (ie, treatment retention). For the in-person condition, the weight loss counselor recorded attendance at each intervention meeting, and sustained participation was calculated as the last intervention session attended. In the Facebook condition, treatment modules were spread over 1 week (weeks 1-15) or 2 weeks (weeks 16-25) to correspond to the frequency of intervention meetings in the in-person condition. Thus, we assessed participation in each treatment module. We captured engagement data from Facebook using Grytics tools (Grytics, Inc) and then manually abstracted identifiers (eg, participants' Facebook usernames), reactions to posts and comments (including who reacted and what the reaction was), and poll responses (who voted for each option).

A second member of the research team reabstracted a random 10% sample of threads (ie, a post plus any associated replies; 99.7% agreement across abstracted data points) to confirm the accuracy of abstraction. We calculated sustained participation as the latest treatment module participated in based on the latest post, reply (comments on posts and comments in replies to comments), poll vote (based on the date of the post that included the poll), or reaction (based on the date of the post or reply reacted to) in the Facebook group. We secondarily calculated whether participants participated in the last (20th) intervention module, and overall participation as the number of intervention modules participated in, and whether they participated in 0 intervention modules, ≥16 (ie, ≥80%), or 20 (ie, 100%). We additionally calculated the total number of posts, replies, polls voted in, and reactions by participants in the Facebook condition.

Contamination

To assess contamination, the 6-month follow-up survey included questions about participation in other weight loss programs (web-based or in person); whether participants sought weight loss support on Facebook or other web-based social networks [48]; and if so, to what extent and reasons they sought this support. One participant in the Facebook group reported during week 13 of the intervention that she had started a 21-week Beachbody program. Although she did not report this in her 6-month survey, we counted this as concurrent use of another weight loss program.

Feasibility of Assessment Procedures

We developed data collection and participant tracking systems and procedures. We assessed the degree of missingness of measures to be included in a large-scale trial to assess intervention efficacy and cost-effectiveness. We created a tracking system in REDCap (Research Electronic Data Capture; Vanderbilt University [49]) for research staff to enter time spent on specific tasks (eg, leading in-person intervention meetings, counseling via the Facebook group, copying participant handouts) [50] that would be needed to implement each intervention in practice (ie, outside the research context) using methods developed by others [51-53]. At baseline, 6 months, and 12 months, the participants completed a quality-of-life measure (PROPr) [35,36].

Acceptability of the Interventions

At 6 months, participants also answered questions regarding intervention acceptability [22]. Participants were asked, “If you had another baby, how likely would you be to participate in this weight loss program again?” and “If you had a friend who recently had a baby, how likely would you be to recommend this program to her?” (response options: “very unlikely,” “unlikely,” “neutral,” “likely,” and “very likely”; dichotomized as likely or very likely vs not). Participants were asked how convenient it was for them to log into the private Facebook group daily (Facebook condition) or attend 90-minute group meetings each week (in-person condition; response options: “very convenient,” “convenient,” “neither convenient nor inconvenient,” “inconvenient,” or “very inconvenient”; dichotomized as convenient or very convenient vs not). Participants in both groups were asked whether they would find attending weekly in-person group meetings or interacting in a private Facebook group daily more convenient (response options: “Facebook much more convenient,” “Facebook more convenient,” “Facebook and in-person groups equally convenient,” “in-person groups more convenient,” and “in-person groups much more convenient”; dichotomized as Facebook much more or more convenient vs not). To help us understand factors influencing intervention participation, after answering acceptability questions, participants were asked: “Thinking about the times when you logged in but did not post or reply to any posts why did you choose not to?” (Facebook condition) or “Thinking about the times when you didn’t come to the in-person group meetings, what was the reason?” (in-person condition). Participants in each condition were provided with a list of possible reasons (see tables for response options) and were asked to select all the answers that applied to them.
**Exploratory Outcome: Weight Change**

At baseline, 6 months, and 12 months, the staff measured weight twice (Tanita C-110 scale), and we calculated the average of the 2 measurements. In wave 1, participants who were unwilling to attend an in-person follow-up visit were asked to self-report their current weight (Facebook: 0/14, 0% at 6 months and 4/14, 29% at 12 months; in-person: 3/15, 20% at 6 months and 5/15, 33% at 12 months). As both follow-up time points for wave 2 occurred during the COVID-19 pandemic (April and October 2020), we pivoted to remote assessments, and participants self-reported their weight at 6 months and 12 months. Thus, all follow-up weights in wave 2 were self-reported. We calculated absolute (lbs) and percent weight change from baseline to 6 months and baseline to 12 months and defined clinically significant weight loss as ≥5% [54,55]. For women who were pregnant at follow-up, we used self-reported prepregnancy weight to calculate weight change. We secondarily calculated weight change assuming no weight change for those missing follow-up weights (baseline observation carried forward).

**Power Calculation**

The purpose of this pilot trial was to examine feasibility and to identify modifications required before conducting a large randomized controlled trial to assess efficacy for weight loss. As recommended [56,57], we based the sample size on necessities for examining feasibility. We decided a priori that retention of ≥80% would indicate feasibility and that a retention rate in either condition <60% would indicate a lack of feasibility. With the target sample of 72 participants (36 per condition), the lower limit of the 95% CI for the observed retention rate in either treatment condition should not be <60%.

**Statistical Analysis**

We used REDCap [49] for participant tracking and participant surveys. Data management and analyses were conducted using SAS (version 9.4; SAS Institute, Inc). We described the feasibility outcomes and exploratory outcome of weight loss in both conditions. We compared retention rates with the a priori benchmark for feasibility. After transcribing the focus group and interview recordings, we conducted a thematic analysis of responses [58]. This analysis focused on participant feedback about their assigned intervention modality that might impact acceptability ratings. Specifically, 3 members of the research team reviewed the focus group and interview transcripts as well as notes from focus group facilitators (familiarization) to create an initial list of feedback themes (generation of initial codes), reread transcripts to identify additional passages (searching for themes), and then consolidated feedback into themes (reviewing and defining themes) [58]. The first author then summarized relevant participant feedback identified by the review team (producing the report) [58].

**Results**

**Study Sample**

We screened 338 women, of whom 78 (23.1%) were eligible at screening and started baseline assessment procedures (Figure 1). We randomized 62 postpartum women. Two participants were withdrawn owing to pregnancy (1 per condition), and 8 dropped out of treatment (2 in the Facebook condition and 6 in the in-person condition; Figure 1). Overall retention was 92% (57/62) at 6 months and 94% (58/62) at 12 months.

Randomized participants (N=62) were on average aged 32.8 (SD 4.0) years and were a median of 6.1 (IQR 3.1-8.3) months post partum at enrollment (Table 1). In total, 60% (37/62) of participants had obesity at baseline, and median BMI was 31.7 (IQR 28.2-37.4) kg/m². Average postpartum weight retention was 13.9 (SD 15.4) pounds. Most (43/62, 69%) of the participants were breastfeeding and 63% (38/62) had ≥2 children. Three-quarters (46/62, 74%) of participants were non-Hispanic White, 85% (53/62) had at least a bachelor’s degree, and 73% (40/62) were employed full-time. Additional characteristics of participants are provided in Table 1.
Figure 1. Participant recruitment and retention. Individuals excluded at eligibility screening and baseline assessment could be excluded for multiple reasons. Only the most common reasons for ineligibility are shown in the figure.
Table 1. Characteristics of postpartum women with overweight or obesity at study enrollment, overall, and by treatment condition.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>All randomized participants (n=62)</th>
<th>Facebook condition (n=30)</th>
<th>In-person condition (n=32)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smartphone typea, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>iPhone</td>
<td>45 (73)</td>
<td>21 (70)</td>
<td>24 (75)</td>
</tr>
<tr>
<td>Android</td>
<td>17 (27)</td>
<td>9 (30)</td>
<td>8 (25)</td>
</tr>
<tr>
<td>Months post partumb, median (IQR)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≥8 weeks but &lt;6 months, n (%)</td>
<td>6.1 (3.1-8.3)</td>
<td>5.8 (3.1-8.3)</td>
<td>6.1 (2.9-8.2)</td>
</tr>
<tr>
<td>≥6 months but &lt;12 months, n (%)</td>
<td>30 (48)</td>
<td>15 (50)</td>
<td>15 (47)</td>
</tr>
<tr>
<td>Singleton gestation, n (%)</td>
<td>59 (95)</td>
<td>28 (93)</td>
<td>31 (97)</td>
</tr>
<tr>
<td>Breastfeeding, n (%)</td>
<td>43 (69)</td>
<td>23 (77)</td>
<td>20 (63)</td>
</tr>
<tr>
<td>&gt;2 children in her householdb, n (%)</td>
<td>38 (63)</td>
<td>21 (70)</td>
<td>17 (57)</td>
</tr>
<tr>
<td>BMI (kg/m²), median (IQR)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overweight, n (%)</td>
<td>25 (40)</td>
<td>12 (40)</td>
<td>13 (41)</td>
</tr>
<tr>
<td>Obesity, n (%)</td>
<td>37 (60)</td>
<td>18 (60)</td>
<td>19 (59)</td>
</tr>
<tr>
<td>Postpartum weight retention (lbs), mean (SD)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (years), mean (SD)</td>
<td>32.8 (4.0)</td>
<td>33.3 (3.5)</td>
<td>32.3 (4.4)</td>
</tr>
<tr>
<td>Race and ethnicity, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-Hispanic White</td>
<td>46 (74)</td>
<td>22 (73)</td>
<td>24 (75)</td>
</tr>
<tr>
<td>Non-Hispanic Black</td>
<td>3 (5)</td>
<td>1 (3)</td>
<td>2 (6)</td>
</tr>
<tr>
<td>Hispanic or Latina</td>
<td>9 (15)</td>
<td>5 (17)</td>
<td>4 (13)</td>
</tr>
<tr>
<td>Non-Hispanic Asian</td>
<td>3 (5)</td>
<td>1 (3)</td>
<td>2 (6)</td>
</tr>
<tr>
<td>Non-Hispanic multiracial</td>
<td>1 (2)</td>
<td>1 (3)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Education, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than bachelor’s degree</td>
<td>9 (15)</td>
<td>1 (3)</td>
<td>8 (25)</td>
</tr>
<tr>
<td>Bachelor’s degree or graduate courses</td>
<td>20 (32)</td>
<td>13 (43)</td>
<td>7 (22)</td>
</tr>
<tr>
<td>Graduate degree</td>
<td>33 (53)</td>
<td>16 (53)</td>
<td>17 (53)</td>
</tr>
<tr>
<td>Marital status, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married</td>
<td>55 (89)</td>
<td>28 (93)</td>
<td>27 (84)</td>
</tr>
<tr>
<td>Living with partner</td>
<td>5 (8)</td>
<td>2 (7)</td>
<td>3 (9)</td>
</tr>
<tr>
<td>Single</td>
<td>2 (3)</td>
<td>0 (0)</td>
<td>2 (6)</td>
</tr>
<tr>
<td>Employment statusb, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed full-time</td>
<td>40 (73)</td>
<td>19 (73)</td>
<td>21 (72)</td>
</tr>
<tr>
<td>Employed part-time</td>
<td>8 (15)</td>
<td>4 (15)</td>
<td>4 (14)</td>
</tr>
<tr>
<td>Stay-at-home mom (not employed)</td>
<td>7 (13)</td>
<td>3 (12)</td>
<td>4 (14)</td>
</tr>
<tr>
<td>Hard to pay for basics, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not at all hard</td>
<td>37 (60)</td>
<td>16 (53)</td>
<td>21 (66)</td>
</tr>
<tr>
<td>Somewhat hard</td>
<td>24 (39)</td>
<td>13 (43)</td>
<td>11 (34)</td>
</tr>
<tr>
<td>Very hard</td>
<td>1 (2)</td>
<td>1 (3)</td>
<td>0 (0)</td>
</tr>
</tbody>
</table>

aRandomization was stratified by smartphone type and months post partum.

b7 participants missing information on employment (n=4 in the Facebook condition and 3 in the in-person condition), and n=2 participants missing information on number of children in her household (both in the in-person condition).
Feasibility of Recruitment

Among individuals who were not interested in the study and therefore not screened for eligibility, 68.6% (72/105) explicitly reported a lack of interest or barriers related to the in-person condition as the reason (Table 2). In contrast, only 2.9% (3/105) were not interested in participating because they were not interested in the Facebook condition.

Among individuals determined to be ineligible at screening, 33.3% (65/195) were ineligible owing to reasons related to one or both treatment modalities, 18.5% (36/195) owing to reasons related to the in-person condition (ie, not available on the day or time of meetings, >45 minutes of travel to the intervention location, or plans to move out of the area in the next 12 months), 2.6% (5/195) owing to unwillingness to be randomized to either condition (all 5 preferred Facebook), and 12.3% (24/195) owing to their Facebook use habits (eg, no Facebook account, does not browse their feed at least daily, or does not post or reply at least weekly).

Table 2. Reasons for potential participants not interested in participating in the study (N=105).

<table>
<thead>
<tr>
<th>Reason</th>
<th>Values, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Any reason related to in-person condition</td>
<td></td>
</tr>
<tr>
<td>Not interested in in-person condition</td>
<td>72 (69)</td>
</tr>
<tr>
<td>Day or time of meetings does not work</td>
<td>51 (49)</td>
</tr>
<tr>
<td>Intervention location too far to travel</td>
<td>29 (28)</td>
</tr>
<tr>
<td>Any reason related to Facebook condition</td>
<td>19 (18)</td>
</tr>
<tr>
<td>Not interested in Facebook condition</td>
<td>3 (3)</td>
</tr>
<tr>
<td>Any reason related to in-person condition</td>
<td>3 (3)</td>
</tr>
<tr>
<td>Reasons not explicitly related to either treatment modality</td>
<td></td>
</tr>
<tr>
<td>Does not have time to participate</td>
<td>24 (23)</td>
</tr>
<tr>
<td>Intervention will not start soon enough</td>
<td>24 (23)</td>
</tr>
<tr>
<td>Intervention will not start soon enough</td>
<td>0 (0)</td>
</tr>
</tbody>
</table>

*Participants could provide multiple reasons for not being interested in participating in the study.

Retention

Overall, retention was 92% (57/62) at 6 months and 94% (58/62) at 12 months. Retention in the Facebook condition was 90% (27/30) at 6 months and 93% (28/30) at 12 months. Retention in the in-person condition was 94% (30/32) at 6 months and 94% (30/32) at 12 months. Retention in both conditions at both time points exceeded our a priori benchmarks of 80%, and the lower limits for 95% CIs were ≥79% for all conditions at all time points, which was substantially higher than the a priori benchmark of 60%.

Because of the disruptions to study procedures caused by the COVID-19 pandemic, we also explored retention by wave. In wave 1, retention in the Facebook condition was 79% (11/14) at 6 months and 86% (12/14) at 12 months and 93% (14/16) at 6 months and 93% (14/15) at 12 months in the in-person condition. In wave 2, retention in the Facebook condition was 100% (16/16) at 6 months and 100% (16/16) at 12 months and 94% (16/17) at 6 months and 94% (16/17) at 12 months in the in-person condition.

Sustained Participation and Engagement

Over the 6-month intervention, participants in the Facebook condition posted 159 original posts and 3318 replies and contributed 614 poll votes and 1996 reactions. Participants posted a median of 3 (IQR 1-7; range 0-28) original posts and a median of 88 (IQR 50-142; range 11-309) replies and contributed a median of 18.5 (IQR 11-29; range 3-59) poll votes and a median of 47 (IQR 24-94; range 7-208) reactions.

In total, 70% (21/30) of the participants in the Facebook condition posted, replied, voted in a poll, or reacted during the last 2 weeks of the intervention (ie, participated in the last intervention module), compared with 31% (10/32) of participants in the in-person condition who attended the final intervention meeting (Table 3). The latest treatment module participated in (of 20 modules) was median 20 (IQR 19-20) for participants in the Facebook condition and median 18 (IQR 2-20) for participants in the in-person condition (Table 3). In a sensitivity analysis that used a stricter definition of participation for participants in the Facebook condition—posting and replying only—63% (19/30) of participants participated in the last intervention module, and the latest treatment module participated in was median 20 (IQR 17-20). Participants posted or replied in a median of 18 (IQR 13-20) treatment modules; 67% (20/30) of participants engaged in ≥16 modules, and 43% (13/30) engaged in all 20 intervention modules.

In wave 2, the last 2 intervention meetings for the in-person condition were held via videoconference calls owing to the COVID-19 pandemic. In wave 1, a total of 33% (5/15) and 33% (5/15) of participants, respectively, attended the 19th and 20th intervention meeting. In wave 2, a total of 35% (6/17) and 29% (5/17) of participants, respectively, attended these last 2 meetings. In the postintervention focus groups, some participants mentioned liking not needing to travel or arrange childcare, but others mentioned “Zoom fatigue,” feeling less connected to other women over video versus in person, or having children in the background was distracting.

When participants in the Facebook condition were asked to select reasons they did not post or reply when they had logged into Facebook, the most common responses selected were not having anything to add to the conversation (22/26, 85%), preferring to lurk rather than actively engaging (13/26, 50%),...
and not wanting to be the only person posting (10/26, 38%; Table 4). In-person participants were similarly asked why they did not attend their in-person meetings. The most common response, endorsed by 93% (25/27) of participants, was the need to attend to other responsibilities that were more important (Table 4). Other common responses included motivation for weight loss declined (4/27, 15%) and forgetting about the meeting (4/27, 15%; Table 4).

Table 3. Sustained participation in the intervention, by treatment condition.

<table>
<thead>
<tr>
<th></th>
<th>Facebook condition (n=30)</th>
<th>In-person condition (n=32)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Latest intervention module participated in, median (IQR)</strong></td>
<td>20 (19-20)</td>
<td>18 (2-20)</td>
</tr>
<tr>
<td>Participated in the last intervention module, n (%)</td>
<td>21 (70)</td>
<td>10 (31)</td>
</tr>
<tr>
<td><strong>Number of intervention modules participated in, median (IQR)</strong></td>
<td>19 (17-20)</td>
<td>10 (2-14)</td>
</tr>
<tr>
<td>Participated in no intervention modules, n (%)</td>
<td>0 (0)</td>
<td>6 (19)</td>
</tr>
<tr>
<td>Participated in ≥16 (ie, ≥80%) intervention modules, n (%)</td>
<td>24 (80)</td>
<td>7 (22)</td>
</tr>
<tr>
<td>Participated in all 20 intervention modules, n (%)</td>
<td>13 (43)</td>
<td>0 (0)</td>
</tr>
</tbody>
</table>

aParticipation in a treatment module was attending the intervention meeting for participants in the in-person condition and posting, replying, voting in a poll, or reacting to a post or comment in the Facebook condition.

Table 4. Reasons participants did not post in the Facebook group or attend in-person intervention meetings, by condition.

<table>
<thead>
<tr>
<th>Reasons participants in the Facebook condition did not post or reply when they logged into the Facebook group (N=26)</th>
<th>Value, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I did not have anything to add to the conversation</td>
<td>22 (85)</td>
</tr>
<tr>
<td>I generally prefer to “lurk”—meaning I like to read posts but not say anything</td>
<td>13 (50)</td>
</tr>
<tr>
<td>It seemed like nobody in the group was posting so I did not want to be the only one</td>
<td>10 (38)</td>
</tr>
<tr>
<td>The topic was not relevant to me</td>
<td>6 (23)</td>
</tr>
<tr>
<td>I did not feel comfortable posting my ideas</td>
<td>4 (15)</td>
</tr>
<tr>
<td>The topic was not interesting to me</td>
<td>4 (15)</td>
</tr>
<tr>
<td>I feared how people would respond to what I would say (eg, I might get judged, ignored, or not supported)</td>
<td>3 (12)</td>
</tr>
<tr>
<td>I did not feel like I was a part of the group</td>
<td>1 (4)</td>
</tr>
<tr>
<td>I did not understand how to post</td>
<td>0 (0)</td>
</tr>
<tr>
<td>I was concerned about privacy in the group</td>
<td>0 (0)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Reasons participants in the in-person condition did not attend the group intervention meetings (N=27)</th>
<th>Value, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I had to attend to other responsibilities that were more important</td>
<td>25 (93)</td>
</tr>
<tr>
<td>My motivation to focus on weight loss declined</td>
<td>4 (15)</td>
</tr>
<tr>
<td>I forgot we had group that day</td>
<td>4 (15)</td>
</tr>
<tr>
<td>I had transportation issues</td>
<td>3 (11)</td>
</tr>
<tr>
<td>It seemed like a lot of people weren’t coming so this reduced my motivation to be a part of the group</td>
<td>3 (11)</td>
</tr>
<tr>
<td>The topics were not interesting or helpful to me</td>
<td>2 (7)</td>
</tr>
<tr>
<td>I did not feel like I was a part of the group</td>
<td>2 (7)</td>
</tr>
<tr>
<td>The topic was not relevant to me</td>
<td>1 (4)</td>
</tr>
<tr>
<td>I did not feel comfortable in the group</td>
<td>1 (4)</td>
</tr>
<tr>
<td>I was concerned about privacy in the group</td>
<td>0 (0)</td>
</tr>
<tr>
<td>I feared how people would respond to me (eg, I might get judged, ignored, or not supported)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>N/A a (I attended all groups)</td>
<td>0 (0)</td>
</tr>
</tbody>
</table>

aN/A: not applicable.
Contamination

In total, 15% (4/26) of participants in the Facebook condition and 4% (1/28) of participants in the in-person condition reported that they had used other in-person or web-based weight loss programs during the intervention period. However, when asked for details about these other weight loss programs, only 2 participants reported a structured program (Weight Watchers, a 21-week Beachbody program). The other 3 participants reported activities that would support their weight loss efforts (eg, saw a nutritionist, used a meal plan from dietitian she has been working with for 4 years, and personal training challenge) but do not represent a structured weight loss program. In total, 35% (9/26) of participants in the Facebook condition and 57% (16/28) of participants in the in-person condition sought weight loss information or support on social media during the intervention period. All reports of contamination were to external resources; no participants reported access to the other study intervention.

Feasibility of Assessment Procedures

Regarding patient-reported data needed to evaluate cost-effectiveness, we were able to obtain measured baseline weights on 100% (62/62) of participants in both conditions and measured or self-reported weights for 90% (27/30) and 93% (28/30) of participants in the Facebook condition at 6 and 12 months, respectively, and 94% (30/32) and 94% (30/32) of participants in the in-person condition, respectively. At baseline, 1 participant in each condition (2/62, 3%) did not complete the quality-of-life measure (PROPr) owing to a license agreement issue that delayed inclusion of another quality-of-life measure in the baseline survey. An additional 4 participants missed one of the PROPr items; at baseline, 87% (26/30) and 94% (30/32) of participants in the Facebook condition and 84% (27/30) and 91% (29/32) of participants in the in-person condition completed this measure in full.

Acceptability

Half (13/26, 50%) of participants in the Facebook condition would be likely or very likely to participate again and 54% (14/26) would be likely or very likely to recommend this program to a friend (Table 5). In the in-person condition, 58% (15/26) of participants would participate again and 70% (19/27) would recommend this program to a friend (Table 5). In postintervention focus groups or interviews, participants in the Facebook condition shared that they appreciated the flexibility of being able to engage with the group anytime and from anywhere. However, participants also noted that a downside of this flexibility was a lack of accountability—that it was easy to put off responding to posts or setting goals because there was no set schedule for participation. Participants also noted that they felt it was hard to get to know other mothers and build a sense of community. In contrast, participants in the in-person condition shared that they really got to know other women in their group and felt a strong sense of community. They also felt that meeting in person—and being weighed at intervention meetings—kept them accountable, and having a set meeting time each week helped them prioritize their health. However, participants noted barriers including time to travel to meetings, variable parking availability, and the need to arrange childcare for older children. A few participants also mentioned feeling guilty leaving their children 1 evening per week.

Table 5. Intervention acceptability by treatment condition.

<table>
<thead>
<tr>
<th>Facebook condition (n=26), n (%)</th>
<th>In-person condition (n=27), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>If you had another baby, how likely would you be to participate in this weight loss program again?</td>
<td>13 (50)</td>
</tr>
<tr>
<td>(likely or very likely)</td>
<td></td>
</tr>
<tr>
<td>If you had a friend who recently had a baby, how likely would you be to recommend this program to her? (likely or very likely)</td>
<td>14 (54)</td>
</tr>
<tr>
<td>How convenient was it for you to log into the private Facebook group each day/attend 90-minute group meetings each week? (convenient or very convenient)</td>
<td>25 (96)</td>
</tr>
<tr>
<td>Thinking about attending weekly in-person group meetings versus interacting in a private Facebook group daily, which would you find more convenient? (Facebook more convenient or Facebook much more convenient)</td>
<td>23 (88)</td>
</tr>
</tbody>
</table>

* n=1 participant in the in-person condition missing information for this question.

Almost all participants (25/26, 96%) in the Facebook condition reported that it was convenient or very convenient for them to log into the private Facebook group each day (Table 5). In contrast, only 7% (2/27) of participants in the in-person condition said it was convenient or very convenient to attend 90-minute group meetings each week. Most of the participants (23/26, 88%) in each condition agreed that interacting in a private Facebook group daily would be more convenient than attending a weekly in-person group (Table 5). In postintervention focus groups, several participants suggested a hybrid approach. A few participants from the Facebook condition suggested adding video meetings to increase accountability and sense of community, whereas others suggested occasional in-person meetings (eg, to start the group or once a month). Participants from the in-person condition suggested adding a Facebook group for connection and support between in-person meetings.

Weight Change (Exploratory Outcome)

At 6 months, participants in the Facebook condition had lost an average of 3.0% (SD 7.2%) of their baseline weight and participants in the in-person condition had lost an average of 3.5% (SD 7.8%) of their baseline weight. However, at 12 months, the weight loss was not statistically significant between the two conditions (n=1 participant in the in-person condition missing information for this question).
5.4% (SD 6.8%; Table 6). Average percent weight loss at 12 months was 2.8% (SD 7.4%) in the Facebook condition and 4.8% (SD 7.6%) in the in-person condition (Table 6). In a sensitivity analysis using a baseline observation carried forward approach (ie, assuming no weight change) for participants missing follow-up weights (3 at 6 months and 2 at 12 months in the Facebook condition and 2 and 2 in the in-person condition), average percent weight loss at 6 months was 2.7% (SD 6.9%) in the Facebook condition and 5.0% (SD 6.7%) in the in-person condition, with 27% (8/30) and 50% (16/32), respectively, achieving ≥5% weight loss. At 12 months, average percent weight loss was 2.6% (SD 7.2%) in the Facebook condition and 4.5% (SD 7.5%) in the in-person condition, with 33% (10/30) and 47% (15/32), respectively, achieving 5% weight loss.

Table 6. Weight change at 6 and 12 months, by treatment condition.

<table>
<thead>
<tr>
<th>Weight change from baseline (lbs), mean (SD)</th>
<th>Facebook condition</th>
<th>In-person condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>6 months</td>
<td>−4.8 (13.8)</td>
<td>−10.0 (13.0)</td>
</tr>
<tr>
<td>12 months</td>
<td>−5.1 (13.8)</td>
<td>−9.2 (15.3)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Weight change from baseline (%), mean (SD)</th>
<th>Facebook condition</th>
<th>In-person condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>6 months</td>
<td>−3.0 (7.2)</td>
<td>−5.4 (6.8)</td>
</tr>
<tr>
<td>12 months</td>
<td>−2.8 (7.4)</td>
<td>−4.8 (7.6)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lost ≥5% of baseline weight, n (%)</th>
<th>Facebook condition</th>
<th>In-person condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>6 months</td>
<td>8 (30)</td>
<td>16 (53)</td>
</tr>
<tr>
<td>12 months</td>
<td>10 (36)</td>
<td>15 (50)</td>
</tr>
</tbody>
</table>

*At 6 months, weights were available for 27 participants in the Facebook condition and 30 participants in the in-person condition. At 12 months, weights were available for 28 participants in the Facebook condition and 30 participants in the in-person condition.

Discussion

Principal Findings

Feasibility trials provide an opportunity to pilot study procedures and measures in preparation for a large-scale efficacy trial. We assessed the feasibility of recruiting a sample of postpartum women willing and able to participate in a lifestyle intervention delivered either via Facebook or in-person groups. The in-person condition posed challenges to recruitment. Among individuals not interested in the study, 68.6% (72/105) were not interested in or could not attend in-person meetings, and 18.5% (36/195) of screened individuals were excluded because of reasons related to participating in the in-person condition. These findings are not unexpected, as the barriers to attending in-person treatment sessions documented in several previous studies [11-14,41,59-61] motivated the current line of research to develop a Facebook-delivered version of the intervention. The numbers of participants contacted, screened, eligible, and enrolled will inform the timeline for subsequent efficacy testing. Overall, retention was 92% at 6 months and 94% at 12 months. Although based on the small numbers (approximately 15 participants per condition per wave), it appears that retention may have been higher in the Facebook condition in wave 2 when in-person assessments were not required. In wave 1, retention at 6 and 12 months was 79% and 86% versus 100% and 100%, respectively, in wave 2. For comparison, retention in the in-person condition was 93% and 93% in wave 1 and 94% and 94% in wave 2 at 6 and 12 months, respectively. It may be that women who were used to connecting with the weight loss counselor and their group remotely perceived attending an in-person visit as more burdensome. The only data collected at follow-up that required an in-person visit were weight. Providing participants digital scales in future trials would allow all follow-up assessments to be conducted remotely [62], which may increase completion of follow-up measures by reducing participant burden. Remote assessments would also allow for national recruitment, thus widening the participant pool.

Average weight losses of 3% in the Facebook condition and 5% in the in-person condition are promising, and it appears that women in the in-person condition lost more weight on average than those in the Facebook condition. Future research should explore the mechanisms through which delivering lifestyle interventions in person versus via digital platforms influences weight loss (eg, through increased accountability, stronger connections with the weight loss counselor or group members, and greater impact on participants’ motivation to engage in behavior change). However, the weight loss in this trial should be interpreted cautiously for 2 reasons. First, participants in wave 2 self-reported their weight at 6 months and 12 months owing to the COVID-19 pandemic-related disruptions in in-person research assessments. Although weights self-reported as part of a digital lifestyle intervention tend to be accurate [63,64], weights measured with home scales that differ by a few pounds from the study scale can bias estimates of weight change, especially when baseline weights are measured by study staff. Second, the COVID-19 pandemic and particularly the early-pandemic school and childcare shutdowns had immeasurable impact on women’s lives and their motivation and ability to make and sustain behavioral changes [65,66]. A study on the impact of the COVID-19 pandemic on current research participants’ ability and desire to engage in research found that among those currently enrolled in a group-based behavioral intervention, 52% reported that the pandemic had...
impacted their ability to adhere to behavioral recommendations a little bit or moderately and 22% reported that the pandemic had impacted their behavior quite a bit or extremely [66]. Indeed, multiple participants in wave 2 reported at their 12-month follow-up assessments that they had regained a substantial amount of weight owing to disruptions and stress related to the pandemic, whereas others said that they lost additional weight owing to changes in their lifestyle (eg, sharp decline in eating out and more exercise). As only a single wave of participants completed the study before the pandemic and a single wave had their experience disrupted by the COVID-19 pandemic, we did not have a sufficiently large sample size to examine the impact of the pandemic on participant experiences or outcomes.

Whether participants stay engaged in treatment influences treatment receipt and, thus, efficacy. Digital health interventions have long been plagued by high dropout rates [67], and systematic reviews of postpartum weight loss interventions have highlighted attrition from treatment as a common challenge [7,8]. In our previous 1-arm pilot of the Facebook-delivered intervention, 63% of participants participated in the last week of the intervention [22]; however, that preliminary pilot study did not provide information on whether participants would stay engaged in treatment for the full 6-month intervention. This feasibility pilot trial examined sustained treatment through the full 6-month intervention period in both the Facebook-delivered and in-person versions of the intervention and found that 70% (21/30) of women in the Facebook condition engaged in the Facebook group during the last intervention module (last 2 weeks of the intervention) and engaged during a median of 19 (IQR 17-20) of the 20 intervention modules. In contrast, only 31% (10/32) of participants in the in-person condition attended their last intervention meeting. Women only attended a median of 10 (IQR 2-14) of the 20 intervention meetings, and 19% (6/32) did not attend a single intervention meeting. To be sure, participating in Facebook requires much less effort than attending a group visit. Indeed, when asked to select from a list of reasons participants did not come to the meetings, 93% (25/27) indicated that they had to attend to other responsibilities, including being sick, caring for an ill child, work, or caring for older children while their spouse worked, emphasizing the challenges of in-person meetings for mothers. Although we defined sustained participation in terms of the latest intervention module participated in (ie, in-person meeting attended or latest intervention module with visible engagement in the Facebook group), this definition would allow participants with large gaps in participation to pop back into the group at the end of treatment and be counted as having sustained participation. Thus, we recommend not only examining the time to last participation but also the number of treatment sessions or modules to provide a more comprehensive picture of treatment receipt.

In addition to examining sustained participation, we also described engagement in the Facebook-delivered intervention. Over the 6-month intervention, participants in the Facebook condition posted a median of 3 (IQR 1-7; range 0-28) original posts and a median of 88 (IQR 50-142; range 11-309) replies. Previous studies delivered a weight loss intervention based on the DPP lifestyle intervention entirely via a commercial social media platform for 12 weeks; thus, we additionally calculated engagement for the first 12 weeks of this study. Participants posted a median of 3 (IQR 1-5) original posts and a median of 65 (IQR 40-93) replies. Engagement over the first 12 weeks was higher in this study than in our previous 1-arm pilot study of a 12-week version of the Facebook-delivered intervention in which participants contributed a median of 2 (IQR 1-3) original posts and a median of 24 (IQR 15-31) replies [22]. We purposefully revised our intervention posts in response to engagement findings and participant feedback. It may be that the updated intervention posts were more effective at eliciting engagement from participants. Engagement in this study also appeared to be higher than engagement in other Facebook-delivered lifestyle interventions. In our previous research of a 12-week Facebook-delivered weight loss intervention with adults with obesity generally, participants shared a median of 37 (IQR 16-76) original posts or replies [47], less than the median of 68 (IQR 40-93) posts and replies shared during the first 12 weeks in this study (median 92.5, IQR 53-153 over 6 months). Women in this study also appeared to engage more than participants randomized to the comparison condition of a pilot study testing an app to track dietary lapses (median 0 posts, IQR 0-1; median 29.5 replies, IQR 17-61) [68]. The median number of replies over the first 12 weeks of the intervention posted by women in this study was also about twice the median number of replies of other Facebook-delivered weight loss interventions among adults [69,70] and higher than the average engagement in pilot trials of postpartum weight loss interventions that delivered some or all content via Facebook [24].

Despite higher engagement than other Facebook-delivered weight loss interventions, when asked to select reasons why they did not post or reply in the group, 38% (10/26) of participants endorsed “It seemed like nobody in the group was posting so I didn’t want to be the only one.” This feedback may be related to participants being hesitant to be the first one to respond to an intervention post, as we have heard from participants in previous studies [22]. This feedback may also be partially explained by when these questions were asked. The weight loss counselor posted in the Facebook group twice per day during weeks 1-15 of the intervention and then once a day in weeks 16-25; therefore, participants’ reports of their experiences at the 6-month follow-up assessment may be biased toward their more recent experiences in the group compared with the activity in the group over the full 6-month intervention. Future studies could explore whether maintaining a posting schedule of twice daily results in greater participant engagement in the latter weeks of the intervention. Future studies could also experiment with ways to encourage participants to start conversation threads, so that the volume of conversation in the group is less dependent on the weight loss counselor’s posts.

Participants also indicated that they did not post or reply in the group because they did not have anything to add to the conversation (22/26, 85%) or the topic was not relevant (6/26, 23%) or interesting (4/26, 15%) to them. In addition, 50% (13/26) of participants noted that they generally preferred lurking over visibly engaging. In one of our previous social media-delivered weight loss interventions, participants who had
not used the social media platform before enrolling in the study engaged less in the intervention [43]. In our 1-arm pilot of the Facebook-delivered postpartum weight loss intervention, participants reported in postintervention focus groups that their typical social media habits influenced their level of engagement in the intervention [22]. Thus, we limited enrollment in this study to women who reported posting or replying on Facebook at least weekly. Future research should explore how to convert lurkers into posters as a strategy to boost engagement in the group. Future research could also explore the potential benefits participants experience from reading conversation threads without visibly engaging in them [71].

Another option to increase engagement in digital weight loss groups may be to increase the number of women receiving a postpartum weight loss intervention via a private Facebook group. Pagoto et al [69] recently conducted a proof-of-concept pilot study comparing engagement in a Facebook-delivered lifestyle intervention in which group membership was allowed to grow with engagement in a group in which membership was static. Although total engagement (original posts, replies, poll votes, and reactions) did not differ among the 40 participants initially randomized to the open enrollment group compared with the 40 participants randomized to the closed group, total engagement was higher among all 94 participants in the open enrollment group, and the total volume of engagement contributed by participants and weight loss counselors was associated with participants’ weight loss [69]. As Facebook’s algorithms prioritize groups with more activity [72], larger groups with more participant posts and replies may be prioritized in women’s Facebook feeds, thus increasing the opportunity to engage and subsequently better treatment receipt.

Although engagement in the Facebook condition in this study was higher than that in our previous work with postpartum women or previous studies with adults with obesity, participants appeared to lose less weight. Average weight loss of 3% over 6 months among participants in the Facebook condition was lower than the average weight loss of 4.8% observed in our previous 1-arm pilot study of a 12-week version of the Facebook-delivered intervention [22]. Weight loss among participants in the Facebook condition in this study was similar to the average weight loss achieved in studies of adults generally over shorter periods (ie, 12 or 16 weeks) [47,69,70]. Differences in the samples, including the requirement of being willing to participate in either an in-person or digital intervention and enrollment of women earlier in the postpartum period (average 3.4 months post partum in the 1-arm pilot vs median 6.1 months in this study), may have also contributed to differences in weight loss. Although our weight loss findings should be interpreted with caution, these findings suggest that a deeper investigation into what types of engagement are associated with weight loss during the postpartum period is warranted. Not all utterances in a Facebook weight loss group are associated with weight loss [47], and additional research is needed on how best to engage participants in interactions that lead to successful behavior changes and subsequently weight loss [73].

Taken together, our findings related to the feasibility of recruitment under conditions of randomization to an in-person or Facebook condition and our findings related to participation in in-person intervention meetings indicate that an in-person weight loss program with numerous visits has limited feasibility for many postpartum persons. Further research is needed to develop and test efficacious postpartum weight loss interventions that work with postpartum persons’ busy lives. Synchronous video meetings may be an option to foster group cohesion and accountability while overcoming the logistic challenges of in-person meetings. Telehealth or video visits offer the opportunity to connect individuals and groups face-to-face while retaining many of the benefits of in-person interactions. The national telehealth landscape has changed significantly since the initiation of this study. The COVID-19 pandemic has inspired a rapid uptake of telehealth in clinical settings [74,75], including obstetric care [76]. Indeed, in this study, the COVID-19 pandemic necessitated a shift of modality for the last 2 intervention meetings for wave 2 from in-person to videoconferencing. Attendance at these meetings was very similar to attendance at the analogous meetings in wave 1, and women liked not having to travel or arrange childcare. However, some participants mentioned “Zoom fatigue” [77], not surprisingly, as this feedback was provided in April 2020, approximately a month after the COVID-19–related shutdowns. As more and more activities resume in person, “Zoom fatigue” is likely to lessen. Other weight loss trials that transitioned from in-person to video meetings also found this modality acceptable, and participants lost weight [78,79]. Weight loss interventions based on the DPP lifestyle intervention have been successfully delivered via video meetings [80]. Women from a wider geographic range can be enrolled without travel constraints to attend in-person intervention meetings. Video meetings might also alleviate barriers to participation related to childcare, as women could participate in groups while their children sleep, engage in other activities at their home, or participate during lunch or another break during their workday. Another option may be a hybrid approach [81], such as an intervention delivered primarily remotely with a few in-person meetings, an approach that has been shown to be effective in low-income postpartum women [82]. Future research could explore the acceptability and efficacy of delivering a postpartum weight loss intervention via synchronous video group meetings, either in place of in-person meetings or in addition to an intervention delivered primarily digitally.

This feasibility trial also provided an opportunity to pilot and reflect on how contamination was measured. When we designed this study, we defined contamination in 2 ways: participation in other digital or in-person weight loss programs and seeking weight loss information or support on Facebook or other digital social networks. As 3 of the 5 participants who responded affirmatively to a question about concurrent participation in a structured weight loss program reported activities that did not meet our definition of a structured program, in future studies, we will revise the survey question and also have staff call participants to obtain additional details about professional assistance with weight loss outside the study intervention. As the study progressed, we realized that defining seeking weight loss information or support on social media as contamination did not match our study protocols, as we directed women in both conditions to a study Pinterest account where we had compiled online resources helpful for their weight loss journeys.
(eg, low-calorie recipes, workout videos, and MyFitnessPal tutorial videos) and encouraged women on Facebook to create a healthy Facebook feed by following Pages by public health organizations (eg, AHALiveHealthy and EatRightNutrition). In future studies, we will focus on contamination tracking of participation in structured weight loss programs or weight loss-specific Facebook groups.

**Limitations**

An additional limitation of this study is its limited racial, ethnic, and socioeconomic diversity. Our sample was more highly educated than US women giving birth overall (53/62, 85% with a bachelor’s or higher education vs 34% nationally), more likely to be non-Hispanic White (46/62, 74% vs 51% nationally), and less likely to be unmarried (7/62, 11% vs 40% nationally) [83]. Many behavioral weight loss trials struggle to recruit racially or ethnically diverse samples [84,85]. In future studies, we will use strategies to diversify the participant pool. Targeted recruitment advertisements and strategic placement of such materials can facilitate the recruitment of an ethnically and economically diverse sample into weight loss trials [86]. Effective strategies to recruit low-income and racially or ethnically diverse postpartum women and parents of young children into behavioral trials include working with community partners (eg, Women, Infants, & Children Nutrition Program [WIC]), hiring culturally representative and sensitive research staff, and having multiple contacts with potential participants [87,88]. In future studies in this line of research, we will ask interested individuals to provide some demographic information (eg, Hispanic ethnicity, race, education, and participation in WIC or Supplemental Nutrition Assistance Program) earlier in the eligibility screening process so that we can monitor participant yield and characteristics from different recruitment approaches and refine our strategies to yield a more racially, ethnically, and socioeconomically diverse sample.

**Conclusions**

Delivering a lifestyle intervention to postpartum women via both in-person and Facebook groups was feasible and acceptable and resulted in weight loss. However, barriers to attending in-person meetings hampered recruitment efforts and attendance at in-person intervention meetings. Although women found the Facebook group convenient and stayed engaged in the group, weight loss appeared lower than that with in-person delivery. Research is needed to further develop care models for postpartum weight loss that balance accessibility with efficacy.

**Acknowledgments**

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**Conflicts of Interest**

SLP has received funding from Weight Watchers, International. The other authors have no conflicts of interest to declare.

**References**


Abbreviations

DPP: Diabetes Prevention Program
EPDS: Edinburgh Postnatal Depression Scale
LAMB: Los Angeles Mommy and Baby
PROPr: PROMIS-Preference
REDCap: Research Electronic Data Capture
WIC: Women, Infants, & Children Nutrition Program

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The Effect of Periodic Email Prompts on Participant Engagement With a Behavior Change mHealth App: Longitudinal Study

Elena Agachi1*, MSc; Tammo H A Bijmolt1*, Prof Dr; Koert van Ittersum1*, Prof Dr; Jochen O Mierau2*, Prof Dr

1Department of Marketing, Faculty of Economics and Business, University of Groningen, Groningen, Netherlands
2Department of Economics, Econometrics & Finance, Faculty of Economics and Business, University of Groningen, Groningen, Netherlands

* all authors contributed equally

Corresponding Author:
Elena Agachi, MSc
Department of Marketing
Faculty of Economics and Business
University of Groningen
Nettelbosje 2
Groningen, 9747 AE
Netherlands
Phone: 31 50 363 3686
Email: e.agachi@rug.nl

Abstract

Background: Following the need for the prevention of noncommunicable diseases, mobile health (mHealth) apps are increasingly used for promoting lifestyle behavior changes. Although mHealth apps have the potential to reach all population segments, providing accessible and personalized services, their effectiveness is often limited by low participant engagement and high attrition rates.

Objective: This study concerns a large-scale, open-access mHealth app, based in the Netherlands, focused on improving the lifestyle behaviors of its participants. The study examines whether periodic email prompts increased participant engagement with the mHealth app and how this effect evolved over time. Points gained from the activities in the app were used as an objective measure of participant engagement with the program. The activities considered were physical workouts tracked through the mHealth app and interactions with the web-based coach.

Methods: The data analyzed covered 22,797 unique participants over a period of 78 weeks. A hidden Markov model (HMM) was used for disentangling the overtime effects of periodic email prompts on participant engagement with the mHealth app. The HMM accounted for transitions between latent activity states, which generated the observed measure of points received in a week.

Results: The HMM indicated that, on average, 70% (15,958/22,797) of the participants were in the inactivity state, gaining 0 points in total per week; 18% (4103/22,797) of the participants were in the average activity state, gaining 27 points per week; and 12% (2736/22,797) of the participants were in the high activity state, gaining 182 points per week. Receiving and opening a generic email was associated with a 3 percentage point increase in the likelihood of becoming active in that week, compared with the weeks when no email was received. Examining detailed email categories revealed that the participants were more likely to increase their activity level following emails that were in line with the program’s goal, such as emails regarding health campaigns, while being resistant to emails that deviated from the program’s goal, such as emails regarding special deals.

Conclusions: Participant engagement with a behavior change mHealth app can be positively influenced by email prompts, albeit to a limited extent. Given the relatively low costs associated with emails and the high population reach that mHealth apps can achieve, such instruments can be a cost-effective means of increasing participant engagement in the stride toward improving program effectiveness.

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KEYWORDS

mobile health; behavior change; mobile app; digital health; engagement; retention; email; hidden Markov model
Introduction

Background
Following the increasing need for the prevention of noncommunicable diseases [1], behavior change programs have emerged as a widely used support tool for health interventions aimed at improving lifestyle behaviors [2]. Digital behavior change programs have the ability to reach a larger population subset at relatively lower costs than their offline counterparts [3,4] while allowing for tailored material based on individual interactions [5].

In recent years, mobile health (mHealth) apps have gained traction as an increasingly preferred method of delivering digital behavior change interventions [4] by further facilitating access for and interaction with participants [6]. An additional benefit of mHealth apps is their ability to also involve the population segment with lower socioeconomic conditions, which generally shows less interest in preventive health interventions [7-9].

Although digital behavior change programs, especially mHealth apps, are promising tools for improving lifestyle behaviors, in practice, these programs often show low participant engagement (defined as “the extent of usage of the digital behavior change intervention” [10]) and high attrition rates [11-13]. One of the main reasons underlying this phenomenon is the passive nature of behavior change programs, where participants need to act by themselves to benefit [14]. Although higher engagement is crucial for achieving effectiveness of mHealth apps [15-18], inducing higher participant engagement over time is a challenging task [12,19], which requires proactive efforts from the program providers [11,20,21].

Objective
Periodic prompts via emails have been examined as a potential tool that can boost participant engagement with behavior change mHealth apps [22,23]. However, most studies examining the means to increase engagement with an mHealth app are based on small sample sizes and short time spans [24,25]. In a literature review including approximately 35 mHealth apps aimed at increasing physical activity, the sample size varied between 8 and 700 participants, with an average study duration of 8 weeks [26]. Given that small sample sizes and especially short time spans of most interventions can lead to an overestimation of the intervention effects [25,27], it is essential to examine whether periodic prompts via emails can impact participant engagement with a behavior change mHealth app within a longer-term, larger-scale, noncontrolled setup [7,28,29].

This study relied on a large-scale (more than 20,000 participants), open-access mHealth app focused on improving the lifestyle behaviors and wellness of its participants. The analysis in this study used a hidden Markov model (HMM) to examine whether periodic email prompts were able to increase participant engagement with the mHealth app and how this effect evolved over time. By investigating the effect of prompts on continued engagement with the mHealth app, this study hoped to assess (1) whether periodic prompts via email can be a viable tool for increasing participant engagement, (2) how the impact of periodic prompts on engagement evolved over time, and (3) how the observed effects differed among participant subgroups.

Methods

Study Sample
This study was based on data from the mobile app of a digital behavior change program operated in the Netherlands. The program’s goal was to improve the wellness and lifestyle behaviors of its participants by promoting physical activity, healthy eating habits, social activity, mental health, good sleep habits, and minimized stress. The mobile app was introduced in October 2017, providing functions such as entering or recording physical activities, reading articles, setting goals, including friends in challenges, answering health questions, being assisted by a web-based coach, and forming a daily “fit-score.” On the basis of the individual activities in the mobile app, participants gain points, which can be used to acquire specific products, vouchers for various services, or make charity contributions.

The data analyzed in this study spanned from January 2018, when the mobile app of the health program reached full functionality, to July 2019, when the observation window ended. Data were collected in 2018 and 2019 and analyzed in 2021 and 2022 within a longitudinal, nonexperimental study design. The analyzed data had a weekly frequency, covering 78 weeks and including 22,797 unique participants who enrolled by themselves in the mobile app at any time during the observation window. Of the 33,825 participants who used the mobile app, 22,797 (67.4%) were included, having at least 1 activity during the period between the mobile app introduction and the end of the observation window, indicating an awareness of the mobile app’s functionality. All program participants were aged between 18 and 80 years and were residents of the Netherlands.

Enrollment in the mHealth app was open and free, and all the participants involved in this study provided their voluntary and informed consent.

Ethics Approval
Ethics approval for this research project based on the health program was obtained from the institutional research board of the University of Groningen (approval number RDMPFEB20180831-7309).

Measures

Participant Engagement
The main objective of a behavior change mHealth app is to improve the lifestyle behaviors of its participants. Achieving effectiveness in behavior change is highly linked to the degree to which participants engage with the app; only when participants interact with the program and continue use can it have an impact on their behavior [15,16].

Participant engagement has been defined as “the extent of usage of the digital behavior change intervention” [10], being separated into temporal patterns—frequency and duration, and depth—specific intervention content use [30,31]. Participant engagement can be assessed as a subjective measure (ie,
self-reported by participants) or an objective measure (ie, measured by the program) [10].

The mHealth app analyzed in this study provided several activities that the participants could perform. For every activity completed, the participants gained points, which varied based on the activity type and duration. Gained points were used as a measure of the activity level of the participants in the mHealth app, which were calculated weekly throughout the observation window. Consequently, this participant engagement measure was objective rather than self-reported, which had the additional benefit of being more robust against reporting bias [32].

The 2 types of activities included in the participant engagement measure were physical activities and web-based coach activities, both of which the participants could access via the mHealth app. Physical activities were activities recorded in the health program with the use of GPS, such as walking, cycling, and running. Web-based coach activities were the interactions that the participants had with regular messages sent via the chat environment programmed by the providers of the mHealth app. The messages in the chat environment were linked to physical activities, health goals that the participants selected, challenges that they joined, or overall health behavior information. For every question answered, the participants received a fixed number of points. Table 1 presents the activity types included in the mHealth app, with the associated number of points.

### Table 1. Activity types and number of points gained.

<table>
<thead>
<tr>
<th>Activity type</th>
<th>Number of points</th>
</tr>
</thead>
<tbody>
<tr>
<td>Web-based coach</td>
<td>1 point gained for any question answered</td>
</tr>
<tr>
<td>GPS recorded activity: walking</td>
<td>From 1 point to 696 points, depending on activity duration (mean 17.25, SD 24.46 points)</td>
</tr>
<tr>
<td>GPS recorded activity: cycling</td>
<td>From 1 point to 699 points, depending on activity duration (mean 21.37, SD 38.36 points)</td>
</tr>
<tr>
<td>GPS recorded activity: running</td>
<td>From 1 point to 695 points, depending on activity duration (mean 39.93, SD 33.06 points)</td>
</tr>
</tbody>
</table>

#### Periodic Email Prompts

In general, mHealth apps suffer from low participant engagement and high dropout rates [33,34]. Capturing the attention of the participants in an attempt to stimulate their active involvement is crucial for program success [20]. Periodic email prompts are often used as tools for improving participant engagement, with mixed results. Although some studies estimated a positive impact of email prompts on participant engagement [23,28,35], additional research is required in this area [36], with a special focus on overtime effects [10,22].

In this study, we examined the ability of periodic email prompts to improve participant engagement with the mHealth app by measuring the effect of emails on transitions between activity states. For every email sent, a randomly selected subset of the participants did not receive the email in question, which served as the control group for that particular email. The emails sent to the participants of the app were either generic or targeted. The generic emails were sent to all the participants in the same format, independent of their current activity level. The targeted emails were sent out in different versions, depending on the participants’ activity level (low activity or high activity); however, it was not possible to identify which participant received which email version. The targeted emails could belong to one of the following categories: welcoming emails, reactivation emails, recruitment emails, newsletters, health campaigns, and special offers.

To correct for any potential effect of targeting, generic emails were the main measure used in this study. The emails included in this category had topics such as welcoming participants to the program, sharing general healthy lifestyle information (at regular intervals), presenting topic-specific health information (eg, healthy nutrition and sleep), inviting participants to engage in activities, and presenting special deals in the web shop.

To measure the effect of email prompts, we distinguished between 3 situations: not having received an email, having received an email but not having opened it, and having received an email and opened it. Section 2 in Multimedia Appendix 1 describes in detail the emails’ content and their categorization.

Between January 2018 and July 2019, the proportion of participants who received a generic email varied between 0.14% (13/9596 participants in the third week of March 2018) and 39.73% (8943/22,508 participants in the second week of May 2019). The proportion of participants who opened the generic email when they received it varied between 26.65% (271/1017 participants in the third week of November 2018) and 76.1% (139/209 participants in the first week of January 2018). Across the weeks in the observation period, the average proportion of participants who received a generic email in a week was 6.6%, the average proportion of participants who opened a generic email in a week was 3.5%, and the average proportion of participants who opened a generic email when they received one was 60.5%.

Figure 1 displays the evolution of the generic emails and participant engagement over the weeks of the observation window, showing the proportion of participants who received and opened a generic email and the proportion of participants who were active during that week (having gained at least 1 point). Figure 1 implies great variability in both measures, highlighting the need to analyze the connection between email prompts and participant engagement in a dynamic manner.
To control for the effect of the individual characteristics of the program participants on their engagement with the behavior change mHealth app [10], gender, age, and neighborhood socioeconomic status (NSES) [37] quintiles were included in the analysis as additional covariates. The NSES quintiles measure follows the methodology outlined in Dekker et al [38], being calculated using nonlinear iterative partial least squares principal component analysis on the following characteristics given on a postcode level: average income, average property value, subsidized renting, share of high-income households, share of owner-occupied properties, share of low-income households, share of population receiving unemployment benefits, share of people receiving disability benefits, and share of people receiving short-term unemployment benefits. A lower NSES quintile corresponds to lower levels of socioeconomic conditions. In addition, to measure whether early adopters of the mHealth app showed higher engagement [39], we included the additional measure of early adoption, which corresponded to the participants who enrolled in the behavior change mHealth app during its first month of existence. In total, 19.06% (4345/22,797) of the mHealth app participants were early adopters.

Statistical Analysis

In this study, we used the number of points gained per week to measure engagement, which reflected the level of activity of a participant in the mHealth app. To model the changing levels of activity over time, an HMM was used, where a participant had a specific level of activity each week (latent state) and could transition between the activity states from week to week [40,41]. Using HMMs allows for the disentanglement of the dynamics of participant behavior over time and the analysis of how specific actions can influence these behaviors [42]. Moreover, the HMM model is preferred because such a latent approach allows for the incorporation of the high dropout and inactivity rates that are specific to behavior change programs [43,44]. To understand the drivers of the dynamics of state transitions, nonhomogeneous Markov modeling was used, which allows the transition probabilities to depend on time-varying covariates [45].

A generic HMM is defined as shown in Figure 2, where $X_t$ is the latent activity state at time $t$, with $t$ ranging from 0 to $T$ ($T$ being the last measurement week); $A$ is the state transition probability; $B$ is the response probability matrix; and $O_t$ contains the observations in the response vector. The Markov process, being separated by the dashed line, was not observed. Instead, only the observations $O_t$ were known; in this study, these were the number of points gained in a week.

The HMM depicted in Figure 2 consists of 3 main elements (as shown below):

1. Initial state probability $P(X_0)$: the probability that participant $i$ is in state $X$ at time 0.
2. Transition probability $P(X_t|X_{t-1})$: the probability that participant $i$ is in state $X$ at time $t$, given the state membership at time $t-1$.
3. Response probability $P(O_t|X_t)$: the probability that participant $i$ displays activity level $O$ at time $t$, given the state membership $X$ at time $t$.
In the setup of this study, the unobserved states that a participant belonged to were activity states, generating the observed measures of points received in a week from differing activities performed in the mHealth app. The initial state distribution reflected the starting state that a participant belonged to at their moment of joining the mHealth app, which depended on the time-constant covariates that reflected the participant’s background (age, gender, NSES, and early adopter). The transitions between the activity states reflected the variability in the participants’ behaviors between weeks, which were allowed to depend on both time-constant covariates (age, gender, NSES, and early adopter) and time-varying covariates (the email prompts and time). Including the email prompts in the transition probability model allowed for the examination of the impact of emails on changes in the activity levels of a participant.

When using the HMM for general inference, traditional model selection criteria, such as Akaike information criterion or Bayesian information criterion, often lead to the selection of much larger numbers of states than expected a priori [46-48]. The reason for this is that the neglected data in the model formulation are absorbed into the additional model states, which do not possess a clear interpretation anymore [49]. A recommended approach for dealing with this uncertainty is analyzing a prespecified number of latent states. In this study, following the goal of differentiating between activity states while prioritizing interpretability, the estimated HMM contained 3 states: inactivity, average activity, and high activity. For the estimation of the model, the Latent GOLD software (Statistical Innovations Inc) was used. The Latent GOLD software supports the analysis of latent class models such as HMMs, with the parameter estimates being computed based on a combination of expectation-maximization and Newton-Raphson iterations, where the E step computations use a forward-backward recursion scheme [50].

Results

Characteristics of the Participants

This study analyzed 22,797 participants between January 2018 and July 2019 for a total of 78 weeks. The mHealth app analyzed being an open-access platform, the participants could enroll at any time within the observation window. Table 2 outlines the characteristics of the mHealth app participants. On average, each participant was observed for 50.8 weeks, resulting in a total of 1,129,706 observation points. Every week, approximately one-third of the study population was active, gaining an average of 28 points weekly. A total of 62.82% (14,321/22,797) of the analyzed participants were women, with the most represented age group being between 37 and 46 years and the highest proportion of participants belonging to the second socioeconomic quintile.

Table 2. Characteristics of the study participants (N=22,797).

<table>
<thead>
<tr>
<th>Key attributes</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total observations, n</td>
<td>1,129,706</td>
</tr>
<tr>
<td>Participants, n</td>
<td>22,797</td>
</tr>
<tr>
<td>Number of weeks in the mobile app, mean (SD)</td>
<td>50.8 (28.7)</td>
</tr>
<tr>
<td>Number of points received weekly, mean (SD)</td>
<td>28.0 (78.8)</td>
</tr>
<tr>
<td>Proportion of active participants per week (%), mean (SD)</td>
<td>31.1 (6.3)</td>
</tr>
<tr>
<td>Early mobile app adopters, n (%)</td>
<td>4345 (19.06)</td>
</tr>
<tr>
<td>Female participants, n (%)</td>
<td>14,321 (62.82)</td>
</tr>
<tr>
<td>Participants per age group (years), n (%)</td>
<td></td>
</tr>
<tr>
<td>18-26</td>
<td>1408 (6.18)</td>
</tr>
<tr>
<td>27-36</td>
<td>5282 (23.17)</td>
</tr>
<tr>
<td>37-46</td>
<td>5406 (23.71)</td>
</tr>
<tr>
<td>47-56</td>
<td>5179 (22.72)</td>
</tr>
<tr>
<td>57-66</td>
<td>3402 (14.92)</td>
</tr>
<tr>
<td>67-80</td>
<td>2120 (9.3)</td>
</tr>
<tr>
<td>Participants per NSES(^a) quintile (from the lowest to the highest socioeconomic conditions), n (%)</td>
<td></td>
</tr>
<tr>
<td>First</td>
<td>4675 (20.51)</td>
</tr>
<tr>
<td>Second</td>
<td>6303 (27.65)</td>
</tr>
<tr>
<td>Third</td>
<td>4662 (20.45)</td>
</tr>
<tr>
<td>Fourth</td>
<td>3611 (15.84)</td>
</tr>
<tr>
<td>Fifth</td>
<td>3546 (15.55)</td>
</tr>
</tbody>
</table>

\(^a\)NSES: neighborhood socioeconomic status.
Model Estimation Results

HMM States and Transitions

Estimating the HMM with 3 states resulted in the outcomes presented in Tables 3 and 4. The 3 states identified by the HMM were labeled as the inactivity state, average activity state, and high activity state. On average, across the weeks of the observation period, 70% (15,958/22,797) of the participants were in the inactivity state, gaining 0 points weekly; 18% (4103/22,797) of the participants were in the average activity state, gaining 27 points weekly; and 12% (2736/22,797) of the participants were in the high activity state, gaining 182 points weekly.

Table 3. Hidden Markov model estimation results: average latent states.

<table>
<thead>
<tr>
<th>State</th>
<th>1: inactivity</th>
<th>2: average activity</th>
<th>3: high activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average state size (%)</td>
<td>70</td>
<td>18</td>
<td>12</td>
</tr>
<tr>
<td>Points received, n</td>
<td>0</td>
<td>27</td>
<td>182</td>
</tr>
</tbody>
</table>

Table 4. Hidden Markov model estimation results: average transition probability matrix\(^a\).

<table>
<thead>
<tr>
<th>State (t)</th>
<th>1: inactivity</th>
<th>2: average activity</th>
<th>3: high activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.91</td>
<td>0.07</td>
<td>0.02</td>
</tr>
<tr>
<td>2</td>
<td>0.31</td>
<td>0.64</td>
<td>0.05</td>
</tr>
<tr>
<td>3</td>
<td>0.09</td>
<td>0.09</td>
<td>0.82</td>
</tr>
</tbody>
</table>

\(^a\)Section 3 in Multimedia Appendix 1 presents detailed model fit criteria and parameter estimates for the hidden Markov model. All the parameter estimates were statistically significant at the 99% confidence level. \(^b\): time point.

The estimated transition matrix (shown in Table 4) reflects the probability of switching between the 3 states across weeks. On average, the inactivity and high activity states were most persistent, for example, a participant who was in the high activity state during week 1 was, on average, 82% likely to remain in that state during week 2. The highest probability of decrease in activity was associated with the transition from the average activity state to the inactivity state: a participant who was in the average activity state during week 1 was 31% likely to transition into the inactivity state during week 2.

HMM Effects of Generic Email Prompts

The relationship of interest in this study is the connection between generic emails and participant engagement. Table 5 shows the estimated posterior probability means of the state distribution depending on whether the participants received and opened a generic email. The posterior probability means indicate the estimated probability that a participant was in each state, given the email prompt. The estimates show that a participant who did not receive a generic email was 68% likely to be in the inactivity state, whereas a participant who received and opened a generic email was 67% likely to be in the inactivity state (a decrease of 1 percentage point). In addition, the participants who received but did not open a generic email were estimated to have a 11 percentage point higher likelihood of inactivity than those who did not receive an email.

Table 5. Hidden Markov model estimation results: posterior probability means associated with the generic email prompts\(^a\).

<table>
<thead>
<tr>
<th>State</th>
<th>1: inactivity</th>
<th>2: average activity</th>
<th>3: high activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>No generic email received</td>
<td>0.68</td>
<td>0.19</td>
<td>0.13</td>
</tr>
<tr>
<td>Generic email received but not opened</td>
<td>0.79</td>
<td>0.14</td>
<td>0.06</td>
</tr>
<tr>
<td>Generic email received and opened</td>
<td>0.67</td>
<td>0.22</td>
<td>0.11</td>
</tr>
</tbody>
</table>

\(^a\)Section 3 in Multimedia Appendix 1 presents detailed model fit criteria and parameter estimates for the hidden Markov model. All the parameter estimates were statistically significant at the 99% confidence level.

As the HMM allowed for the dynamics of switching between states, Table 6 shows the estimated transition matrices depending on the generic email. On the basis of the estimated transition matrices, the likelihood that a participant remained in the inactivity state between weeks \(t\) and \(t+1\) was 91% when no email was received, as opposed to 88% when a generic email was received and opened. This translates into a 3 percentage point decrease in the probability of remaining inactive or, alternatively, a 3 percentage point increase in the probability of moving into one of the activity states after receiving and opening a generic email.

<table>
<thead>
<tr>
<th>State (t)</th>
<th>Transition matrix: no generic email received</th>
<th>Transition matrix: generic email received but not opened</th>
<th>Transition matrix: generic email received and opened</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>1</td>
<td>0.91</td>
<td>0.07</td>
<td>0.02</td>
</tr>
<tr>
<td>2</td>
<td>0.31</td>
<td>0.64</td>
<td>0.05</td>
</tr>
<tr>
<td>3</td>
<td>0.09</td>
<td>0.09</td>
<td>0.82</td>
</tr>
</tbody>
</table>

*t: time point.

HMM Effects of Detailed Email Prompts

To examine whether the effect of the email prompts differed based on email type, the estimated posterior probability means of the state distribution were formulated depending on whether the participants received and opened an email using detailed email categories (Table 7). On the basis of the posterior probability means shown in Table 7, both positive and negative effects could be identified, where a positive effect reflects an increase in participant activity linked to receiving and opening an email, whereas a negative effect reflects the opposite. A positive effect was associated with opening a welcome email (decreased likelihood of inactivity by 12 percentage points) and opening a health campaign email (decreased likelihood of inactivity by 3 percentage points). A negative effect was associated with opening a newsletter or special offer email (increased likelihood of inactivity by 2 percentage points) and opening a reactivation email (increased likelihood of inactivity by 5 percentage points).

Table 7. Hidden Markov model estimation results: posterior probability means accounting for detailed email prompts.

<table>
<thead>
<tr>
<th>Email Type</th>
<th>1: inactivity</th>
<th>2: average activity</th>
<th>3: high activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>No email received</td>
<td>0.68</td>
<td>0.19</td>
<td>0.13</td>
</tr>
<tr>
<td>Welcome email</td>
<td>Email received but not opened</td>
<td>0.70</td>
<td>0.24</td>
</tr>
<tr>
<td>Email received and opened</td>
<td>0.56</td>
<td>0.34</td>
<td>0.10</td>
</tr>
<tr>
<td>Reactivation email</td>
<td>Email received but not opened</td>
<td>0.85</td>
<td>0.11</td>
</tr>
<tr>
<td>Email received and opened</td>
<td>0.73</td>
<td>0.18</td>
<td>0.09</td>
</tr>
<tr>
<td>Newsletter email</td>
<td>Email received but not opened</td>
<td>0.80</td>
<td>0.13</td>
</tr>
<tr>
<td>Email received and opened</td>
<td>0.70</td>
<td>0.18</td>
<td>0.12</td>
</tr>
<tr>
<td>Health campaign email</td>
<td>Email received but not opened</td>
<td>0.75</td>
<td>0.19</td>
</tr>
<tr>
<td>Email received and opened</td>
<td>0.65</td>
<td>0.26</td>
<td>0.09</td>
</tr>
<tr>
<td>Special offer email</td>
<td>Email received but not opened</td>
<td>0.83</td>
<td>0.12</td>
</tr>
<tr>
<td>Email received and opened</td>
<td>0.70</td>
<td>0.19</td>
<td>0.11</td>
</tr>
</tbody>
</table>

*Section 3 in Multimedia Appendix 1 presents detailed model fit criteria and parameter estimates for the hidden Markov model. All parameter estimates were statistically significant at the 95% confidence level.

HMM Effects of Time and Background Characteristics

Examining the impact of generic email prompts on participant engagement over time revealed the estimated transition matrices and posterior probability means provided in section 4 in Multimedia Appendix 1. During the first half year, 72% (16,413/22,797) of the participants were estimated to be in the inactivity state, which decreased to 65% (14,818/22,797) during the second half year. For the last half year observed, 69% (15,730/22,797) of the participants were estimated to be in the inactivity state. The impact of receiving and opening a generic email on the transition probabilities did not change much over time, being associated with a decreased likelihood of remaining in the inactivity state by 2 percentage points in the first and third half years and 3 percentage points in the second half year. The background characteristics of the participants were also linked to differences in activity levels. On the basis of the estimated HMM model (transition matrices and posterior...
probability means shown in section 5 in Multimedia Appendix 1), female participants were more likely to be in the inactivity state and less likely to be in the high activity state compared with male participants (with a difference of 6 percentage points). The lowest socioeconomic group and the youngest age group were associated with a higher likelihood of inactivity, whereas the age group from 47 to 56 years was the most active. Finally, being an early mHealth app adopter was associated with a 5 percentage point decrease in the likelihood of being in the inactivity state (with the same level of increase in the likelihood of being in the high activity state).

The impact of the generic email prompts on participant engagement did not vary substantially between participants depending on their age, gender, or NSES quintile, with the only difference being that the participants in the oldest age group (67 to 80 years) had a higher likelihood of transitioning toward one of the activity states after opening a generic email than the other age groups (an effect of 4 percentage points).

To examine the robustness of the above-discussed results, several additional models were estimated, with the results confirming those presented in this study. Section 6 in Multimedia Appendix 1 contains several alternative specifications of the HMM model and their estimation results, namely using an indicator for any email received (independent of the email type or targeting nature) and incorporating the email prompts as covariates in the response probabilities model. In addition, following the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) recommendations, the checklist presented in Multimedia Appendix 2 was completed.

Discussion

Principal Findings

Digital behavior change programs are widely implemented as a means of improving lifestyle behaviors and population health. However, such programs often exhibit low participant engagement rates, with additional effort needed from the program providers to stimulate and maintain engagement. This study analyzed the ability of email prompts to increase participant engagement with an mHealth app aimed at supporting behavior change. Although email prompts showed some positive results in stimulating engagement, their effect in a large-scale, nonexperimental setting with a longer time span is still unclear.

The analysis in this study used an HMM to disentangle the dynamics around email prompts and participant engagement. The estimated HMM with 3 latent states revealed that, on average, 70% (15,958/22,797) of the participants were in the inactivity state, gaining 0 points weekly; 18% (4103/22,797) of the participants were in the average activity state—gaining 27 points weekly; and 12% (2736/22,797) of the participants were in the high activity state—gaining 182 points weekly.

Focusing on the effect of generic emails, the estimation results indicated that when allowing for time dependency, receiving and opening a generic email was associated with a 3 percentage point lower likelihood of remaining inactive than when no email was received (equivalent to a 3 percentage point increase in the likelihood of transitioning from inactivity to one of the activity states). By contrast, receiving but not opening a generic email was associated with a higher likelihood of inactivity. This observed negative impact that receiving but not opening an email had on participant engagement can be explained by the higher proportion of inactive participants in the group that did not open the email than in the group that did not receive an email. Given that the average opening rate of the emails sent within the analyzed mHealth app was above 60%, it can be argued that some increase in participant engagement is possible with the use of generic emails; however, additional effort should be directed at ensuring high opening rates for the emails sent.

Allowing the effect of generic emails to vary over time revealed a relatively stable pattern: in all 3 half-year periods analyzed, the likelihood of moving out of inactivity after opening a generic email was between 2 and 3 percentage points, with the strongest effect corresponding to the second half year of the observation period. Estimating the association of the effects observed with participant background characteristics showed that being a male, being older, having a higher socioeconomic status, and being an early adopter of the mHealth app were all factors associated with higher participant engagement. The impact of the generic emails did not significantly depend on the participants’ age, gender, or NSES quintile, with the only difference being that the participants in the age group of 67 to 80 years were more likely to move out of inactivity after receiving and opening a generic email than those in the other age groups.

This study further analyzed the impact of detailed email categories on participant engagement, revealing both negative and positive effects. On one hand, it was estimated that emails welcoming participants to the program and emails containing health-related information were associated with an increase in activity levels (12 and 3 percentage points, respectively). On the other hand, emails that contained generic program information, promoted special offers on products in the web shop, or were aimed at reactivating inactive users were linked to a decrease in activity levels (2, 2, and 5 percentage points, respectively). These findings imply that participants were more reactive to health-related information, which was in line with the program’s goals and potentially with the participants’ motivation for using the mHealth app, while being resistant to emails that deviated from the program’s goal of improving health behaviors. Moreover, the negative effect of the reactivation email implies that it is difficult to stimulate activity in participants who have been inactive for long periods, highlighting the importance of focusing on preventing participants from becoming inactive.

Comparison With Previous Work

Digital behavior change programs often exhibit low participant engagement [11-13]. On the basis of a systematic review, Kelders et al [11] estimated that the average adherence to web-based lifestyle interventions is 23%, which is similar to the 30% of active participants identified in the mHealth app in this study. The slightly higher proportion of active participants estimated here can be because of the mobile app format of the
behavior change intervention, which is associated with higher flexibility of use and more personalized content [51].

In an attempt to identify means of improving participant engagement, email prompts have been examined in the context of behavior change programs, with studies reporting small to moderate effects [23]. However, the effects of email prompts on participant engagement are often analyzed over a short period [25,27], subsequently diminishing [12,52] or even disappearing [25]. This study estimated that participant engagement increased by approximately 3 percentage points when an email was received and opened. A similar impact was seen in the study of Ryan et al [52], who based on average activity levels, observed an increase of approximately 3% in the steps taken on the days on which an email was sent. A possible reason for the limited effect of email prompts on engagement is that participants can find such reminders annoying [53]. Alternatively, in the case of targeted emails, inadequate personalization is another factor linked to low participant engagement [54]. Finally, inducing higher participant engagement over time is a challenging task [12,19], partially because of the passive nature of behavior change programs, where participants need to act by themselves to benefit [14].

Participant background characteristics are linked to their engagement with the mHealth app [55]. Similar to the findings in this study, previous work has also shown that males [52,56], older age groups [10,56,57], higher socioeconomic status participants [10,52], and early adopters [38] have higher engagement with mHealth apps. The observation that older age groups are more responsive to emails than other age groups can be explained by their appreciation of reminders within mHealth apps [58], indicating that such tools are especially efficient in increasing activity levels among the older population group.

The results of this study show that although email prompts can achieve a small to moderate increase in participant engagement, this tool alone is likely insufficient for increasing activity levels in an mHealth behavior change app. However, given that the costs associated with email prompts are relatively low, they may be a cost-effective means to improve participant engagement with an mHealth app when the program achieves a high population reach [7,59]. In addition, alternative program efforts, such as expert consultation or real-time feedback [7] could be used next to email prompts to further reduce participant dropout and improve the program effectiveness.

Limitations and Future Research

There are several limitations around this study.

First, as a measure of participant engagement, this study solely used the activities recorded within the mHealth app. However, it is likely that the participants performed additional activities that were not recorded in the app environment. To overcome this limitation, one approach could be to combine the currently used objective measure of participant engagement with an additional subjective measure through which participants themselves can report their perceived activity level. Alternatively, a more accurate measure of activity could be achieved by extending the mHealth app to also include a wearable device, which could measure physical activity in a more precise manner.

Second, it is not a given that whenever a participant opens an email, they become aware of its content. It could be the case that some participants briefly open the email only to delete it, without reading any of its elements. In the setup of this study, we consider the action of opening the email to be a sufficient indication that the participant has been exposed to a reminder about the mHealth program analyzed. As a future extension to the current analysis, it could be of interest to examine whether reading the emails can lead to a higher impact on participant engagement. One possible way to measure whether participants read through the emails could be through the use of a clickable follow-up link, which can help distinguish between participants who pay attention to the content of the email and those who do not.

Third, the participants of the mHealth app analyzed in this study were older than 18 years. This excludes children and teenagers, with unclear insights into how the email prompts would work in increasing activity levels among these population groups. Given the importance of developing healthy lifestyle choices from a young age, a further extension to this study could be examining whether and how email prompts help increase activity among the younger population.

Finally, it is highly likely that the specific wording and topics addressed in an email have an impact on its effectiveness in increasing participant engagement. Although data on the detailed elements of the emails were not available in this study, analyzing such information could be a valuable extension. Namely, it would be of interest to examine how varying phrasing of the same topic and different levels of email personalization affect subsequent participant engagement.

Conclusions

In this study, email prompts were examined as a tool for increasing participant engagement with a large-scale, open-access mHealth app with the goal of lifestyle behavior change. On the basis of an HMM allowing for weekly transitions between latent activity states, it was estimated that receiving and opening an email was associated with a small to moderate increase in participant engagement, which persisted over the 78 weeks analyzed. This finding suggests that email prompts can be used for improving participant engagement, albeit to a limited extent. However, given the relatively low costs associated with emails and the high population reach that mHealth apps can achieve, such instruments can be a cost-effective means of improving participant engagement to reduce dropout and improve the effectiveness of behavior change programs.

Acknowledgments

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Authors' Contributions

All authors contributed equally to the conception and design of the study, data acquisition, data analysis and interpretation, writing and revising the paper, and reading and approving the final version of the submitted manuscript.

Conflicts of Interest

EA was funded by Menzis (the health insurance company that introduced the mHealth app) in her position as a Doctor of Philosophy candidate.

Multimedia Appendix 1

Web-based appendix with additional analysis information.

[DOCX File, 1474 KB - mhealth_v11i1e43033_app1.docx]

Multimedia Appendix 2

Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) checklist.

[DOCX File, 32 KB - mhealth_v11i1e43033_app2.docx]

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Abbreviations

HMM: hidden Markov model
mHealth: mobile health
NSES: neighborhood socioeconomic status
STROBE: Strengthening the Reporting of Observational Studies in Epidemiology

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How Notifications Affect Engagement With a Behavior Change App: Results From a Micro-Randomized Trial

Lauren Bell1,2, MSc; Claire Garnett3, PhD; Yihan Bao4, MA; Zhaoxi Cheng5, BSc; Tianchen Qian6, PhD; Olga Perski3, PhD; Henry W W Potts2, PhD; Elizabeth Williamson1, PhD

1Department of Medical Statistics, The London School of Hygiene and Tropical Medicine, London, United Kingdom
2Medical Research Council Biostatistics Unit, University of Cambridge, Cambridge, United Kingdom
3Research Department of Behavioural Science and Health, University College London, London, United Kingdom
4Department of Statistics and Data Science, Yale University, New Haven, CT, United States
5Department of Biostatistics, Harvard University, Cambridge, MA, United States
6Department of Statistics, University of California Irvine, Irvine, CA, United States
7Institute of Health Informatics, University College London, London, United Kingdom

Corresponding Author:
Henry W W Potts, PhD
Institute of Health Informatics
University College London
222 Euston Road
London, NW1 2DA
United Kingdom
Phone: 44 02035495303
Email: h.potts@ucl.ac.uk

Abstract

Background: Drink Less is a behavior change app to help higher-risk drinkers in the United Kingdom reduce their alcohol consumption. The app includes a daily notification asking users to “Please complete your drinks and mood diary,” yet we did not understand the causal effect of the notification on engagement nor how to improve this component of Drink Less. We developed a new bank of 30 new messages to increase users’ reflective motivation to engage with Drink Less. This study aimed to determine how standard and new notifications affect engagement.

Objective: Our objective was to estimate the causal effect of the notification on near-term engagement, to explore whether this effect changed over time, and to create an evidence base to further inform the optimization of the notification policy.

Methods: We conducted a micro-randomized trial (MRT) with 2 additional parallel arms. Inclusion criteria were Drink Less users who consented to participate in the trial, self-reported a baseline Alcohol Use Disorders Identification Test score of ≥8, resided in the United Kingdom, were aged ≥18 years, and reported interest in drinking less alcohol. Our MRT randomized 350 new users to test whether receiving a notification, compared with receiving no notification, increased the probability of opening the app in the subsequent hour, over the first 30 days since downloading Drink Less. Each day at 8 PM, users were randomized with a 30% probability of receiving the standard message, a 30% probability of receiving a new message, or a 40% probability of receiving no message. We additionally explored time to disengagement, with the allocation of 60% of eligible users randomized to the MRT (n=350) and 40% of eligible users randomized in equal number to the 2 parallel arms, either receiving the no notification policy (n=98) or the standard notification policy (n=121). Ancillary analyses explored effect moderation by recent states of habituation and engagement.

Results: Receiving a notification, compared with not receiving a notification, increased the probability of opening the app in the next hour by 3.5-fold (95% CI 2.91-4.25). Both types of messages were similarly effective. The effect of the notification did not change significantly over time. A user being in a state of already engaged lowered the new notification effect by 0.80 (95% CI 0.55-1.16), although not significantly. Across the 3 arms, time to disengagement was not significantly different.

Conclusions: We found a strong near-term effect of engagement on the notification, but no overall difference in time to disengagement between users receiving the standard fixed notification, no notification at all, or the random sequence of notifications within the MRT. The strong near-term effect of the notification presents an opportunity to target notifications to increase “in-the-moment” engagement. Further optimization is required to improve the long-term engagement.
Introduction

Background

Hazardous and harmful alcohol consumption is one of the major risk factors for many disease outcomes and poses a major public health burden [1,2]. Delivering brief interventions to reduce hazardous and harmful alcohol consumption is known to be effective [3]; however, such efforts are challenged by the sheer prevalence of harmful drinking and limited capacity of services [4,5]. There is a long-standing recognition of the need to broaden the reach of and access to brief, effective interventions to reduce harmful alcohol consumption for help-seeking individuals [6].

A promising solution is behavior change apps, as these are complex interventions that can capture dynamic patterns in human behavior and deliver support when an individual needs this the most [7-9]. Building on evidence that supports SMS text messaging as interventions to help individuals [10], behavior change apps can provide comprehensive, everyday support within people’s homes and diverse communities to maintain healthy behaviors [11]. However, a major concern is that insufficient engagement with an app is likely to hinder behavior change, particularly if a user disengages with the app soon after downloading it [12,13]. Engagement, a construct of both experiential and behavioral aspects [14], fluctuates within and between users over time and is influenced not only by the static content of the intervention but also by internal (eg, the user’s momentary mood, cognitive state, and recent patterns of engagement and drinking) and external (eg, the user’s current environment) factors [15-18].

Push notifications (reminders or pop-up messages on the screen) are often implemented to increase engagement with a behavior change app [13,19,20] and can have small, positive effects on engagement over a 24-hour period [21]. However, a more immediate causal effect (eg, within the next hour) of a push notification on engagement with behavior change apps has not yet been established [21,22]. We undertook a trial to estimate the causal effect of the notification on near-term engagement in the behavior change app Drink Less and to consider how the notification policy could be further optimized to improve engagement.

The Drink Less App

Drink Less is a behavior change app that aims to help higher-risk drinkers in the UK adult population reduce their alcohol consumption. The app is freely available to people seeking help with their alcohol consumption, although it has not been advertised or targeted to specific groups of people. Drink Less was developed in line with the Medical Research Council guidelines for developing and evaluating a complex intervention [23-25] and the Multiphase Optimisation Strategy (MOST) framework [26,27] and is freely available on the Apple App Store. Drink Less is an evidence- and theory-informed intervention with several modules. The overall development and refinement of Drink Less, including how the behavior change modules were selected, can be found in previous publications [28,29]. The standard version of the app delivers a local daily notification at 11 AM, asking the user to “Please complete your mood and drinks diary” (Multimedia Appendix 1 provides a visual of the Drink Less notification). Daily notifications aim to remind users to self-monitor their drinking habits. The National Institute for Health and Care Excellence for the United Kingdom recommends self-monitoring as an effective technique for the act of noticing recent behavior and how this relates to their goals [30]. However, if a user has already engaged with the app to self-monitor their drinking that day, the notification may be an unnecessary reminder and may ultimately annoy the user over time.

The notification appears on the users’ notification center, and tapping the notification opens to the Drink Less landing page. The standard version of Drink Less sends a daily notification that aims to increase self-monitoring by tracking recent alcohol units consumed (ie, the day before). The delivery time at 11 AM allows users to complete their morning routines before engaging with the app. User feedback was received via the App Store, with the suggestion that a reminder to report drinking diaries in the evenings would be more helpful.

Engagement With Drink Less

We previously reported exploratory research that visualized temporal patterns of engagement with Drink Less [31]. The visualizations showed limited depth of engagement, with 85% of sessions occurring within the Self-Monitoring and Feedback module, and a natural peak near 8 PM of both frequency (ie, number of log-ins) and time spent on the app observed in the evenings. This suggested that evenings are opportune moments to engage with Drink Less for longer sessions. In the evening, users may be more susceptible to harmful drinking and intervening at this moment of vulnerability and, at an opportune moment to engage, may be more conducive to reducing harmful patterns of drinking. In addition, our exploratory research discovered different trajectories of use, with 50% of users disengaging with the app 22 days after download. We hypothesized that a fixed notification policy may suit some users to maintain engagement, whereas other users may habituate to the daily notification policy and disengage sooner.

Specific Aims and Objectives

We conducted a micro-randomized trial (MRT), a design in which users recruited for the MRT were repeatedly randomized...
to notifications over time, with outcomes measured after each randomization [32-36]. We aimed to provide evidence of how notifications affect near-term engagement as well as to consider further improvement of the push notification policy. The primary objective was to assess whether sending a notification at 8 PM increases behavioral engagement (opening the app) in the subsequent hour with Drink Less. The secondary objectives included the comparison of 2 different types of notifications. We also explored effect moderation by time and the exploration of effect moderation by user context (with context being a user’s dynamic state of engagement or habituation). We also aimed to understand the role of a notification policy more generally for time to disengagement. In addition, we aimed to compare 3 policies on time to disengagement (each policy being the decision rule of delivering notifications used in 1 of the 3 arms). This is the first step in our wider aspiration to optimize the notification policy of Drink Less, an aspiration we return to in the Discussion section.

Methods

Trial Design

Our study had a 30-day MRT with 2 additional parallel arms. Three different notification policies are implemented in the 2 arms and MRT to address the secondary objectives: (1) a standard policy of sending a daily message of “Please complete your mood and drinks diary” sent at 11 AM; (2) the MRT, a random policy that varies the content and sequence of the notifications; and (3) a no notification policy, a policy that does not send notifications. For the secondary objectives, the three policies are referred to as (1) standard notification policy, (2) random notification policy, and (3) no notification policy.

In total, 60% of eligible users were randomized to the MRT, and 40% of eligible users were randomized in equal number to the 2 parallel arms, either receiving the no notification policy or the standard notification policy of “Please complete your mood and drinking diary” at 11 AM.

For users randomized to the MRT, each user was randomized daily at 8 PM to receive 1 of the 3 options: no notification (with 40% probability), the standard message (with 30% probability), or a notification randomly selected with replacement from a bank of new messages (with 30% probability).

Following our MRT protocol [37] and the CONSORT (Consolidated Standards of Reporting Trials) 2010 guidelines [38], we reported the primary and some secondary results here.

Participants

The recruitment period ran from January 2, 2020, to April 1, 2020. Drink Less is freely available on the Apple App Store, and individuals who downloaded the app during the recruitment period were eligible to participate in the trial if they self-reported a baseline Alcohol Use Disorders Identification Test (AUDIT) score of ≥ 28, which indicates excessive alcohol consumption [39]; resided in the United Kingdom; were aged ≥18 years; and reported being interested in drinking less alcohol.

The app prompted eligible users to read the privacy notice (Multimedia Appendix 2) and participant information sheet (Multimedia Appendix 3) before enrolling in the trial. During the informed consent process, users were informed that they could opt out of the trial at any time and that they would receive the standard version of the Drink Less app if they withdrew their consent.

The date of download is defined as the date when the onboarding process is completed by each user. The onboarding process involved users completing a registration section where they completed the AUDIT and sociodemographic assessment and then received normative feedback (personalized feedback on how their drinking compares with the behaviors of others). It is only after the completion of the onboarding process that users were then assessed for eligibility and consequently randomized to 1 of the 3 arms.

On enrollment in the study, we turned the permission function off within the app. This was intended to ensure that the participants received the notification policy to which they were randomized. Participants could, however, go into the settings and turn the notification policy off, which is applicable for all apps on the Apple App Store and is beyond the control of any app developer.

Data

Preprocessing of the original use data was required. The raw engagement data are captured by a series of screen views, comprising time stamps of when a new screen is opened in the app. Clearing or swiping away the notification is not registered as any use [40]. The length of a session is calculated as the difference (in microseconds) between the first and last screen views, with a new session defined after 30 minutes of inactivity between screen views [41]. This method of calculating the length of sessions means that our measures of the length of time spent on the app are always underestimated because we do not know how long the user observes the last screen view [41]. We did not impose a threshold on our outcome (in terms of the amount or depth of app use), so simply opening the app is measured as engagement. When a user opens Drink Less, they are presented with a dashboard with various information about their drinking habits as well as a toolbox of features to access if they want. As such, simply opening the app and viewing the dashboard and toolbox present an opportunity for users to benefit from engaging with Drink Less. All time stamps were appropriately adjusted from Coordinated Universal Time to British Summer Time.

Time-Fixed Measures (Baseline)

Time-fixed covariates, measured at baseline, were age, sex, type of employment (manual, nonmanual, or other), and baseline AUDIT score (0-40) [39,42,43]. The AUDIT risk zones were hazardous (8-15), harmful (16-19), and at risk for alcohol dependence (20-40). The participants self-selected the employment status they identified with for the options they were provided. They were not provided with a definition of employment type.

Time-Varying Measures

Time-varying engagement measures within the MRT are the time stamps of when the user opens the app and the length of
time (in seconds) spent on the app. This includes the time-varying variables: (1) “Did the user open the app before 8 PM on day of randomization? (yes/no)” and (2) “Did the user open the app any time after 9 PM the day before? (yes/no).”

Time-varying covariates, used as part of post hoc analyses to explore effect moderation, were “habituation” and “already engaged.” “Habituation” was captured using the binary measure “Did the user receive a notification the day before? (yes/no),” “Already engaged” was captured using the binary measure “Did the user open the app between 8 PM-9 PM the day before? (yes/no).”

Interventions
The MRT tested 2 notification types. This trial tested the existing notification with the message of “Please complete your mood and drinking diary” and a new notification bank of 30 novel messages (Multimedia Appendix 4). The development of the new notification bank was informed by research with Drink Less, which found that the perceived usefulness of the app (the belief that using the app will help the user achieve their goal or goals and an indicator of users’ reflective motivation to engage) was associated with increased engagement for some users. Therefore, the new bank of notifications was designed (with feedback on the content sought from a group of behavioral scientists) to increase users’ reflective motivation to engage with a particular intervention module [44]. All messages contained the phrase “(using a particular module in the app) can help you drink less.” Examples include “Recording if-then plans can help you drink less” and “Setting a doable goal can help you drink less. Take a moment to set a doable goal.” The notification does not lock the user’s screen, and there is no expiry time for notification.

Outcomes
The primary outcome was whether the user opened the app (yes or no) in the hour between 8 PM and 9 PM, following the randomization of receiving a notification at 8 PM. This is a time-varying, binary, and near-term measure of engagement.

We also defined a post hoc outcome of whether the user opened the app between 8 PM on the day of randomization to 8 PM the following day to explore the effect over a 24-hour period.

The secondary outcomes captured across the 3 different policies include the number of days to disengagement, with disengagement defined as the first day in a period of ≥7 consecutive days of no use.

Sample Size
We powered the MRT for the important secondary objective of effect moderation over time, which guarantees at least as much power for the primary objective of detecting a marginal effect. Using a simulation informed by observational Drink Less data [31], we determined that a sample of 1200 users was sufficient to provide 80% power, with a type 1 error of 5%, to detect effect moderation over time, assuming a marginal notification effect of 2.16 decaying by 0.911 per day since download (Multimedia Appendix 5). We powered the secondary arms, implementing different notification policies, to detect a minimum absolute difference in time to disengagement of 10%, assuming 55% disengagement by day 22 under the standard policy compared with 65% under the no notification policy. To achieve 80% power with type 1 error of 5%, 372 users were required to receive each notification policy. This was rounded to 400 to simplify the randomization process. Overall, we aimed to recruit 1200 users to the MRT, 400 users to the standard notification policy, and 400 users to the no notification policy.

Previous download trends revealed, on average, an estimate of at least 33 eligible users per day who downloaded Drink Less and consented to the privacy notice. We expected the available recruitment window (January 2 to April 1, 2020) to be sufficient to reach our recruitment target of 2000 users. However, we fell short of this target of 2000 users and randomized 598 users in total for three reasons: (1) a large proportion of users (40%) did not give their informed consent to be part of the study; (2) the number of downloads, particularly for March 2020, was less than predicted, based on 2019 trends; and (3) extending the recruitment period to achieve the desired sample size was not possible because of the commencement of a prescheduled National Institute for Health Research–funded randomized controlled trial [45]. Consequently, the primary objective was sufficiently powered; however, we did not achieve the prespecified sample size for the secondary objectives of effect moderation over time and time to disengagement.

Randomization
Simple randomization (unstratified and no blocking) was used. An external engineer generated the randomization sequence and coded it into the app. Together, 2 coauthors (LB and CG) pilot tested the randomization schedule. To further verify the randomization process, 10 volunteers also participated in a pilot test. The 10 volunteers were randomized into 3 different arms and asked to record the notifications received and the use of the app. We confirmed that the randomization process functioned as planned, and all uses were correctly captured.

Statistical Methods Within the MRT
Descriptive statistics (frequency distributions and measures of central tendency) were used to describe the baseline variables of participants.

The primary outcome, within the MRT, was summarized separately for the standard notification, new notification, and no notification by the number of person-days where the app was opened between 8 PM and 9 PM then divided by the number of person-days in the MRT and expressed as a proportion.

The near-term effect of the notification on the primary outcome was expressed on the relative risk (RR) scale and pooled over the longitudinal data across all participants using the Estimator for the Marginal Excursion Effect (EMEE) [46]. The EMEE was developed to estimate the causal effects of time-varying treatments with binary outcomes. The EMEE does not require the correct specification of the marginal mean model (ie, how the time-varying engagement depends on a user’s time-varying contexts), providing robustness to highly complex and stochastic engagement patterns.

The effect of receiving a push notification versus not receiving a notification was estimated overall and then separately for the
new message bank and standard notification. All models from the MRT were adjusted for the continuous variables of age, AUDIT score, days since download, the categorical variables of sex and employment type, and the time-varying variables “Did the user open the app before 8 PM that day?” and “Did the users open the app after 9 PM the day before?” The time-varying measures were included to increase the precision of our near-term notification effect, as they were likely highly correlated with the outcome. The covariates of “habituation” and “already engaged” are for the purpose of exploring how these recent states modify the near-term effect of the notification.

Statistical Methods Across Arms
Baseline descriptive statistics and measures of use—the median number of sessions per user and the median length of sessions (seconds)—were reported across the 3 policies. A user was classified as having disengaged on the first day of a period of 7 consecutive days of no use. This outcome was only defined for the first 23 days after follow-up, which lasted 30 days in total. Survival curves were plotted using the Kaplan-Meier estimator [47] and compared using a log-rank test.

Owing to technical glitches, there were some unanticipated missing categorical baseline data. We reported the number of missing values for each arm. We used modal imputation for the baseline variables. To assess the sensitivity of our conclusions to our missing data approach, we imputed the data with the second most common value.

All analyses were conducted using R (version 4.0.5; R Foundation for Statistical Computing) [48] with the dplyr [49], lubridate [50], gtssummary [51], zoo [52], ForImp [53], and survminer [54] packages.

Ethics Approval
Ethical approval for this study was granted by the University College of London’s Departmental Research Ethics Committee (CEHP/2016/556) on October 11, 2019, and The London School of Hygiene and Tropical Medicine Interventions Research Ethics Committee (17929) on November 27, 2019.

Results
Overview
The anonymized data sets, including data dictionaries, are publicly available [55]. The code for EMEE is openly available on the GitHub account [56]. Figure 1 presents the CONSORT flow diagram of the progress through the MRT.
Recruitment

The trial recruitment period ran from January 2, 2020, to April 1, 2020 (app version 2.0.1). We analyzed a total of 566 users. The mean age was 44 (SD 12) years, with 43.6% (247/566) male and 45.8% (259/566) female users. A total of 62.4% (353/566) of users reported being in nonmanual employment, 12.5% (71/566) reported being in manual employment, and 14.5% (82/566) reported being in other employment types. A total of 48.8% (276/566) of users reported hazardous alcohol consumption, 20.1% (114/566) reported harmful alcohol consumption, and 31.1% (176/566) reported being at risk of alcohol dependence. A total of 68.2% (386/566) of users were disengaged by day 23 or earlier.

Data on sex and employment type were not recorded for the 60 users (standard arm, n=5; MRT, n=40; and no notification arm, n=5). We used modal imputation to set these missing values of sex to female and employment type as nonmanual (Table 1).
Table 1. Description of trial participants by randomized arm.

<table>
<thead>
<tr>
<th>User characteristics</th>
<th>Baseline summary</th>
<th>MRT(^a) (n=349)</th>
<th>No notification arm (n=97)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ge (years), median (IQR; n=566)</td>
<td>45 (35-55)</td>
<td>43 (34-51)</td>
<td>43 (34-52)</td>
</tr>
<tr>
<td>Sex (n=506; standard arm: n=105; MRT: n=309; no notification arm: n=92), n (%)(^b)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male, n (%)</td>
<td>43 (41)</td>
<td>155 (50.2)</td>
<td>49 (53)</td>
</tr>
<tr>
<td>Female, n (%)</td>
<td>62 (59)</td>
<td>154 (49.8)</td>
<td>43 (47)</td>
</tr>
<tr>
<td>Employment type (n=506; standard arm: n=105; MRT: n=309; no notification arm: n=92), n (%)(^b)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonmanual, n (%)</td>
<td>66 (62.8)</td>
<td>224 (72.5)</td>
<td>63 (68)</td>
</tr>
<tr>
<td>Manual, n (%)</td>
<td>19 (18.1)</td>
<td>37 (12)</td>
<td>15 (16)</td>
</tr>
<tr>
<td>Other, n (%)</td>
<td>20 (19)</td>
<td>48 (15.5)</td>
<td>14 (15)</td>
</tr>
<tr>
<td>AUDIT score (n=566), n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hazardous (8-15)</td>
<td>48 (40)</td>
<td>142 (40.7)</td>
<td>49 (51)</td>
</tr>
<tr>
<td>Harmful (16-19)</td>
<td>29 (24.2)</td>
<td>84 (24.1)</td>
<td>18 (19)</td>
</tr>
<tr>
<td>At risk of alcohol dependence (20-40)</td>
<td>43 (35.8)</td>
<td>123 (35.2)</td>
<td>30 (31)</td>
</tr>
</tbody>
</table>

\(^a\)MRT: micro-randomized trial.  
\(^b\)Missing: standard arm: n=15; MRT: n=40; and no notification arm: n=5.

Outcomes and Estimation

In the MRT, 349 users were randomized each day for 30 days, resulting in 10,470 measurements for the primary outcome. There were 30.05% (3146/10,470) of measurements for the new message, 29.72% (3112/10,470) of measurements for the standard notification, and 40.23% (4212/10,470) of measurements for no notification. The proportion of the primary outcome (opening the app between 8 PM and 9 PM) was 0.122 for the new message, 0.131 for the standard message, and 0.036 for no message. For the post hoc 24-hour outcome (from 8 PM to 8 PM the next day), the proportion of opening the app was 0.351 for the new message, 0.342 for the standard message, and 0.280 for no message.

Main Results

Table 2 provides the results for the estimate of the near-term effect of the notifications on engagement. This demonstrates that, on average, the probability of opening Drink Less within the hour of receiving a standard notification increased 3.66-fold (95% CI 2.99-4.48) and the probability of opening the Drink Less within the hour of receiving a new notification increasing 3.39-fold (95% CI 2.77-4.13).

Table 3 reports the results for how the effect of the notification changes over the first 30 days since download. We did not detect any significant changes over time, with an estimated decay by a factor of 0.993 per day with a 95% CI (0.975-1.012). Although not statistically significant, the point estimate of the decay in effect over time is larger in magnitude for the standard notification compared with the new notification; however, the wide CIs reflect large uncertainties in these estimates.

The summative engagement measures (median number of sessions and median length of sessions) under the 3 policies had a similar number of sessions and length of sessions over the first 30 days since download (Table 4). Users randomized to the no notification policy had, on average, slightly fewer but longer sessions, with a median of 43 seconds in length compared with 36 seconds for the standard policy and 35 seconds for the random policy (MRT).

Table 2. Primary objective—estimated near-term notification effect.

<table>
<thead>
<tr>
<th>Notification type(^a)</th>
<th>Relative risk (95% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pooled notifications (both standard and new)</td>
<td>3.523 (2.918-4.255)</td>
</tr>
<tr>
<td>Standard notification</td>
<td>3.664 (2.993-4.485)</td>
</tr>
<tr>
<td>New notification</td>
<td>3.385 (2.774-4.131)</td>
</tr>
</tbody>
</table>

\(^a\)Adjusted for the continuous variables of age, Alcohol Use Disorders Identification Test score, days since download, the categorical variables of sex and employment type, and the time-varying variables “Did the user use the app before 8 PM that day?” and “Did the users use the app after 9 PM the day before?”
Table 3. Change of near-term notification effect over time.

<table>
<thead>
<tr>
<th>Notification type</th>
<th>Relative risk on the first day after download (95% CI)</th>
<th>Multiplicative change in effect (95% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pooled notifications (both standard and new)</td>
<td>3.849 (2.811-5.270)</td>
<td>0.993 (0.975-1.012)</td>
</tr>
<tr>
<td>Standard notification</td>
<td>4.193 (3.004-5.854)</td>
<td>0.989 (0.970-1.001)</td>
</tr>
<tr>
<td>New notification</td>
<td>3.534 (2.536-4.924)</td>
<td>0.997 (0.976-1.017)</td>
</tr>
</tbody>
</table>

*Multiplicative change in relative risk per day since download. Adjusted for the continuous variables of age, Alcohol Use Disorders Identification Test score, days since download, the categorical variables of sex and employment type, and the time-varying variables “Did the use user the app before 8 PM that day?” and “Did the users use the app after 9 PM the day before?”

Table 4. Median number of sessions per user and median length of sessions (seconds), across 3 arms for the first 30 days since download.

<table>
<thead>
<tr>
<th>Policy implemented within arm</th>
<th>Number of sessions, median (IQR)</th>
<th>Length of sessions (seconds), median (IQR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard policy</td>
<td>10.5 (4-23)</td>
<td>36 (9-115)</td>
</tr>
<tr>
<td>Random policy (MRT)</td>
<td>9 (3-27)</td>
<td>35 (9-113)</td>
</tr>
<tr>
<td>No notification policy</td>
<td>6 (3-21)</td>
<td>43 (12-129)</td>
</tr>
</tbody>
</table>

*MRT: micro-randomized trial.

Time to Disengagement—Survival Analysis

The median time to disengagement was 11 days for users randomized to the standard policy, 11 days for those randomized to the random policy (MRT), and 7 days for those randomized to the no notification policy. The number of disengaged users was 83 for the standard policy, 232 for the random policy (MRT), and 71 for the no notification policy. The log-rank $\chi^2$ test statistic is 1.7, and the corresponding $P$ value is .42.

Figure 2 presents the Kaplan-Meier plot of time to disengagement across the 3 notification policies. This plot provides the estimated survival fraction over the first 30 days from the date of download between the 3 policies with 95% CIs. Although the survival fraction of the no notification policy may seem to accelerate at a faster rate than the other policies over the first week, all 3 policies had similar survival rates by day 23.

Figure 2. Kaplan-Meier plot of time to disengagement across the 3 notification policies. MRT: micro-randomized trial.
Ancillary Analyses

Table 5 reports the estimates of the moderation of near-term notification effect, by recent engagement states, calculated from the MRT. We reported the estimated near-term notification effect for both message types pooled, and by notification type, and the effect is separated out by recent engagement states of habituation (yes or no) and recently engaged (yes or no). We reported the multiplicative difference in the notification effect, which demonstrates how the recent states of engagement modify the notification’s near-term effect. The near-term effect of both message types remains, and none of the estimates of effect moderation are statistically significant because of a limitation of the study lacking in power. If a user received a notification the day before, the near-term notification effect of a standard message is reduced by 11% (RR 0.889, 95% CI 0.60-1.31), whereas the effect of the new notification remains stable (RR 1.013, 95% CI 0.68-1.52). If a user is “already engaged” (they opened the app between 8 PM and 9 PM the day before), the near-term effect of the standard notification remained relatively stable (RR 0.97, 95% CI 0.65-1.42), whereas the near-term effect of the new notification decreased by 20% (RR 0.80, 95% CI 0.55-1.17).

The reported near-term notification effect for a 24-hour period is presented in Table 6. This demonstrates that notifications increase the probability of opening the app by 1.3-fold over a 24-hour period. Both notification types have a similar magnitude of effect.

Table 5. Estimated effect moderation by recent habituation and engagement.

<table>
<thead>
<tr>
<th>Notification type</th>
<th>Estimated effect moderation</th>
<th>Estimated effect moderation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Habituation—“Did the user receive a notification the day before?”</td>
<td>Already engaged—“Did the user open the app between 8 PM and 9 PM the day before?”</td>
</tr>
<tr>
<td></td>
<td>Multiplicative difference in effect (95% CI)</td>
<td>Multiplicative difference in effect (95% CI)</td>
</tr>
<tr>
<td></td>
<td>Relative risk (95% CI)</td>
<td>Ratio (yes or no)</td>
</tr>
<tr>
<td>No</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Pooled</td>
<td>3.645 (2.665-4.987)</td>
<td>3.449 (2.761-4.308)</td>
</tr>
<tr>
<td>Standard</td>
<td>3.935 (2.837-5.458)</td>
<td>3.497 (2.739-4.465)</td>
</tr>
<tr>
<td>New message</td>
<td>3.357 (2.381-4.732)</td>
<td>3.401 (2.692-4.298)</td>
</tr>
</tbody>
</table>

All models are adjusted for the continuous variables of age; Alcohol Use Disorders Identification Test score; days since download; the categorical variables of sex and employment type; the time-varying variables “Did the users open the app before 8 PM that day?” and “Did the users open the app after 9 PM the day before?”; and the effect moderation variable of habituation.

Table 6. Post hoc analysis—estimated near-term notification effect, defined over 24 hours (from 8 PM to 8 PM the next day).

<table>
<thead>
<tr>
<th>Notification type</th>
<th>Relative risk (95% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pooled</td>
<td>1.260 (1.187-1.337)</td>
</tr>
<tr>
<td>Standard</td>
<td>1.245 (1.161-1.336)</td>
</tr>
<tr>
<td>New message</td>
<td>1.274 (1.193-1.360)</td>
</tr>
</tbody>
</table>

All models are adjusted for the continuous variables of age, Alcohol Use Disorders Identification Test score, days since download, the categorical variables of sex and employment type, and the time-varying variables “Did the user the app before 8 PM that day?” and “Did the users use the app after 9 PM the day before?”

Discussion

Principal Findings

We have shown that for Drink Less, there is a large near-term (3.5-fold) positive effect on engagement. The near-term notification effect for either the standard message type or a message from the new bank has similar effects on increasing engagement in the subsequent hour. Over a 24-hour period, a smaller, significant effect (1.3-fold) remained. We did not detect a significant change in the effects of notifications over time. The effect of receiving a new message that aims to reengage users was not significantly reduced by 20% if the user was already engaged. Furthermore, the effect of receiving a standard message was not significantly reduced by 12% if the user received a notification the previous day. There was no significant difference in (1) the mean number of days to disengagement, (2) the number of sessions, and (3) the length of sessions across the 3 different notification policies. However, a slightly longer median length of time was observed for a session under the no notification policy. One might hypothesize that unprompted behavioral engagement may include more attentive interest and cognitive investment.

In our study, despite evidence of a large positive notification effect on near-term engagement, an overall policy of sending a fixed daily notification or a random mix of notifications did not...
lengthen the time to disengagement or increase the amount of engagement during the first 30 days of since download. The results of the effect moderation analyses, although requiring confirmation in larger studies, suggest that notifications may be better served as dynamic interventions that adapt to a user’s fluctuating patterns of engagement. For example, by sending a notification to users when they are at an increased risk of disengagement, targeting them at that point with a notification intended to increase their perception of the usefulness of the app.

**Future Research to Optimize the Notification Policy**

Our study demonstrated that for *Drink Less*, notification increases near-term engagement. This finding offers the opportunity for behavior change scientists to directly target the precise momentary states of an individual and to develop and implement dynamic theories for behavior change with *Drink Less*.

Efforts to maintain or increase engagement through consistent notifications could overburden or annoy a user, resulting in a state of disengagement with interventions from a previously motivated user [19]. Our findings suggest that the optimal role of notifications in improving long-term engagement is unlikely to be fixed or random components but better placed as dynamic components (ie, varying not randomly but in response to the user’s changing state of engagement and habituation).

The open question now is when do we program notifications to be sent to balance goals of (1) intervening for maximum therapeutic effect based on a user’s internal history with *Drink Less* and external environmental factors; and (2) avoiding states of disengagement because of the burden of unhelpful notifications. To begin to answer this question, we will undertake further modeling of this MRT data to explore the within- and between-user effect of the notification over time and the balance of near-term and long-term effects. We will further analyze the data to understand if cue-to-action messages resulted in the task and to determine if the suggested module was engaged with. We imagine that a further optimized policy would (1) keep more users in a state of engagement for longer by sending fewer notifications than the random or fixed notification policies tested here, (2) have a higher near-term notification effect, and (3) ultimately improve the effectiveness of *Drink Less*. A type of machine learning called reinforcement learning may be helpful to personalize and optimizing the sequence of notifications over time [54,57,58]. The available data from our trial can provide a rich source of information to help guide the initial steps (ie, provide a “warm-start”) of the learning process of a reinforcement learning algorithm to improve engagement for *Drink Less* or other similar behavior change apps [57,59-61].

**Limitations**

**Overview**

Our study was sufficiently powered for the primary objective, to detect a near-term notification effect. However, because we did not achieve our planned sample size, the important secondary objectives of effect moderation over time and time to disengagement between policies were not adequately powered. This resulted in wide CIs and large *P* values for the effect moderation analyses, leaving uncertainties about the existence and magnitude of these effects for the secondary objectives. Further studies with larger sample sizes are required to explore these effects.

There were missing data for a minority of the baseline values for sex and employment type, although our sensitivity analyses showed that the results were not sensitive to how the missing values were imputed.

The values entered for alcohol units consumed as diary entries were deemed too noisy to represent alcohol consumption over time for reasons of bias, extensive missing data, and backfilling (ie, users bulk reporting their drinking outcomes days later). Owing to the priority of not overburdening users with too many notifications sent within a day, our research does not provide a comparison of the near-term effect of the notification for different times of the day.

**Generalizability**

The recruitment period was from January 2 to April 1, 2020, which began with a typical surge in downloads in the new year and ended during the United Kingdom’s first COVID-19 lockdown. Such exogenous shocks to the users’ overall environment during the trial are likely to influence the underlying thoughts, emotions, and behaviors of reducing drinking levels (ie, people were mainly housebound) [62] and hence impact the patterns of engagement with *Drink Less*. The interpretation of the results is an average over this period only, with most of the recruitment occurring before the widespread outbreak in the United Kingdom (Multimedia Appendix 6). We also noted that the median time to disengagement in the standard policy arm (11 days) was much sooner than our data visualization cohort experienced (22 days; [31]).

**Conclusions**

We found a large causal effect of sending notifications on near-term engagement. The probability of opening the app in the immediate hour increased 3.5-fold when receiving a notification compared with not receiving a notification. Notifications are important and effective components of behavior change apps; however, a policy of sending a fixed daily notification or a randomly chosen series of notifications did not increase the amount of engagement or length of time to disengagement for users compared with a policy of no notifications. This suggests that notifications may serve users better when they are implemented as dynamic components, such as sending a notification to increase the perceived usefulness of the app only when the users’ engagement patterns show that they are at risk of disengaging.

Further optimization of the notification policy is required to improve long-term engagement. The next stage of research is to explore how our findings would help develop a policy for *Drink Less* to intervene when a user is likely to benefit from support and keep more users engaged in the first 30 days after download.
Acknowledgments

The development of the Drink Less app was funded by the National Institute for Health Research (NIHR) School for Public Health Research, Society for the Study of Addiction, Cancer Research UK, and the United Kingdom Centre for Tobacco and Alcohol Studies. The NIHR School for Public Health Research is a partnership between the Universities of Sheffield, Bristol, Cambridge, and Imperial; University College London; The London School for Hygiene and Tropical Medicine; The Liverpool and Lancaster Universities Collaboration for Public Health Research (LiLaC); and Fuse—The Centre for Translational Research in Public Health: collaboration between Newcastle, Durham, Northumbria, Sunderland, and Teeside Universities. The views expressed are those of the authors and not necessarily those of the NIHR or Department of Health and Social Care. The United Kingdom Centre for Tobacco and Alcohol Studies is part of the UK Clinical Research Collaboration, Public Health Research Centre of Excellence. Funding from the Medical Research Council, British Heart Foundation, Cancer Research UK, Economic and Social Research Council, and NIHR under the auspices of the UK Clinical Research Collaboration is gratefully acknowledged. The authors would like to thank Dr Dave Crane for his important role in the development and factorial screening trial of the Drink Less app and the National University of Singapore’s Institute of Mathematical Sciences for funding LB and TQ’s visit to the program on the Statistical Methods section for Developing Personalized Mobile Health Interventions. The authors also thank the University College London Tobacco and Alcohol Research Group for their helpful feedback on the draft of this paper.

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Conflicts of Interest

CG is part of the team that developed and evaluated the Drink Less app as part of a randomized controlled trial (ISRCTN64052601) and is a paid scientific consultant for behavior change and lifestyle organization “One Year No Beer.” HWWP has received additional salary support from Public Health England and NHS England. He has a Doctor of Philosophy student who works at and has fees paid by Astra Zeneca and another who works at Better Points. He has research collaborations with Thrive Therapeutic Software Ltd and has one collaboration with Six to Start. He has an engagement project in collaboration with DigitalHealth.London, ZINC, and BMJ Innovations. Other authors declare no conflicts of interest.

Editorial Notice

The editor granted an exception from ICMJE rules mandating prospective registration of randomized trials, because the primary outcome is an engagement measure and not a health outcome. Readers are advised to carefully assess the validity of any potential explicit or implicit claims related to primary outcomes or effectiveness. However, note that the authors made publicly available the submitted preprint of the trial protocol (through JMIR Research Protocols) during recruitment and prior to database lock, clearly stating their trial design, objectives, and outcome measures.

Multimedia Appendix 1

Visual of Drink Less notification as it appears on the users’ notification center.
[DOCX File, 72 KB - mhealth_v11i1e38342_app1.docx ]

Multimedia Appendix 2

Privacy notice.
[DOCX File, 22 KB - mhealth_v11i1e38342_app2.docx ]

Multimedia Appendix 3

Information Sheet.
[DOCX File, 14 KB - mhealth_v11i1e38342_app3.docx ]

Multimedia Appendix 4
References


Bell et al


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53. Bell et alJMIR MHEALTH AND UHEALTH


59. Bell et alJMIR MHEALTH AND UHEALTH


Abbreviations

AUDIT: Alcohol Use Disorders Identification Test
CONSORT: Consolidated Standards of Reporting Trials
EMEE: Estimator for the Marginal Excursion Effect
MOST: Multiphase Optimisation Strategy
MRT: micro-randomized trial
RR: relative risk

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A Smartphone-Based Implicit Theories Intervention for Health Behavior Change: Randomized Trial

Mike Schreiber¹,², DPhil; Simone Dohle²,³, Prof Dr

¹Faculty of Psychology, University of Vienna, Vienna, Austria
²Social Cognition Center Cologne, Department of Psychology, University of Cologne, Cologne, Germany
³Institute of General Practice and Family Medicine, University Hospital Bonn, University of Bonn, Bonn, Germany

Corresponding Author: Mike Schreiber, DPhil
Faculty of Psychology
University of Vienna
Universitätsstr 7
Vienna, 1010
Austria
Phone: 43 1427747353
Email: mike.schreiber@univie.ac.at

Abstract

Background: Implicit theories of health describe individuals’ beliefs about the malleability of health. Individuals with an incremental theory of health believe that health, in general, is malleable, whereas individuals with an entity theory of health endorse the idea that health is largely fixed and predetermined. Previous research has shown that an incremental theory of health is associated with beneficial health outcomes and behaviors. A mobile health implicit theories intervention could be an effective way to increase health-promoting behaviors in the general population.

Objective: The aim of this study was to estimate the effect of a smartphone-based intervention designed to promote an incremental theory of health on the frequency of health-promoting behaviors in everyday life. The study used ecological momentary assessment to measure health behavior change.

Methods: This 2-arm, single-blind, delayed intervention design included 149 German participants (mean age 30.58, SD 9.71 years; n=79 female). Participants were asked to report their engagement in 10 health-promoting behaviors throughout the day for 3 weeks. Participants were randomly assigned to either an early intervention group (n=72) or a delayed intervention group (n=77). The intervention materials, designed to promote an incremental theory of health, were provided to participants after 1 week (early intervention group) or 2 weeks (delayed intervention group) of baseline behavior measurement. Data for this study were collected between September 2019 and October 2019.

Results: A paired-samples 2-tailed t test revealed that participants reported a stronger incremental theory after responding to the intervention materials (mean 5.58, SE 0.07) compared with incremental theory measured in an entry questionnaire (mean 5.29, SE 0.08; t₁₄₈=4.07, SE 0.07; P<.001; 95% CI 0.15-0.43; d=0.33). Multilevel analyses showed that participants reported engaging in health-promoting behaviors more often after being presented with the intervention materials compared with baseline across conditions (b=0.14; t₁₄₆.₆₅=2.06, SE 0.07; P=.04; 95% CI 0.01-0.28). However, when the analysis was conducted separately for the early and delayed intervention groups, the intervention effect was only significant for the delayed intervention group (b=0.27; t₁₄₉.₂₇=3.50, SE 0.08; P<.001; 95% CI 0.12-0.42). There was no significant increase in health-promoting behaviors for the early intervention group (b=0.02; t₆₉.₂₃=0.14, SE 0.11; P=.89; 95% CI -0.2 to 0.23).

Conclusions: This study suggests that a smartphone-based intervention designed to promote an incremental theory of health is a cost- and time-effective approach to increase the frequency of engaging in health-promoting behaviors. However, research is needed to understand the reasons for the difference in intervention effects between the early and delayed intervention groups. The results of this study can guide the development of future digital health interventions that focus on implicit theories to promote health behavior change.

Trial Registration: DRKS – German Clinical Trials Register DRKS00017379; https://drks.de/search/de/trial/DRKS00017379

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KEYWORDS
daily diary; ecological momentary assessment; health behavior; implicit theories; lay theories; mindsets; multiple health behavior change; randomized trial; smartphone-based intervention

Introduction

Background

According to the World Health Organization [1], 71% of all worldwide deaths are attributed to noncommunicable diseases like cardiovascular diseases, cancer, respiratory diseases, or diabetes. The risk of having such a disease can decrease by adopting a healthier lifestyle that includes sufficient physical activity, a healthy diet, and avoiding harmful substances like tobacco or alcohol [1,2]. Engagement in such health-promoting behaviors often involves a high level of self-regulatory strategies [3,4]. An essential prerequisite for successful self-regulatory processes is implicit theories [5]. Implicit theories (sometimes also framed as mindsets or lay theories) refer to people’s beliefs about the changeability of human attributes and characteristics [5,6]. According to Dweck’s [6] framework, people differ in the extent to which they hold an incremental theory, that is, assuming that a given attribute is developable and malleable, versus an entity theory, that is, assuming that an attribute is fixed and stable. Recent research shows that a stronger incremental theory of health has a positive influence on maintaining a healthy lifestyle across multiple health behavior domains [7-10]. Extending these findings, the main aim of this randomized trial was to investigate whether promoting an incremental theory of health increases the frequency of performing health-promoting behaviors in daily life.

Implicit Theories

Early research about implicit theories mainly focused on assumptions about the changeability of intelligence [11,12] or personality [13]. Since this first research, implicit theories have been studied across a wide array of domains like willpower [14,15], morality [16], stereotypes [17], and interpersonal relationships [18]. The majority of studies found that holding a stronger incremental theory in one domain (ie, assuming that the given characteristic is malleable) leads to positive outcomes [5,19]. For example, in a meta-analysis across 113 studies, holding an incremental theory was found to predict successful goal setting, goal monitoring, and goal operating, and, in turn, better self-regulation [5]. Therefore, researchers have developed many interventions to foster an incremental theory to create positive changes for individuals. The modes of delivering such interventions range from single-session approaches [20,21] to multisession approaches [12,22] and large-scale educational programs (eg, the Project for Educational Research That Scales [23]).

In the past decade, research about implicit theories has also become popular in different health domains, like weight management [22,24-26], physical activity [27,28], smoking [29,30], addiction [31,32], and mental health [21,33]. For example, it has been shown that an incremental theory can protect against setback-related weight gain [22], is related to higher motivation and intention to achieve a healthy weight [26], leads to greater motivation to quit smoking [31], and decreases anxiety and depressive symptoms [21].

Implicit theories in different domains are not necessarily interconnected [6,34]. For example, one might believe that one’s body weight is rather fixed around a given set point while also thinking that smoking behavior can be changed easily. Therefore, implicit theories have not only been studied in single health domains but also for health in general. Such generalized implicit theories have been examined concerning their impact on multiple health behavior domains [7-10]. In that sense, an incremental theory of (general) health regards the assumption that health is malleable and changeable, whereas an entity theory of health implies that health is perceived as fixed and stable [7-9]. Correlational research has shown that holding an incremental theory of health is related to performing health-promoting [7] and health-protective behaviors [10]. In addition, experimental findings suggest that a strengthened incremental theory of health leads to more positive attitudes toward different health-promoting behaviors [7], stronger intentions to eat healthily [8], and healthier food choices [7]. Previous research is therefore limited. Although correlational research shows evidence for the importance of an incremental theory of health for a healthy lifestyle, it cannot be interpreted causally. Existing experimental studies, on the other hand, generally focus only on one health behavior (eg, eating behavior). Therefore, the main purpose of this study is to investigate whether an intervention that promotes an incremental theory of health influences a variety of health-promoting behaviors. Compared with an intervention that focuses only on implicit theories in a single health domain (eg, body weight or physical activity), focusing on implicit theories of general health may serve as an efficient strategy to encourage multiple health behavior change. In contrast to stationary settings, the delivery of this intervention via digital technologies offers the opportunity to reach a larger audience in a sustainable manner while minimizing implementation costs [35,36]. To increase ecological validity and to minimize recall and retrieval bias, engagement in health-promoting behaviors is measured using ecological momentary assessment in the form of daily diaries [37]. Similarly, it has been shown that stronger incremental theories of health were connected to a higher frequency of performing health-promoting behaviors in daily life measured using experience sampling (study 4) [7]. As these results were only correlational, the present research aims to provide causal insights into whether an intervention to foster incremental theories increases health behaviors in daily life. Therefore, we make the following hypothesis: Being confronted with a smartphone-based intervention to foster incremental theories of health increases the frequency of performing health-promoting behaviors in daily life.
Methods

Study Design

We conducted a 2-arm, randomized trial to investigate whether fostering an incremental theory of health increases the frequency of performing health-promoting behaviors in daily life. The intervention was conceptualized as a delayed-start design [38,39], in which both groups received intervention material at different times. The intervention was delivered via participants’ smartphones using Qualtrics (Qualtrics International) questionnaires and included that participants kept a daily diary for 3 weeks. Participants were randomly assigned (single-blind) to an early or delayed intervention group using Qualtrics’ randomizer while maintaining an evenly distributed number of participants in each group (1:1 block randomization).

At the beginning of the study (day 0), all participants responded to an entry questionnaire to measure implicit theories of health, health locus of control, health-related self-efficacy, health-related outcome expectancy, health status, health value, health change motivation, and anthropometric (height and weight) and demographic variables (age, gender, education, and occupation). One day after responding to the entry questionnaire, the daily diary phase started. Over the course of 3 weeks (21 days), participants received daily invitations to complete a short questionnaire via texting distributed via SurveySignal [40]. Participants received the invitations daily at 8 PM and had to respond within 4 hours. In these daily questionnaires, participants were asked to indicate whether they performed 10 different health-promoting behaviors throughout the respective day. The number of daily performed health-promoting behaviors served as primary outcome measure. Depending on the assigned condition, participants received intervention materials to foster an incremental theory either after 7 (early intervention group) or 14 days (delayed intervention group) of baseline behavior measurement. After 21 days, we invited participants to participate in a follow-up questionnaire measuring the same constructs—except anthropometric and demographic items—as in the entry questionnaire. Table 1 provides an overview of the study’s design.

We chose the delayed-start design as it allows testing for intervention effects between and within both intervention arms [38,39] and helps to disentangle the effects of the intervention itself and the self-monitoring due to the daily diaries. Furthermore, including a baseline in both groups helps participants to get used to the daily diary approach and allows for longitudinal comparisons (before vs after reading the intervention materials).

<table>
<thead>
<tr>
<th>Group</th>
<th>Day 0</th>
<th>Days 1-7</th>
<th>Days 8-14</th>
<th>Days 15-21</th>
<th>Day 22</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early intervention</td>
<td>Entry questionnaire</td>
<td>Baseline measurement</td>
<td>Postintervention measurement</td>
<td>Postintervention measurement</td>
<td>Follow-up questionnaire</td>
</tr>
<tr>
<td>group</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Delayed intervention</td>
<td>Entry questionnaire</td>
<td>Baseline measurement</td>
<td>Baseline measurement</td>
<td>Postintervention measurement</td>
<td>Follow-up questionnaire</td>
</tr>
<tr>
<td>group</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Ethics Approval

Data collection for this study was performed between September 13, 2019, and October 10, 2019. The study was approved by the faculty’s ethics commission (ID MSHF0047). It was registered as a randomized trial in the German Clinical Trials Register (trial number DRKS00017379) and was preregistered in the Open Science Framework (OSF [41]).

Sample Size Calculation

Sample size was determined before data collection using G*Power (version 3; Heinrich-Heine-Universität Düsseldorf) [42] based on an expected effect size of $f = 0.15$ (with $\alpha = .05$ and $1-\beta = .90$). The calculation resulted in a required total sample size of 96 participants. Because we also planned to run multilevel models, a total sample size of 120 was targeted to increase the probability of achieving model convergence. As described further in the Results section, main analyses were performed using data from 149 participants.

Recruitment, Eligibility Criteria, and Compensation

Participants were recruited via the institutes’ participant pool and social media postings. Eligibility criteria were a minimum age of 18 years, owning a smartphone with touch display and mobile internet access, and being able to answer daily questionnaires for 21 days. All participants received financial compensation for their participation: €3 (US $3.26) each for completing the entry and follow-up questionnaire, €4 (US $4.35) for responding to the intervention materials, €0.25 (US $0.27) for each completed daily questionnaire, and a bonus of €10 (US $10.87) for responding to more than 17 (80%) of the daily questionnaires (in total, up to €25.25; US $27.46).

Measures

Table 2 provides an overview of the measures included in the different questionnaires of the intervention and informs about the internal consistency of the included scales. Internal consistency of all scales ranged between $\alpha = .74$ and $\alpha = .88$ and can be considered good.
Table 2. Overview of variables and Cronbach α of the scales measured in different intervention parts. Check marks indicate that a measure was used in that part of the study.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Entry</th>
<th>Intervention</th>
<th>Follow-up</th>
</tr>
</thead>
<tbody>
<tr>
<td>Implicit Theories of Health Scale</td>
<td>✓ (α=.88)</td>
<td>✓ (α=.85)</td>
<td>✓ (α=.87)</td>
</tr>
<tr>
<td>Internal health locus of control</td>
<td>✓ (α=.76)</td>
<td>✓ (α=.83)</td>
<td>✓ (α=.85)</td>
</tr>
<tr>
<td>Chance health locus of control</td>
<td>✓ (α=.82)</td>
<td>✓ (α=.88)</td>
<td>✓ (α=.80)</td>
</tr>
<tr>
<td>Powerful others locus of control</td>
<td>✓ (α=.74)</td>
<td>✓ (α=.80)</td>
<td>✓ (α=.79)</td>
</tr>
<tr>
<td>Health-related self-efficacy</td>
<td>✓ (α=.85)</td>
<td>✓ (α=.83)</td>
<td>✓ (α=.79)</td>
</tr>
<tr>
<td>Health-related outcome expectancy</td>
<td>✓ (α=.77)</td>
<td>✓ (α=.79)</td>
<td>✓ (α=.79)</td>
</tr>
<tr>
<td>Health status</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Health value</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Change motivation (self)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Change motivation (others)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Age</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Gender</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Height</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Weight</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Education</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Occupation</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

**Implicit Theories**

The Implicit Theories of Health Scale (ITHS) [7] was used to measure implicit theories of health. The scale consists of 6 items (eg, “You can substantially change your own health”). Three items represent an incremental theory of health, and 3 items represent an entity theory of health (which were recoded). Answers were given on 7-point Likert scales (1=strongly disagree to 7=strongly agree). A mean across all items was computed, with higher values indicating a stronger incremental theory.

**Health-Promoting Behaviors**

In the daily diaries, participants were asked every day whether they performed 10 health-promoting behaviors throughout the respective day (see Textbox 1; 0=no, 1=yes). We measured only behaviors (1) that could be performed during a regular day, (2) that were based on national recommendations from public health authorities (eg, Federal Centre for Health Education), and (3) that showed no ceiling or floor effect regarding the frequency of performing these behaviors, determined in a pretest (n=325). Concerning the latter, we did not include behaviors such as brushing one’s teeth or washing one’s hands because the pretest showed that almost all participants conducted these behaviors daily. The sum of performed health-promoting behaviors per day served as the primary outcome measure.
Textbox 1. Items to measure the frequency of performing health-promoting behaviors.

<table>
<thead>
<tr>
<th>Nutrition</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>I ate at least 2 servings of fruit</td>
<td></td>
</tr>
<tr>
<td>I ate at least 3 servings of vegetables</td>
<td></td>
</tr>
<tr>
<td>I did not eat sweets</td>
<td></td>
</tr>
<tr>
<td>I drank at least 2 liters of water</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Physical activity</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>I have been physically active for at least 30 minutes, so I started to sweat and/or was slightly out of breath</td>
<td></td>
</tr>
<tr>
<td>I walked or cycled at least 6.5 kilometers</td>
<td></td>
</tr>
<tr>
<td>I exercised</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Relaxation</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>I took some time to relax</td>
<td></td>
</tr>
<tr>
<td>I slept for at least 7 hours</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Hygiene</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>I used dental floss</td>
<td></td>
</tr>
</tbody>
</table>

Control Variables

Additionally, we measured health-related locus of control, self-efficacy, outcome expectancy, change motivation, health status, and health value. We included these variables to ensure (1) that the 2 intervention groups did not differ significantly regarding these constructs at baseline and (2) that the intervention only leads to changes in implicit theories and not the other constructs.

Health Locus of Control

The Health- and Illness-Related Locus of Control Questionnaire (Kontrollüberzeugung zu Krankheit und Gesundheit; KKG) [43] was used to measure health locus of control. The KKG consists of 21 items, all answered on 6-point Likert scales (1=strongly disagree to 6=strongly agree). Similar to its English equivalent [44], the KKG consists of 3 subscales (with 7 items each) to measure internal (eg, “If I do not feel well physically, I have to blame myself”), powerful others (eg, “If I feel well physically, then I owe it mainly to the advice and help of others”), and chance health locus of control (eg, “Whether my symptoms last longer depends mainly on chance”).

Health-Related Self-Efficacy

The Perceived Health Competence Scale [45] was used to measure health-related self-efficacy. The scale consists of 8 items (eg, “I’m generally able to accomplish my goals with respect to my health”) measured on 5-point Likert scales (1=strongly disagree to 5=strongly agree).

Health-Related Outcome Expectancy

Health-related outcome expectancy was measured using 6 statements to assess how much participants agree that specific health behaviors can influence one’s own health (“Your health is strongly influenced by...eating behavior...physical activity and exercising...consumption of harmful substances...enough sleep and relaxation...personal and dental hygiene...regular doctor visits, and checkups”). Participants’ agreement was assessed via 7-point Likert scales (1=strongly disagree to 7=strongly agree).

Further Health-Related Variables

Single items measured current subjective health status (“How would you describe your health status in general?”; 1=bad to 7=excellent), health value (“How important is your health to you?”; 1=not at all important to 7=very important), and the extent to which participants think that they should change their health from their point of view (“It is important to me to change something about my health”; 1=strongly disagree to 7=strongly agree) and from the perspective of others (“From the perspective of others, I should change something about my health”; 1=strongly disagree to 7=strongly agree).

Intervention Materials

Participants received a link to the intervention materials on their smartphones either after 7 (early intervention group) or 14 days (delayed intervention group) of baseline measurement. The links to view the intervention materials were sent out at 8 AM on the specified day (day 8 or 15), and the individual links were available until 8 PM on that day. Like other interventions to promote incremental theories [12,20,22], the intervention materials consisted of informative, exemplary, and reflective components. More precisely, the intervention materials included (1) a (fictitious) newspaper article that described health as mainly influenced by lifestyle and engagement in health-promoting behavior [7], (2) three fictitious blog posts in which individuals reported positive health changes, (3) an essay priming in which participants were asked to describe health changes in their lives, and (4) an article that focused on the benefits of beliefs in changeability in other domains. The materials are available in the OSF repository [41]. After reading the articles and the 3 blog posts, participants answered one question regarding the content of the materials as an attention check.
check. In addition, an independent rater checked the content of the essays to determine whether the participants followed the task description. On the basis of this, we calculated an attention check score, ranging from 1 to 4, with 4 points indicating that all content questions were answered correctly and that the essay fitted the instruction.

**Results**

**Participants**

Initially, 393 participants were screened regarding eligibility criteria (see the CONSORT [Consolidated Standards of Reporting Trials] flow diagram, Figure 1). A total of 254 participants were randomly assigned to 1 of the 2 intervention arms (early vs delayed intervention). As some participants discontinued their participation or did not respond to the intervention materials, 162 participants received the allocated intervention (81 participants in both intervention arms). Participants were excluded from data analysis when they did not complete the entry questionnaire (early intervention: \( n=8 \); delayed intervention: \( n=4 \)) or did not respond to the daily diaries during the first week (early intervention: \( n=1 \)). No participants were excluded based on their attention check scores, as all remaining participants scored 2 points or higher. Further, a regression analysis revealed that the attention check scores did not have an impact on the change in implicit theories measured in the entry questionnaire versus directly after seeing the intervention materials (\( b = 0.19; t_{147} = 0.73, SE = 0.26; P = .47; 95\% CI = -0.32 \) to 0.70). Consequently, main analyses were performed with 149 participants (early intervention: \( n=72 \); delayed intervention: \( n=77 \)). The mean age of the analyzed sample was 30.58 (SD 9.71) years, with 52% (79/149) female and 47% (70/149) male participants. Table 3 includes other demographic characteristics, and the CONSORT flow diagram (Figure 1) provides an overview of participant flow and informs about dropout reasons in each intervention group. For additional follow-up analyses, data of 138 participants were available.

**Figure 1.** CONSORT (Consolidated Standards of Reporting Trials) flow diagram.
Table 3. Baseline characteristics of participants in total and by intervention group (n=149).

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Overall (n=147)</th>
<th>Early (n=72)</th>
<th>Delayed (n=75)</th>
<th>Condition difference</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years), mean (SD)</td>
<td>30.58 (9.71)</td>
<td>31.31 (10.44)</td>
<td>29.91 (8.98)</td>
<td>0.88 (147)</td>
<td>.38</td>
</tr>
<tr>
<td>Implicit theories, mean (SD)</td>
<td>5.29 (0.99)</td>
<td>5.36 (1.06)</td>
<td>5.22 (0.92)</td>
<td>0.86 (147)</td>
<td>.39</td>
</tr>
<tr>
<td>Internal locus, mean (SD)</td>
<td>3.78 (0.70)</td>
<td>3.87 (0.72)</td>
<td>3.69 (0.67)</td>
<td>1.61 (147)</td>
<td>.11</td>
</tr>
<tr>
<td>Powerful others locus, mean (SD)</td>
<td>2.90 (0.73)</td>
<td>2.92 (0.73)</td>
<td>2.88 (0.73)</td>
<td>0.34 (147)</td>
<td>.73</td>
</tr>
<tr>
<td>Chance locus, mean (SD)</td>
<td>2.35 (0.74)</td>
<td>2.39 (0.79)</td>
<td>2.32 (0.70)</td>
<td>0.60 (147)</td>
<td>.55</td>
</tr>
<tr>
<td>Self-efficacy, mean (SD)</td>
<td>3.52 (0.68)</td>
<td>3.54 (0.71)</td>
<td>3.51 (0.64)</td>
<td>0.26 (147)</td>
<td>.80</td>
</tr>
<tr>
<td>Outcome-expectancy, mean (SD)</td>
<td>5.56 (0.83)</td>
<td>5.63 (0.81)</td>
<td>5.49 (0.84)</td>
<td>1.02 (147)</td>
<td>.31</td>
</tr>
<tr>
<td>Height (in meters), mean (SD)</td>
<td>174.60 (9.63)</td>
<td>175.21 (9.38)</td>
<td>174.04 (9.89)</td>
<td>0.74 (147)</td>
<td>.46</td>
</tr>
<tr>
<td>Weight (in kilogram), mean (SD)</td>
<td>77.82 (18.88)</td>
<td>78.18 (21.26)</td>
<td>77.49 (16.51)</td>
<td>0.22 (146)</td>
<td>.82</td>
</tr>
<tr>
<td>BMI, mean (SD)</td>
<td>25.37 (5.17)</td>
<td>25.22 (5.43)</td>
<td>25.52 (4.95)</td>
<td>0.35 (146)</td>
<td>.72</td>
</tr>
<tr>
<td>Health status, mean (SD)</td>
<td>4.99 (1.15)</td>
<td>4.97 (1.13)</td>
<td>5.00 (1.18)</td>
<td>0.15 (147)</td>
<td>.88</td>
</tr>
<tr>
<td>Health value, mean (SD)</td>
<td>6.11 (0.98)</td>
<td>5.97 (1.07)</td>
<td>6.23 (0.87)</td>
<td>1.64 (147)</td>
<td>.10</td>
</tr>
<tr>
<td>Change motivation (self), mean (SD)</td>
<td>5.50 (1.22)</td>
<td>5.43 (1.27)</td>
<td>5.56 (1.18)</td>
<td>0.64 (147)</td>
<td>.52</td>
</tr>
<tr>
<td>Change motivation (others), mean (SD)</td>
<td>3.37 (1.77)</td>
<td>3.44 (1.68)</td>
<td>3.30 (1.86)</td>
<td>0.50 (147)</td>
<td>.62</td>
</tr>
</tbody>
</table>

Gender, n (%)

<table>
<thead>
<tr>
<th></th>
<th>Overall (n=147)</th>
<th>Early (n=72)</th>
<th>Delayed (n=75)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>70 (47)</td>
<td>29 (40)</td>
<td>41 (53)</td>
<td>2.51 (1)</td>
</tr>
<tr>
<td>Female</td>
<td>79 (53)</td>
<td>43 (60)</td>
<td>36 (47)</td>
<td></td>
</tr>
</tbody>
</table>

Education, n (%)

<table>
<thead>
<tr>
<th></th>
<th>Overall (n=147)</th>
<th>Early (n=72)</th>
<th>Delayed (n=75)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower secondary school</td>
<td>4 (2.7)</td>
<td>2 (3)</td>
<td>2 (3)</td>
<td>3.66 (4)</td>
</tr>
<tr>
<td>Secondary school</td>
<td>10 (6.7)</td>
<td>4 (6)</td>
<td>6 (8)</td>
<td></td>
</tr>
<tr>
<td>Entitlement to study at a university of applied sciences</td>
<td>3 (2)</td>
<td>3 (4)</td>
<td>0 (0)</td>
<td></td>
</tr>
<tr>
<td>Higher education entrance qualification (&quot;Abitur&quot;)</td>
<td>61 (40.9)</td>
<td>28 (39)</td>
<td>33 (43)</td>
<td></td>
</tr>
<tr>
<td>University degree</td>
<td>71 (47.7)</td>
<td>35 (49)</td>
<td>36 (47)</td>
<td>8.90 (6)</td>
</tr>
</tbody>
</table>

Occupation, n (%)

<table>
<thead>
<tr>
<th></th>
<th>Overall (n=147)</th>
<th>Early (n=72)</th>
<th>Delayed (n=75)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full-time employed</td>
<td>40 (26.8)</td>
<td>24 (33)</td>
<td>16 (21)</td>
<td></td>
</tr>
<tr>
<td>Part-time employed</td>
<td>13 (8.7)</td>
<td>4 (6)</td>
<td>9 (12)</td>
<td></td>
</tr>
<tr>
<td>Studying</td>
<td>81 (54.4)</td>
<td>36 (50)</td>
<td>45 (58)</td>
<td></td>
</tr>
<tr>
<td>Stay-at-home spouse</td>
<td>3 (2)</td>
<td>0 (0)</td>
<td>3 (4)</td>
<td></td>
</tr>
<tr>
<td>Retired</td>
<td>5 (3.4)</td>
<td>3 (4)</td>
<td>2 (3)</td>
<td></td>
</tr>
<tr>
<td>Occupational disability</td>
<td>3 (2)</td>
<td>2 (3)</td>
<td>1 (1)</td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>4 (2.7)</td>
<td>3 (4)</td>
<td>1 (1)</td>
<td></td>
</tr>
</tbody>
</table>

a These values are the t (df).
b These values are the chi-square.

Precursory Analyses

As depicted in Table 2, there were no significant differences between the 2 intervention groups regarding demographics or other measures included in the entry questionnaire, suggesting that the randomization was successful. Participants answered a total of 3015 daily questionnaires; on average, each participant answered 20.23 (SD 1.42, range 12-21) questionnaires.
As a manipulation check, a paired-samples 2-tailed $t$ test with ITHS scores measured in the entry questionnaire and ITHS scores after responding to the intervention materials was performed to test whether the intervention led participants to adopt a stronger incremental theory. This $t$ test revealed that participants reported a stronger incremental theory after responding to intervention materials (mean 5.58, SE 0.07), compared with the entry questionnaire (mean 5.29, SE 0.08; $t_{148}=4.07$, SE 0.07, $P<.001$, 95% CI 0.15-0.43, $d=0.33$). Further, a 2 (intervention group: early vs delayed) by 2 (time of assessment: entry questionnaire vs directly after seeing the intervention materials) mixed ANOVA revealed that the intervention led to an increase in incremental theories in both groups indicated by a significant main effect of time of implicit theories assessment ($F_{1,147}=16.42; P<.001; \eta^2_p=10$), a nonsignificant main effect of intervention group ($F_{1,147}=1.19; P=.28; \eta^2_p=.01$), and a nonsignificant interaction ($F_{1,147}=0.02; P=.89; \eta^2_p<.01$).

### Main Analyses

Based on the preregistration [41], a mixed ANOVA was conducted to test whether the intervention increased the frequency of performing health-promoting behaviors on a weekly level. As within-subject factor, the mean number of health-promoting behaviors per day was aggregated for every week, and intervention group (early versus delayed) was entered as between-subject factor. The results of the mixed ANOVA showed no significant main effect of the intervention group ($F_{1,147}=0.92; P=.34; \eta^2_p=.01$). There was also no significant difference between mean daily performed behaviors per week ($F_{2,294}=1.46; P=.23; \eta^2_p=.01$). However, a significant interaction between the intervention group and week emerged ($F_{2,294}=3.06; P=.048; \eta^2_p=.02$). Table 4 shows marginal means, SEs, and 95% CIs for daily performed behaviors per week for both intervention groups, and Figure 2 illustrates the interaction.

### Table 4. Marginal means, SEs, and 95% CIs for mean performed health behaviors per day as a result of the condition × time in a mixed ANOVA.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Mean (SE)</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Early intervention</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Week 1</td>
<td>4.60 (0.17)</td>
<td>4.27-4.92</td>
</tr>
<tr>
<td>Week 2</td>
<td>4.64 (0.18)</td>
<td>4.29-4.99</td>
</tr>
<tr>
<td>Week 3</td>
<td>4.56 (0.18)</td>
<td>4.21-4.91</td>
</tr>
<tr>
<td><strong>Delayed intervention</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Week 1</td>
<td>4.70 (0.16)</td>
<td>4.38-5.01</td>
</tr>
<tr>
<td>Week 2</td>
<td>4.75 (0.17)</td>
<td>4.42-5.09</td>
</tr>
<tr>
<td>Week 3</td>
<td>4.99 (0.17)</td>
<td>4.65-5.33</td>
</tr>
</tbody>
</table>

**Figure 2.** Mean number of performed health-promoting behaviors per day aggregated on a weekly level for both intervention groups.
As the marginal means and their corresponding confidence intervals did not show significant differences between both groups in any week, the preregistered t tests were not conducted. However, as depicted in Figure 2 and indicated by the significant interaction between time and condition, the delayed intervention group may have benefitted from viewing the intervention materials. Therefore, the preregistered multilevel models were performed to test whether the intervention increased the frequency of performing health-promoting behaviors on a daily level. Day was treated as the level 1 unit and participant as the level 2 unit. Intervention status (0=before intervention, 1=after intervention) served as the level 1 predictor, whereas the number of performed health-promoting behaviors served as the level 1–dependent variable. A deviance test was conducted for each analysis to test whether a random-slope or a random-intercept model results in a better model fit. Across both intervention groups, the better fitting random-slope model showed an increase in the number of performed health-promoting behaviors after responding to the intervention materials ($b=0.14; t_{146.65}=2.06, SE 0.07; P=.04, 95% CI 0.01-0.28$). Because of the significant interaction between time and condition found in the mixed ANOVA, additional multilevel models were conducted separately for both intervention groups. These multilevel models revealed that the effect of the intervention only appeared for the delayed intervention group ($b=0.27; t_{140.27}=3.50, SE 0.08; P<.001$; 95% CI 0.12-0.42). In contrast, no difference before and after the intervention was detected for the early intervention group (random-slope model, $b=0.02; t_{69.23}=0.14, SE 0.11; P=.89; 95% CI −0.2 to 0.23$). The information criteria and results of the likelihood-ratio tests for comparing the multilevel models are available in Table S1 in Multimedia Appendix 1.

### Additional Analyses

Additional analyses revealed that participants did also report a stronger incremental theory in the follow-up questionnaire (mean 5.42, SE 0.08) compared with the entry questionnaire (mean 5.24, SE 0.08; $t_{137}=2.42, SE 0.07; P=.02; 95% CI 0.03-0.32; d=0.20$). Furthermore, participants reported a stronger internal health locus of control in the follow-up questionnaire (mean 3.92, SE 0.06) compared with the entry questionnaire (mean 3.78, SE 0.06; $t_{137}=3.17, SE 0.04; P=.002; 95% CI 0.05-0.23; d=0.28$). To test whether our intervention also led to an increase in health-promoting behaviors when controlling for the change in internal health locus of control, we performed additional multilevel models, including the change in internal health locus of control as the level 2 predictor. Table 5 shows that these robustness checks led to the same conclusions as the multilevel models described in the previous section. For all other health-related variables, no significant difference between the entry and follow-up questionnaire emerged.

### Table 5.

<table>
<thead>
<tr>
<th>Variable</th>
<th>$B$</th>
<th>SE</th>
<th>$t$ (df)</th>
<th>$P$ value</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicting health-promoting behaviors per day (across conditions)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>4.70</td>
<td>0.11</td>
<td>39.54 (135.72)</td>
<td>$&lt;.001$</td>
<td>4.46 to 4.93</td>
</tr>
<tr>
<td>Time (0=before intervention; 1=after intervention)</td>
<td>0.15</td>
<td>0.07</td>
<td>2.15 (135.78)</td>
<td>.03</td>
<td>0.01 to 0.29</td>
</tr>
<tr>
<td>Change (internal health locus)</td>
<td>0.13</td>
<td>0.22</td>
<td>0.61 (136.14)</td>
<td>.54</td>
<td>−0.29 to 0.56</td>
</tr>
<tr>
<td>Predicting health-promoting behaviors per day (early intervention group)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>4.69</td>
<td>0.18</td>
<td>26.07 (63.58)</td>
<td>$&lt;.001$</td>
<td>4.33 to 5.05</td>
</tr>
<tr>
<td>Time (0=before intervention; 1=after intervention)</td>
<td>0.04</td>
<td>0.11</td>
<td>0.37 (64.44)</td>
<td>.71</td>
<td>−0.18 to 0.26</td>
</tr>
<tr>
<td>Change (internal health locus)</td>
<td>0.40</td>
<td>0.33</td>
<td>1.22 (65.83)</td>
<td>.23</td>
<td>−0.25 to 1.05</td>
</tr>
<tr>
<td>Predicting health-promoting behaviors per day (delayed intervention group)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>4.78</td>
<td>0.17</td>
<td>27.54 (72.11)</td>
<td>$&lt;.001$</td>
<td>4.44 to 5.13</td>
</tr>
<tr>
<td>Time (0=before intervention; 1=after intervention)</td>
<td>0.26</td>
<td>0.08</td>
<td>3.30 (1374.34)</td>
<td>$&lt;.001$</td>
<td>0.11 to 0.42</td>
</tr>
<tr>
<td>Change (internal health locus)</td>
<td>−0.14</td>
<td>0.30</td>
<td>−0.46 (68.83)</td>
<td>.65</td>
<td>−0.74 to 0.46</td>
</tr>
</tbody>
</table>

### Discussion

#### Principal Findings

The present research aimed to examine whether a smartphone-based intervention to foster incremental theories of health increases the frequency of performing health-promoting behaviors in daily life measured via ecological momentary assessment. Indicated by our manipulation check, we found that the intervention led to stronger incremental theories of health. Furthermore, across conditions, participants showed a significant increase in the frequency of performing health-promoting behaviors after being confronted with the intervention materials. However, this effect was only driven by the delayed intervention group, whereas the early intervention group did not increase in health-promoting behaviors.

One possible explanation for why the effectiveness of the intervention differed between intervention groups may be that incremental theories may only have a beneficial effect in the long run. As depicted in Figure 2, both intervention groups showed a slight increase in health-promoting behaviors between the first and second week. This could be due to the involvement of self-monitoring evoked by the daily diaries, which can have...
an intervention effect itself [46]. Being confronted with the intervention materials at an early stage (week 1) did not seem to have any additional motivational benefit for the early intervention group. On the other hand, the delayed intervention group was confronted with the fact that they only showed half of the measured behaviors every day for 2 weeks. Being shown the intervention materials at this point in time (week 2) had an additional motivating effect beyond the effect of self-monitoring. Instead, the early intervention group shows a decline in health-promoting behaviors in the third week without an additional boost in motivation. This pattern fits Yeager and Dweck’s [47] argument that incremental theories are especially helpful when challenges arise (like continually maintaining the motivation to engage in health-promoting behaviors over 3 weeks). As this explanation is only speculative, further research is needed to investigate whether the observed time-dependent effectiveness of the intervention replicates consistently or has resulted by chance.

Although no intervention effect emerged for the early intervention group, the introduced intervention led to changes in health behavior for the delayed intervention group. Thus, this study is the first to show that implicit theories of health can be influenced through an intervention delivered in people’s daily lives. It provides further evidence of the relevance of these theories for health behavior change across multiple health domains and extends the existing correlative and experimental findings on implicit theories of health [7-10]. The results show that even a one-shot implicit theory intervention via web-based materials can increase engagement in health-promoting behaviors. Hence, this approach represents a time-, effort-, and cost-efficient way for health promotion. This study also increases the ecological validity of previous findings by measuring health-promoting behaviors using ecological momentary assessment [37]. We show that incremental theories are relevant not only in laboratory research or one-shot web-based questionnaires but also to everyday behavior.

Additional analyses revealed that the intervention-based increase in incremental theories of health is not just short-term, as participants also reported stronger incremental theories in the follow-up questionnaire (compared with the entry questionnaire). In addition, the present intervention led to a stronger internal health locus of control. This is consistent with previous findings showing that a stronger internal health locus of control mediates the effect of an implicit theories of health manipulation on health-promoting outcomes [7]. It also fits findings that an incremental theory of personality intervention increases primary control in the context of mental illness [20,21]. It remains to be tested whether the change in internal health locus of control stems from the intervention materials, the daily diary assessment, or the combination of both.

**Limitations and Generalizability**

We chose a delayed-start design to test for intervention effects between and within both intervention groups. However, we did not find a difference in health behavior engagement between the 2 groups in the second week of our assessment. Future trials should include a no-treatment control group that does not receive intervention materials. This approach makes it possible to determine whether the pre-post difference in behavior in the delayed intervention group appeared because of the intervention materials or because of the combination of the intervention materials with daily diaries.

We incorporated ecological momentary assessment in which participants were asked daily whether they performed 10 health-promoting behaviors using a simple yes-no format. This format allows for more objective and reliable measures of self-reported health behavior engagement with less recall and retrieval bias compared with standard forms of measurement in which individuals usually have to recall behavior engagement over longer periods (like weeks or months) [37]. However, these self-reports can still be affected by social desirability. Therefore, future studies could incorporate more objective measurements of health behavior engagement, like taking pictures of meals to measure eating behavior or using smartwatches or other devices to measure physical activity (for a physical activity example, see Henderson et al [48]).

Regarding the generalizability of findings, it is essential to note that the surveyed sample differs from the general population, especially regarding age, educational level, and student proportion. Participation in the study required owning a smartphone with internet access, and recruitment was realized via social media and mailing lists. This has limited the study’s accessibility for individuals of older age. Moreover, participants reported high values on other health-relevant measures at baseline (eg, health status, health change motivation, and self-efficacy; see Table 1). It may have been easier for individuals with such characteristics to engage in health-promoting behaviors or adopt new behavioral routines. On the other hand, the present intervention even led to positive changes in health-promoting behaviors for individuals already starting with such advantageous conditions. Thus, individuals lacking these attributes might benefit even more from the intervention introduced.

Recently, the relevance of implicit theories interventions has been seriously tackled in 2 meta-analyses concluding that they only produce weak effects in educational settings [49]. According to classic convictions [50], the reported effect sizes or regression coefficients in the present research also fall in this category. However, it has been argued that these convictions should be used with caution, and effect sizes should be evaluated considering the area or context investigated [50,51]. Especially in health or educational research, even small effects can have far-reaching consequences when evaluated in a broader context [23,51].

This study is in line with the majority of research showing that a stronger incremental theory leads to beneficial outcomes [5]. However, holding an entity theory can be instrumental under specific circumstances. A stronger incremental theory of health not only implies that one’s health can improve but also means that one’s health might worsen. For this reason, an incremental theory would be less adaptive when a prevention focus is present [52,53], that is, when one is trying to conserve a given health status. For individuals being confronted with the process of aging or suffering from long-lasting diseases, it may be more beneficial to believe in the stability of health.
Theoretical and Practical Implications

As introduced in the present research, addressing implicit theories of health serves as a new approach for achieving positive health behavior change. The expanding research of implicit theories in the health domain [7-10] may guide the development of health interventions or could be integrated into health education. Nevertheless, further steps are needed to test whether the present findings replicate and can be generalized. First, direct replications could test whether the effectiveness of an incremental theories intervention is indeed time-sensitive, as demonstrated in this study. In addition, future studies should also focus on testing the longevity of the intervention effect. Investigating whether the increase in incremental theories can be sustained over longer periods and whether this increase translates into sustained improvements in health behaviors is essential. Therefore, studies with increased follow-up periods are necessary to test the longevity of the intervention effect and the respective impact on health behaviors. Next, conceptual replications could investigate what modes of delivering an implicit theories intervention are most effective and for whom. For example, the effectiveness might be higher when the changeability of health is emphasized several times over an extended course of time. A useful tool in this respect could be an app that tracks and visualizes changes in one’s health behavior over time. Finally, the generalizability to different populations and different health behavior measures needs to be ensured.

Research on implicit theories of health would also benefit greatly from examining the antecedents and determinants that lead to adopting an incremental versus entity theory [7]. Auster-Gussman and Rothman [24] found that incremental theories of body weight are more common among young and White individuals with a higher level of income and education. These variables, as well as one’s medical history or that of close others, should also play a significant role in the formation of implicit theories [7]. This study shows that even a rather young and educated sample with high self-reported health and high incremental theories at baseline benefits from an incremental theories intervention. Effects might be stronger when studying population groups with higher entity theories of health.

Conclusions

This study is the first randomized trial demonstrating that incremental theories of health can increase because of a single-session smartphone-based intervention. Contrary to our assumptions, the intervention only led to an increase in performing health-promoting behaviors when delivered at a later point in time. Further studies are crucial to assure whether the observed time-dependent variation in effectiveness replicates. Incremental theories interventions might be most effective for individuals holding a stronger entity theory of health. Factors that favor the development of an entity theory of health should be investigated to identify population groups that would benefit most from the interventional approach introduced in this paper.

Acknowledgments

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Conflicts of Interest

None declared.

Multimedia Appendix 1
Table S1. Regression coefficients and information criteria for comparing the multilevel models to predict health behavior engagement per day.
[DOCX File, 26 KB - mhealth_v11i1e36578_app1.docx ]

Multimedia Appendix 2
CONSORT-eHEALTH checklist (V 1.6.1).
[PDF File (Adobe PDF File), 1354 KB - mhealth_v11i1e36578_app2.pdf ]

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**Abbreviations**

BMI: body mass index

CONSORT: Consolidated Standards of Reporting Trials

ITHS: Implicit Theories of Health Scale
KKG: Kontrollüberzeugung zu Krankheit und Gesundheit (Health- and Illness- Related Locus of Control Questionnaire)

OSF: Open Science Framework

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Using Smartphone Survey and GPS Data to Inform Smoking Cessation Intervention Delivery: Case Study

Amanda Luken¹, MHS; Michael R Desjardins²,³, MA, PhD; Meghan B Moran⁴, MA, PhD; Tamar Mendelson¹, MA, PhD; Vadim Zipunnikov⁵, PhD; Thomas R Kirchner⁶,⁷, MS, PhD; Felix Naughton⁸, MSc, PhD; Carl Latkin⁴, PhD; Johannes Thrul¹,⁹,¹⁰, MS, PhD

¹Department of Mental Health, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD, United States
²Spatial Science for Public Health Center, Johns Hopkins University, Baltimore, MD, United States
³Department of Epidemiology, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD, United States
⁴Department of Health, Behavior and Society, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD, United States
⁵Department of Biostatistics, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD, United States
⁶Department of Social and Behavioral Sciences, New York University School of Global Public Health, New York, NY, United States
⁷Center for Urban Science and Progress, New York University Tandon School of Engineering, New York, NY, United States
⁸Behavioural and Implementation Science Research Group, University of East Anglia, Norwich, United Kingdom
⁹Sidney Kimmel Comprehensive Cancer Center, Baltimore, MD, United States
¹⁰Centre for Alcohol Policy Research, La Trobe University, Melbourne, Australia

Corresponding Author:
Amanda Luken, MHS
Department of Mental Health
Johns Hopkins Bloomberg School of Public Health
624 N Broadway
Baltimore, MD, 21205
United States
Phone: 1 732 690 2886
Email: aluk95@gmail.com

Abstract

Background: Interest in quitting smoking is common among young adults who smoke, but it can prove challenging. Although evidence-based smoking cessation interventions exist and are effective, a lack of access to these interventions specifically designed for young adults remains a major barrier for this population to successfully quit smoking. Therefore, researchers have begun to develop modern, smartphone-based interventions to deliver smoking cessation messages at the appropriate place and time for an individual. A promising approach is the delivery of interventions using geofences—spatial buffers around high-risk locations for smoking that trigger intervention messages when an individual’s phone enters the perimeter. Despite growth in personalized and ubiquitous smoking cessation interventions, few studies have incorporated spatial methods to optimize intervention delivery using place and time information.

Objective: This study demonstrates an exploratory method of generating person-specific geofences around high-risk areas for smoking by presenting 4 case studies using a combination of self-reported smartphone-based surveys and passively tracked location data. The study also examines which geofence construction method could inform a subsequent study design that will automate the process of deploying coping messages when young adults enter geofence boundaries.

Methods: Data came from an ecological momentary assessment study with young adult smokers conducted from 2016 to 2017 in the San Francisco Bay area. Participants reported smoking and nonsmoking events through a smartphone app for 30 days, and GPS data was recorded by the app. We sampled 4 cases along ecological momentary assessment compliance quartiles and constructed person-specific geofences around locations with self-reported smoking events for each 3-hour time interval using zones with normalized mean kernel density estimates exceeding 0.7. We assessed the percentage of smoking events captured within geofences constructed for 3 types of zones (census blocks, 500 ft² fishnet grids, and 1000 ft² fishnet grids). Descriptive comparisons were made across the 4 cases to better understand the strengths and limitations of each geofence construction method.
Results: The number of reported past 30-day smoking events ranged from 12 to 177 for the 4 cases. Each 3-hour geofence for 3 of the 4 cases captured over 50% of smoking events. The 1000 ft² fishnet grid captured the highest percentage of smoking events compared to census blocks across the 4 cases. Across 3-hour periods except for 3:00 AM-5:59 AM for 1 case, geofences contained an average of 36.4%-100% of smoking events. Findings showed that fishnet grid geofences may capture more smoking events compared to census blocks.

Conclusions: Our findings suggest that this geofence construction method can identify high-risk smoking situations by time and place and has potential for generating individually tailored geofences for smoking cessation intervention delivery. In a subsequent smartphone-based smoking cessation intervention study, we plan to use fishnet grid geofences to inform the delivery of intervention messages.

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KEYWORDS
adult; application; case study; cessation; delivery; GIS; GPS; health interventions; mHealth; mobile phone; smartphone application; smartphone; smoker; smoking cessation; smoking

Introduction

Cigarette Smoking and Smoking Cessation Among Young Adults

Although cigarette use has declined in recent decades, of a weighted sample of 4200 young adults (ages 19-30 years), 491 (11.7%) young adults in the United States reported current (past 30-day) cigarette smoking in 2019 [1]. Smoking cessation interventions can provide societal and health care cost savings, as well as immediate and long-term health benefits for young adults (eg, decreased risk of cardiovascular diseases, chronic obstructive pulmonary disease, and several types of cancer) [2].

Young adults who smoke rarely use evidence-based smoking cessation strategies in their quit attempts. We need novel interventions that can reach young people and help them quit smoking. A recent study using data from the Population Assessment of Tobacco and Health found that almost all young adults who smoke would like to quit at some point in their lives, but few young adults with a recent quit attempt relied on evidence-based cessation strategies [3]. One explanation for this may be that many interventions for young adults attempt to prevent smoking initiation rather than support smoking cessation [4].

Mobile Phones for Smoking Cessation

The ubiquity of smartphones may help enhance the feasibility, acceptability, and reach of smoking cessation interventions. Almost all 18- to 29-year-olds in the United States own a smartphone [5]. As a result, GPS-enabled smartphones allow researchers to study the behaviors, mobility, and activity spaces of individuals and deliver mobile health (mHealth) interventions that were previously not feasible for potential consumers to access [6]. However, the efficacy of mHealth is understudied in many areas of public health, including smoking cessation.

Few interventions with location information (eg, GPS) include formal spatial science components that may improve intervention delivery. Smoking is often a geographically triggered behavior; people may regularly smoke in the same locations (eg, bars) or have cravings due to an environmental exposure (eg, product or advertisement exposure in a convenience store) [7,8]. GPS-enabled smartphones can register when an individual is near or at a location at-risk for smoking and deliver just-in-time cessation support to resist environmental triggers [9].

Spatial methods are essential for improving smoking cessation by examining the nexus between health and place [8,10,11]. For example, 1 study developed a deep learning model to predict smoking events based on GPS smartphone data [12]. The authors were able to predict smoking events accurately on weekdays and weekends (mean 0.87, SD 0.08) using a 1D convolutional neural network [12]. Overall, the literature using fine-grained geographic information to inform smoking cessation intervention delivery on smartphone apps is scarce, and this proof-of-concept study aims to address this gap.

Geofences for Smoking Cessation

Geofences are virtual perimeters or zones that can trigger smartphone notifications for individuals when entering, exiting, or dwelling within a specified geographic area [13]. Geofences may benefit mHealth interventions since individuals can receive interventions at high-risk locations [14]. Using participants’ mobility patterns to generate geofences with the goal of promoting positive behavior change is a growing area of interest in geography and public health research [15,16]. For example, geoencing applications have been developed to support dentist accessibility [17], gambling cessation [18], awareness of air pollution exposure [19], COVID-19 surveillance [20], and tobacco retail exposure for smoking cessation [8], among other uses.

In the context of smoking cessation, Naughton et al [9] studied a cohort of 15 individuals in the United Kingdom and disseminated geofenced-triggered messages to participants when they entered high-risk smoking zones (ie, circular zones with a 100 m radius containing at least 4 self-reported smoking events); the study, however, did not use formal spatial analytical techniques to generate geofences. To extend this previous research, our goal for this study is to generate geofences around high-risk locations for smoking using a kernel density estimation (KDE) approach, which is reliable for analyzing GPS-based activity space data [21]. KDE is a proven spatial method that identifies hot spots of point patterns in space and time. Although other point-pattern techniques are available, KDE is very flexible regarding its parameter customization (eg, bandwidth, output...
resolution of the density surface, and kernel functions), which is described more in the Methods section [22]. However, the literature on using KDE approaches to generate high-risk geofences is very limited (eg, transportation injury prevention [23,24]) and has been underused for creating geofences tailored to individuals’ spatiotemporal patterns of health risk behaviors.

Additionally, the uncertain geographic context problem (UGCoP) poses a challenge for geofence construction [25]. UGCoP represents the concern that the geographic units used for analyses may not represent the “true causally relevant” geographical context [25]. UGCoP is an issue for geofence construction because the geofenced location influences a person’s smoking behaviors across space and time, but as presented in UGCoP, the appropriate spatial and temporal dimensions for geofence construction are uncertain. Individuals often report smoking at home, outside, or in the car [26], which could constitute the “true causally relevant” geographic context [25], but few interventions sensitive to capturing the “true causally relevant” geographic context have been developed or tested.

**Research Objectives and Anticipated Contributions**

This study uses self-reported smartphone surveys and passively tracked GPS data collected from young adults who smoke. The objective is to develop a spatial analytical approach to identify hot spots of self-reported smoking events and to produce KDE-informed geofences for catered smoking cessation intervention delivery in future studies. The proposed method, which incorporates spatial methods, may be applicable to intervene on other health conditions or other substance use as well. In this study, we demonstrate an exploratory method of generating person-specific geofences for high-risk smoking areas by presenting 4 case studies. We chose to test this method on 4 participants as a case study rather than the entire sample to examine the nuances of this methodological approach that would be more difficult to observe within the entire sample. By focusing on 4 participants, we can identify individual-level variation in smoking behaviors and locations that may influence geofence construction and performance. More importantly, we can better understand why this method may not have worked for certain situations or individuals. Although these 4 participants do not capture the full variation of smoking behaviors, they provide an important first step to evaluating this method in light of unanticipated situations and circumstances. For the 4 cases, we create individually tailored geofences that vary temporally, accounting for behavioral changes over the course of a day. A KDE-informed approach can capture the intersection of place and health by taking a person-centered, data-driven approach. To address UGCoP, we experiment with time-specific geofences constructed by various geographical zones and assess how well the different geofences capture smoking events for each case. We operationalize geofence performance as the percent of smoking events captured, such that an ability to capture greater than 80% of smoking events within geofences for a particular time frame was considered good, while greater than 50% was considered adequate.

**Methods**

**Study Design**

Young adults from Alameda and San Francisco counties participated in an ecological momentary assessment (EMA) study for 30 days that captured individual-level, spatiotemporal patterns of smoking behaviors. Demographic information, smoking history, and alcohol use were assessed through Qualtrics [27] at baseline. For 30 days, participants reported smoking events and completed 3 daily surveys distributed randomly throughout the day through the PiLR Health app [28]. In the app, participants recorded if they were about to smoke (ie, a smoking event), after which some were asked to complete a smoking survey based on the average number of daily cigarettes smoked at baseline (eg, a baseline rate of 10 cigarettes per day was associated with a 33% chance of receiving a smoking survey). To minimize the burden of participation, smoking surveys were limited to at most 3 per day. Each submitted survey was date-, time-, and GPS-stamped. See previous publications for more information on data collection procedures [29-31].

We selected 4 participants for the case study based on their overall compliance with EMA data collection procedures. The total available data, which includes both smoking and nonsmoking reports, served as a proxy for compliance. We selected 4 case study participants from the total available data quartiles. This sampling strategy was chosen to investigate the feasibility of geospatial analyses for participants with different rates of EMA self-report compliance and to improve the generalizability of findings.

**Ethics Approval**

All study procedures were approved by the San Francisco Committee on Human Research, University of California (15-18033).

**Participants**

Eligible participants were recruited using Facebook and Instagram advertisements between 2016 and 2017, were between 18 and 26 years of age, were established smokers (ie, at least 100 cigarettes per lifetime), and reported currently smoking at least one cigarette per day on at least 3 days per week. Study eligibility also required daily smartphone use with GPS capabilities. Women identifying as a sexual minority were oversampled for a nested qualitative study [29]. Study consent was provided electronically on Qualtrics. To confirm their identity, participants were required to send a photo of their ID.

**Measures**

**Smoking Events**

The outcome of interest was self-reported cigarette smoking events (yes or no). EMA data included smoking events (eg, cigarette self-reports) and nonsmoking events (eg, random surveys with nonsmoking events) with a linked GPS location. Smoking events reported within 5 minutes of another smoking event were dropped to correct for measurement errors due to technical difficulties with the app. GPS locations were converted to North American Datum 1983 California Zone 3 in US feet.
**Time**

EMA data included time stamps that were collected in Coordinated Universal Time (UTC) and converted to Pacific Time for analyses. Time was categorized into 3-hour periods (eg, midnight-2:59 AM, 3 AM-5:59 AM, 6 AM-8:59 AM, and 9 AM-11:59 AM).

**Baseline Demographics**

Demographic data (eg, age, gender, race or ethnicity, and education) were collected at baseline. The frequency of past 30-day cigarette use was also obtained.

**Spatial Analyses**

### Framework of KDE

We employed KDE to identify high-risk zones for each individual. In other words, KDE was run separately for each participant to effectively tailor the resulting geofences to each individual. KDE is a moving window method that calculates the density as the number of events based on their distance to the center of a circle with a radius of the specified bandwidth \( \tau \), which determines the degree of spatial smoothing [32]. The window moves and centers along the intersections of a grid and calculates the density at each intersection, which is then considered in unison to provide a weighted average for a location. Events (ie, points) closer to the center of the search radius receive higher weight [33]. The KDE function is defined in Equation 1:

\[
\hat{f}(x; \tau) = \frac{1}{(2\pi \tau)^{d/2}} \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2} \left( \frac{g_i - x}{\tau} \right)^2 \right) f(g) \, dg
\]

where \( \hat{f}(x; \tau) \) is the kernel density value at grid point \( g \); is the Euclidean distance between grid point \( g \) and event \( i \); and \( f(g) \) is the weight where its value equals “0” at distance \( \tau \) [34]. To identify high-risk areas for smoking for each participant, we plotted a kernel density plot of smoking events with a bandwidth of 1320 ft (ie, 0.25 miles), a proxy for comfortable walking distance [35], and a raster cell output size of 150 ft \(^2\). We then extracted high-risk zones using zonal statistics. Zonal statistics calculate a statistic of interest for raster values falling within a “zone” chosen by researchers in another data set [36]. For our study, we averaged KDE raster values within 3 zones: 2020 US census blocks, 500 ft \(^2\) fishnet grid cells, and 1000 ft \(^2\) fishnet grid cells. We then minimum-maximum normalized the mean KDE to the range of 0 to 1 and retained zones with normalized mean KEDs above a threshold chosen during sensitivity analyses. To distinguish risk levels within zones, we categorized zones with normalized mean KEDs above the threshold into terciles (ie, low, medium, and high risk) for each case.

To identify the threshold for “high-risk,” we assessed the performance of geofences constructed for normalized mean KED thresholds of 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 for the 4 case studies. We identified the high-risk normalized mean KED threshold at the block-level. Performance was assessed by examining the percent of smoking events captured within geofences, irrespective of time of day.

### Zonal Statistics by Census Block

We had first chosen census blocks as the “zone” because census blocks are the smallest geographical unit with demographic data and are a federally recognized statistical area [37]. A geographical unit tied to demographic data could be useful for researchers interested in controlling societal-level demographic variables. Further, the census block is a stable geographical unit across the United States with a unique identifier determined by the US Census Bureau. In terms of stability, the census block is reconsidered once every decade [37].

The census block, however, is constructed by both physical (eg, roads, streams, and railroad lines) and nonphysical structures (eg, property lines and city limits), which leads to variability in census block size [37] and thus a normalized mean KDE. Census blocks may be the size of a city block in urban environments or up to hundreds of square miles in rural areas [37]. As a result, differences in census block size may affect block-level normalized mean KEDs (eg, smaller blocks may have fewer raster values to average across than larger blocks). Larger blocks may also have more heterogeneity in raster values than smaller blocks, decreasing the precision of the mean KDE.

Moreover, identifying a large census block as high-risk poses some challenges for intervention delivery. Based on our method, the geofence around the entire census block would trigger the intervention for a large area even though the participant may smoke only in a small subarea of the census block. Census blocks, however, may still offer value in cities where blocks are often equivalent to city blocks and in studies seeking to account for demographic variables [37].

### Zonal Statistics by Fishnet Grid

Alternatively, we can create uniform zones by overlaying a fishnet grid over the area of interest (eg, Alameda and San Francisco counties). A fishnet grid is an array of square cells fitted within a geographical area [38]. We repeated the same process of finding the normalized mean KDE and labeling high-risk areas as zones with a normalized mean KDE above the threshold chosen from the census block analyses, except that the zone was a cell in the fishnet grid rather than a census block. We created 2 fishnets, one with 500 ft \(^2\) cells and another with 1000 ft \(^2\) cells.

### Geofence Construction

For each 3-hour time interval, high-risk zones were identified as those with (1) normalized mean KEDs above the threshold of 0.3 and (2) at least one smoking event. Normalized mean KEDs were based on all observations of a given participant. For example, each block has the same normalized mean KDE value across all hours of the day and for each day of the week. A block, however, may be high-risk at 1 time of day (eg, evening) yet low-risk at another time of day (eg, morning) only because the participant has no history of smoking during the time of day it is considered low-risk (eg, morning). Once the high-risk blocks were identified, geofences were constructed by generating 100-m buffers around groups of adjacent high-risk blocks or cells. All spatial analyses were conducted in ArcGIS Pro (version 2.8.0) [39].
Results

Sample
The population included 144 participants with a mean age of 22.7 (SD 2.6) years at baseline; 76 of 144 (52.8%) were female; and 57 of 144 (39.6%) identified as non-Hispanic White, 31 of 144 (21.5%) as Hispanic or Latino, and 30 of 144 (20.8%) as Asian (Table 1). Most of the population had either completed some college (54/144, 37.5%) or received an associate or bachelor’s degree (51/144, 35.4%). The median number of days with at least one cigarette smoked was 30 (IQR 24-30). On days with at least one smoking event, participants reported smoking a median of 5 (IQR 3-8) cigarettes per day.

Table 1. Baseline characteristics.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Overall (N=144)</th>
<th>Cases not sampled (N=140)</th>
<th>Cases sampled (N=4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years), mean (SD)</td>
<td>22.7 (2.5)</td>
<td>22.7 (2.4)</td>
<td>21.3 (2.6)</td>
</tr>
<tr>
<td>Sex, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>68 (47.2)</td>
<td>66 (47.1)</td>
<td>2 (50)</td>
</tr>
<tr>
<td>Female</td>
<td>76 (52.8)</td>
<td>74 (52.9)</td>
<td>2 (50)</td>
</tr>
<tr>
<td>Highest education, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than or equal to high school</td>
<td>57 (39.6)</td>
<td>54 (38.6)</td>
<td>3 (75)</td>
</tr>
<tr>
<td>Some college</td>
<td>6 (4.2)</td>
<td>6 (4.3)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Associate or bachelor’s degree</td>
<td>30 (20.8)</td>
<td>29 (20.7)</td>
<td>1 (25)</td>
</tr>
<tr>
<td>Master’s degree or higher</td>
<td>8 (5.6)</td>
<td>8 (5.7)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Race or Ethnicity, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-Hispanic White</td>
<td>57 (39.6)</td>
<td>54 (38.6)</td>
<td>3 (75)</td>
</tr>
<tr>
<td>Non-Hispanic Black</td>
<td>6 (4.2)</td>
<td>6 (4.3)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Asian</td>
<td>30 (20.8)</td>
<td>29 (20.7)</td>
<td>1 (25)</td>
</tr>
<tr>
<td>American Indian or Alaska Native</td>
<td>1 (0.7)</td>
<td>1 (0.7)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Native Hawaiian or Pacific Islander</td>
<td>2 (1.4)</td>
<td>2 (1.4)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>31 (21.5)</td>
<td>31 (22.1)</td>
<td>1 (25)</td>
</tr>
<tr>
<td>Other or Multiracial</td>
<td>17 (11.8)</td>
<td>17 (12.1)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Cigarettes per smoking day, median (range)</td>
<td>3.5 (3-5)</td>
<td>5 (1-30)</td>
<td>30 (25-30)</td>
</tr>
<tr>
<td>Smoking days in the past 30 days, median (range)</td>
<td>30 (0-30)</td>
<td>0 (0-30)</td>
<td>30 (0-30)</td>
</tr>
</tbody>
</table>

Cases Selected for Analysis
Of the 4 cases sampled; their ages ranged from 19 to 25 years, with an average age of 21.3 (SD 2.6) years at baseline. Two were male and 2 were female at birth. Three participants identified as non-Hispanic White and one as Asian. One had less than or equal to a high school education, 2 had some college, and 1 had an associate’s or bachelor’s degree. Three of the cases reported daily smoking in the past 30 days, while one reported smoking on 25 of the past 30 days. The cases reported smoking between 3 and 5 cigarettes per smoking day in the baseline assessment.

The number of smoking events reported by these 4 cases in EMA data ranged from 16 to 177, while the number of nonsmoking events ranged from 8 to 67 (Table 2). All smoking events were in San Francisco and Alameda counties.

Table 2. Smoking and nonsmoking events of cases.

<table>
<thead>
<tr>
<th>Quartile</th>
<th>Smoking events, n (%)</th>
<th>Nonsmoking events, n (%)</th>
<th>Total reports, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>25th</td>
<td>16 (66.7)</td>
<td>8 (33.3)</td>
<td>24 (5.7)</td>
</tr>
<tr>
<td>50th</td>
<td>12 (20.3)</td>
<td>47 (79.7)</td>
<td>59 (14.1)</td>
</tr>
<tr>
<td>75th</td>
<td>31 (31.6)</td>
<td>67 (67.4)</td>
<td>98 (23.4)</td>
</tr>
<tr>
<td>100th</td>
<td>177 (74.7)</td>
<td>61 (74.4)</td>
<td>238 (56.8)</td>
</tr>
</tbody>
</table>

Threshold for Identifying High-Risk Census Blocks
The percent of smoking events captured in time-independent geofences at varying normalized mean KDE thresholds of high-risk for census blocks are presented in Figure 1. The figure displays the percentage of smoking events contained within constructed geofences if zones with normalized mean KDE values above each threshold are retained. For all but 1 participant, a normalized mean KDE threshold of 0.5 captured...
50% or more of all possible smoking events within generated geofences.

We proceeded to construct geofences across 3-hour time intervals for census blocks with normalized mean KDEs greater than or equal to 0.3 because they captured at least 80% of smoking events for all but 1 case.

**Figure 1.** Percent of smoking events within geofences for census blocks among 4 participants at quartiles of ecological momentary assessment self-reported data.

Of note, 3 participants had no geofences generated for census blocks with a normalized mean KDE of 1.0 due to rounding differences (e.g., rounding was done to 6 decimal places such that 0.999998 would not be included for this threshold). A 0.0 threshold should capture every block with at least one smoking event reported; however, we had 2 participants that were missing 1 block with at least one smoking event reported in it. This occurred because these smoking events occurred in very small, narrow blocks that were part of roadways, which consequently did not rasterize for a cell output size of 150 ft². In other words, these blocks were missing normalized mean KDE values because the blocks were smaller than the cell’s output size. In some cases, this may have left out a block at risk for smoking. See Table S1 in Multimedia Appendix 1 for summary statistics of the 4 cases’ normalized mean KDEs.

**Comparison of Geofence Construction Methods of Census Blocks Compared to Fishnet Grid Across 3-Hour Time Intervals for Each Case**

Across 3-hour time intervals, the average percentage of smoking events within geofences ranged from 36.4% to 100%. Geofences contained the highest percentage of smoking events between midnight and 3 AM and between 9 AM and 11:59 AM. Conversely, geofences contained the lowest percentage of smoking events reported between 6 AM and 8:59 AM.

Across the 4 cases, the 1000 ft² fishnet grid captured the highest percentage of smoking events for each 3-hour interval (Figure 2), both within cases and averaged across cases. Although there was no difference in the percentage of smoking events captured across geofence construction methods between midnight and noon, the constructed geofences looked very different from each other. **Figure 3** compares the geofences constructed by the census block and 500 ft² fishnet grid methods for 1 case between noon and 2:59 PM. The census block method’s geofence covers a larger area than the 500 ft² fishnet grid method’s geofence from noon to 2:59 PM, even though they capture the same percentage of smoking events. Further, the census block method generated a wider range of high-risk blocks (normalized mean KDEs between 0.35 and 1.00) across the whole day, whereas the 500 ft² fishnet grid method generated a smaller range of high-risk cells (normalized mean KDEs between 0.64 and 1.00). By depicting the tertiles, we can identify how the distribution of normalized mean KDEs changed spatially across time and method within individuals. For example, **Figure 3** tells us that in this period of noon to 2:59 PM, the 500 ft² fishnet grid method created a geofence only around a high-risk cell, whereas the census block method’s geofence encompassed potentially low-risk blocks, yet both capture the same percentage of smoking events for this participant at this time of day. From this, we may visually compare geofence methods and ensure
that the highest-risk areas within a geofence are captured, even if the geofence perimeter may differ by method.

Although the 500 ft² fishnet grid method captured a slightly higher percentage of smoking events from 9 AM to 6 PM for the case with the most data, the 100th percentile case (Figure 2), it captured the same percentage of smoking events at all other hours relative to the census block method. To understand why this may have happened, we examined the 100th percentile’s smoking profile. Figure 4 shows where the 100th percentile participant smoked over 26 noncontiguous blocks generated without any thresholds. The blocks are predominantly yellow, representative of normalized mean KDEs below 0.2. This means that many of these blocks contain fewer smoking events. In fact, 73 of 177 (41.8%) smoking events occurred across 2 block areas, while the remaining 104 of 177 (58.2%) smoking events were dispersed across 24 noncontiguous block areas. This is highlighted in census block normalized mean KDE quintiles, in which the bottom 4 quintiles have normalized mean KDEs below 0.35.

As a result, a majority of the 100th percentile case’s zones with smoking events will not result in a geofence to inform intervention delivery because only zones with normalized mean KDEs above 0.3 were retained. For this participant, our method identified that most zones were low-risk relative to other zones, and these low-risk zones would result in a low percentage of smoking events captured in geofences.

**Figure 2.** Percent of smoking events captured within each geofence method for 4 participants.
Figure 3. Geofences constructed by the census block versus 500 ft$^2$ fishnet grid at noon to 2:59 PM for 1 case. KDE: kernel density estimation.
Figure 4. Census blocks with any smoking reports for 100th percentile case across all hours of the day.

Discussion

Overview

This study’s objective was to design a spatial approach to identify and construct geofences around person- and time-specific high-risk smoking areas. We collected self-reported, smartphone-delivered surveys on smoking behaviors with passive GPS tracking from young adults who smoke.

Our study found that a kernel density approach for geofence construction could systematically label locations at high risk for smoking. Second, of the 3 methods we used to construct the geofence, the 1000 ft² fishnet grid captured the highest percentage of smoking events within and across the 4 cases. Last, we found that although methods may capture the same percentage of smoking events in the early and late hours of the day, the physical geofences appeared different from each other, which may affect intervention delivery.

Identified Locations at High Risk for Smoking Through Kernel Density Methods

To our knowledge, this is the first study to examine an individual’s smoking risk profile using KDE methods. Kernel density approaches have already been applied in the tobacco literature to define risk in terms of the tobacco environment (e.g., tobacco outlet density) [11,40], and this study demonstrates that KDE methods may also hold value for informing smartphone-based smoking cessation intervention delivery. For our case studies, we found that a normalized mean KDE threshold of 0.3 adequately defined smoking risk.

A KDE approach allowed us to define high-risk locations specific to an individual’s smoking profile. Previous studies have examined risks unspecific to the individual, such as the occurrence of more than 4 smoking events within a geographical region [9]. Four smoking events, however, may be considered high-risk for some individuals and low-risk for others, relative to an individual’s smoking patterns. If we had generated geofences around blocks with smoking events without classifying person-specific, high- and low-risk locations, the intervention delivery would be triggered at locations where the individual rarely smoked relative to other locations. For an ecological momentary intervention, the cumulation of intervention delivery at both efficient and inefficient times and appropriate and inappropriate locations could lead to intervention burden, which may undermine intervention effectiveness and adherence [41]. Prioritizing these high-risk locations and times may be able to reduce intervention burden and improve intervention delivery effectiveness.

The fact that the KDE methods captured most smoking events also highlights their use for people who smoke, especially if they tend to smoke in the same locations. We saw that our methods captured over 50% of smoking events for 3 of the 4
cases. The fourth case, however, was the heaviest smoker based on the self-reported data and frequently smoked in new locations. This may be due to the fact that more frequent smoking indicates greater nicotine dependence and, hence, a more regular need to maintain blood nicotine levels to avoid withdrawal [42]. In addition, this individual may have a more variable activity space than the other 3 cases, resulting in a more spatially dispersed smoking profile. Other strategies than the 1 employed here may be needed to improve intervention delivery for individuals with spatially dispersed smoking profiles.

**Fishnet Grid Geofences Captured More Smoking Events Than Census Block Geofences**

We recognized that the UGCoP may result in missing the “true causally relevant” geographic context [25] for smoking cessation geofences, so we generated geofences with 3 different geographical areas—census blocks, 500 ft\(^2\) fishnet grid cells, and 1000 ft\(^2\) fishnet grid cells. Of these 3 geographical areas, the 1000 ft\(^2\) fishnet grid captured the highest percentage of smoking events, followed by the 500 ft\(^2\) fishnet grid and census blocks. Even the most limited method (census blocks) still effectively captured over half of smoking events. Furthermore, the buffer size of 100 m around adjacent high-risk blocks helped capture some smoking events that would not have been captured otherwise.

Census blocks, however, are often delineated by roads [37] and may misrepresent smoking on the road (eg, the road itself is a very small block below the cell output size, or the smoking event may be forced to one of the adjacent blocks). In the transportation literature, a fishnet grid of half a mile predicted how people traveled better than aggregating to census blocks [43]. Thus, it is possible that the 1000 ft\(^2\) fishnet grid may have captured more smoking if our cases were smoking in the car, which may have been missed in the 500 ft\(^2\) fishnet grid and census block methods. Future studies can ask for the smoking location context to discern if this may be the case.

**Selected Method for Effective Intervention Delivery**

We found that interventions using the census blocks to create geofences will cover a wider area and may trigger more intervention delivery than interventions using 500 ft\(^2\) fishnet grid cells for geofence construction. In another study that constructed geofences around locations with more than 4 smoking events, participants had mixed reviews for the frequency of intervention delivery, such that some reported too many alerts and others reported too few [9]. Aligned with the census block method, some participants may want more proactive alerts slightly further away from their usual smoking location, triggered by larger geofences. Future studies may want to compare these different geofence construction methods and their impact on intervention delivery and participant satisfaction.

As researchers seek to define how spaces are categorized as risky or not risky, the modifiable area unit problem needs to be considered as well [44]. As different geofence construction methods may yield different results in intervention delivery, there is a need for a standardized approach for constructing geofences to improve cross-study comparisons. Census blocks are stable for 10 years [37], while fishnet grid cells can shift based on entered parameters [38]. Clear descriptions of all parameters chosen to construct geofences are needed for reproducibility and to help the field develop standards. Depending on the study goal, studies that want to include demographic census data may use census blocks, while those solely interested in optimal intervention delivery may choose fishnet grids. There are also other methods that can weight noncensus data with demographic information [45] that can be further explored.

While a large number of smoking cessation apps are available on the Apple and Google Play app stores, many lack scientific evidence [46,47]. To support individuals in quitting smoking, we need evidence-based interventions that can promote behavior change through positive engagement and personal relevance (eg, appropriate time and place of intervention delivery) [48,49]. Our approach of identifying hot spots of self-reported smoking events and producing geofences that represent high-risk areas for smoking may be helpful to inform future smartphone-based smoking cessation interventions. The proposed approach for generating geofences will be used in an ongoing smoking cessation intervention study with young adults. Given its ability to capture a good percentage of smoking events across compliance levels and the specificity of the constructed geofences, we plan to automate a version of the 1000 ft\(^2\) fishnet grids to create geofences for participants of an app-based smoking cessation intervention.

**Limitations**

Our study has several limitations. First, this was an observational study with individuals who were not ready to quit smoking, which may have impacted compliance to report all smoking events. We attempted to address this issue of compliance by selecting cases to study at quartiles of available data to evaluate the method’s performance for various compliance scenarios. However, EMA compliance may vary significantly between locations, which could potentially affect the results. Second, we assumed smoking reports within 5 minutes of another report were due to technical issues or double reporting based on expert opinion and dropped these reports. Future studies would benefit from including an app feature that sends a follow-up survey to participants after reporting a high volume of smoking events to confirm the number of cigarettes smoked. Third, some census blocks did not rasterize, meaning they were missing a normalized mean KDE due to the block size being smaller than the cell output size. The fishnet grid method captured any of these points that were not rasterized in the census blocks method. Fourth, the risk threshold was determined solely based on the census blocks to allow for a comparison across methods. The census blocks had the greatest variability in normalized mean KDE, and the fishnet grids captured as many or more smoking events than the census blocks. Fifth, our KDE approach used a fixed kernel with a constant bandwidth (which tends to over smooth), whereas adaptive kernels can better capture the scale at which the point pattern process operates [50]. However, we ran KDE for each individual; therefore, the bandwidths were tailored to the individual. Finally, the temporal snapshots of the geofences may not accurately depict the “true” spatiotemporal
point-pattern process since we employed a spatial KDE approach. Therefore, future research will employ spatiotemporal point-pattern methods, such as space-time KDE [50] to fully capture the space-time dynamics of the participants and the subsequent creation of geofences for smoking cessation interventions.

**Conclusions**

For ecological momentary interventions, it is important to optimize intervention message delivery to minimize intervention burden for participants. Prioritizing intervention delivery to high-risk locations and times may make these interventions relevant for individual participants and consequently improve intervention efficacy. A spatial approach of generating geofences based on high-risk zones (e.g., fishnet grids for capturing a greater percentage of events or census blocks for linking spatial data with demographic information) identified through normalized mean KDE surpassing a chosen threshold may assist with prioritizing high-risk locations for intervention delivery, tailored to the needs of an individual participant. By stratifying event occurrence by periods of time, intervention messages can also be appropriately delivered throughout the day. Our study demonstrates that this method can capture a good percentage of smoking events within an urban and suburban environment and illustrates the potential for assessing if it improves person-specific smoking cessation intervention delivery and efficacy. Most importantly, this study highlights that researchers must carefully consider the implications of their chosen geographical unit when designing place-based interventions.

**Acknowledgments**

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**Authors' Contributions**

JT conceptualized this study. AL and MRD created the geofence method. AL performed all analyses with help from MRD, who also created the fishnet grids. AL drafted the manuscript, which all authors reviewed and edited.

**Conflicts of Interest**

MBM served as a paid expert witness in litigation sponsored by the Public Health Advocacy Institute against RJ Reynolds. This arrangement has been reviewed and approved by Johns Hopkins University in accordance with its conflict of interest policies.

**Multimedia Appendix 1**

Normalized mean KDE statistics per case. 
[DOCX File , 17 KB - mhealth_v11i1e43990_app1.docx ]

**References**


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Abbreviations

- EMA: ecological momentary assessment
- KDE: kernel density estimation
- mHealth: mobile health
- UGC: uncertain geographic context problem
- UTC: Coordinated Universal Time
Incorporating Consumers’ Needs in Nutrition Apps to Promote and Maintain Use: Mixed Methods Study

Sandra van der Haar1, MSc; Ireen Raaijmakers2, MSc; Muriel C D Verain2, PhD; Saskia Meijboom1, BSc

1Wageningen Food & Biobased Research, Wageningen University & Research, Wageningen, Netherlands
2Wageningen Economic Research, Wageningen University & Research, Wageningen, Netherlands

Corresponding Author:
Sandra van der Haar, MSc
Wageningen Food & Biobased Research
Wageningen University & Research
Bornse Weiland 9
Wageningen, 6708 WG
Netherlands
Phone: 31 317480171
Email: sandra.vanderhaar@wur.nl

Abstract

Background: Nutrition apps seem to be promising tools for supporting consumers toward healthier eating habits. There is a wide variety of nutrition apps available; however, users often discontinue app use at an early stage before a permanent change in dietary behavior can be achieved.

Objective: The main objective of this study was to identify, from both a user and nonuser perspective, which functionalities should be included in nutrition apps to increase intentions to start and maintain use of these apps. A secondary objective was to gain insight into reasons to quit using nutrition apps at an early stage.

Methods: This study used a mixed methods approach and included a qualitative and a quantitative study. The qualitative study (n=40) consisted of a home-use test with 6 commercially available nutrition apps, followed by 6 focus group discussions (FGDs) to investigate user experiences. The quantitative study was a large-scale survey (n=1420), which was performed in a representative sample of the Dutch population to quantify the FGDs’ results. In the survey, several app functionalities were rated on 7-point Likert scales ranging from 1 (very unimportant) to 7 (very important).

Results: A total of 3 different phases of app use, subdivided into 10 user-centric app aspects and 46 associated app functionalities, were identified as relevant nutrition app elements in the FGDs. Relevance was confirmed in the survey, as all user-centric aspects and almost all app functionalities were rated as important to include in a nutrition app. In the starting phase, a clear introduction (mean 5.45, SD 1.32), purpose (mean 5.40, SD 1.40), and flexible food tracking options (mean 5.33, SD 1.45) were the most important functionalities. In the use phase, a complete and reliable food product database (mean 5.58, SD 1.41), easy navigation (mean 5.56, SD 1.36), and limited advertisements (mean 5.53, SD 1.51) were the most important functionalities. In the end phase, the possibility of setting realistic goals (mean 5.23, SD 1.44), new personal goals (mean 5.13, SD 1.45), and continuously offering new information (mean 4.88, SD 1.44) were the most important functionalities. No large differences between users, former users, and nonusers were found. The main reason for quitting a nutrition app in the survey was the high time investment (14/38, 37%). This was also identified as a barrier in the FGDs.

Conclusions: Nutrition apps should be supportive in all 3 phases of use (start, use, and end) to increase consumers’ intentions to start and maintain the use of these apps and achieve a change in dietary behavior. Each phase includes several key app functionalities that require specific attention from app developers. High time investment is an important reason to quit nutrition app use at an early stage.

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KEYWORDS
mobile health; mHealth; mHealth apps; nutrition apps; diet apps; consumer needs; app; use; nutrition; tool; consumer; eating; habit; users; dietary behavior; reliable; food; database; time; developers; mobile phone
Introduction

Background

Healthy dietary habits play a crucial role in preventing obesity and noncommunicable diseases such as cardiovascular diseases, cancer, and diabetes mellitus [1,2]. Despite its importance, the dietary intake of many consumers in the Western world is suboptimal (eg, excessive intake of sodium and insufficient intake of whole grains and fruits), leading to a high global disease burden [3]. Therefore, there is an urgent need for interventions and tools that stimulate and support a healthy eating pattern. Increased access to smartphones, tablets, and wearables has caused an increase in the popularity of mobile health (mHealth) apps. Currently, over 350,000 mHealth apps are available in the health and fitness category in various app stores worldwide [4]. There is evidence that mHealth apps are effective or likely to be effective in stimulating healthier behaviors, such as increasing physical activity [5,6], reducing sedentary behavior [5], improving dietary habits and intake [5-7], and losing weight [8,9]. Nutrition apps are a part of the mHealth category and specifically focus on tracking food intake and providing dietary advice. Most of these apps function as food diaries in which users log their daily food intake, either by a text search or a barcode scanner [10]. The app subsequently gives the user an overview of daily amounts of calories and other nutrients consumed and provides them with dietary advice. Nutrition apps are considered promising tools for supporting consumers in the transition toward a healthier diet. A study by Wang et al [11] showed that consumers perceive the effectiveness of nutrition apps as rather high. In their study, they included both nutrition and physical activity apps. The use of both types of apps influenced action, consciousness, self-education about nutrition and physical activity, and social life (eg, by sharing dietary experiences in web-based social networks). Furthermore, it facilitated maintaining a healthy diet and exercising more [11].

An important question is which elements are important for nutrition apps to be effective in achieving healthy eating behaviors. Several studies examined the application of behavior change techniques (BCTs) in mHealth apps. BCTs are components of behavior change interventions that can be used alone or in combination with other BCTs, such as goal setting, self-monitoring, and feedback [12]. The inclusion of BCTs seems beneficial to the quality of mHealth apps [13-15] and might in turn influence consumer behavior [16]. This is in line with previous research showing that health behavior interventions are more effective when they integrate such techniques [17,18]. According to several studies, the extent to which BCTs are incorporated into mHealth apps is still insufficient at this point [15,16,19] or is only sufficient in paid versions of the app [20].

Besides the incorporation of science-based components in mHealth interventions, such as BCTs, it is of great importance to focus on the issue of implementation. A key factor in mHealth implementation is the willingness and capability of users to successfully engage with a tool or app [21]. This is an important precondition for both the efficacy, the capacity of a given mHealth intervention in a controlled setting, and the effectiveness, to have a meaningful effect on users in real life [22]. The user-friendliness of mHealth app use of advertisements, price, and protection of personal data and privacy are examples of aspects that potentially influence the implementation and acceptance of these tools [23-26].

Nowadays, a wide variety of nutrition apps are available; however, only a small group of Dutch consumers (11%) make use of such apps [27]. Users often prematurely discontinue use before a change in dietary behavior can be achieved, indicating possible issues with the implementation of these apps. This was shown by Helander et al [28] in a retrospective study. They concluded that most people who tried out a free mobile app for dietary self-monitoring did not continue using it actively [28]. There might be various barriers for consumers to use a nutrition app or to quit its use at an early stage. A recent systematic literature review by König et al [29] identified 328 barriers and facilitators for nutrition app use. The usability of the app was the most frequently identified barrier in this review [29]. The user burden of nutrition apps is rather high because tracking all eating and drinking moments is a time-consuming activity. Furthermore, there can be several issues with the food tracking feature and the underlying food database in nutrition apps. A study by Ziesemer et al [30] demonstrated that usability issues related to tracking food intake might impact the willingness to record eating events. In addition, Vasiloglou et al [25] showed that consumers would not select nutrition apps that have issues related to their food and nutrient databases, such as an incomplete product list or incorrect estimations of nutrients.

Objectives

To summarize, several factors could contribute to consumers’ intentions to use nutrition apps and the early discontinuation of these apps. Therefore, the main objective of this study was to identify, from both a user and nonuser perspective, which functionalities should be included in nutrition apps to increase intentions to start and maintain use of these apps. A secondary objective was to gain insight into reasons to quit using nutrition apps at an early stage.

Methods

Study Design

The study followed a mixed methods approach and consisted of 2 parts: a qualitative and a quantitative study. The qualitative study consisted of a home-use test with commercially available nutrition apps, followed by focus group discussions (FGDs). The results of the FGDs served as a basis for the quantitative part, a survey that aimed to quantify these results in a large, representative sample of the Dutch population.

Ethics Approval and Informed Consent

All participants provided written informed consent for participation in the study. In addition, participants in the qualitative study provided consent for audio recordings of the discussions. Ethics approval for the study was obtained from the Social Ethics Committee of Wageningen University & Research in the Netherlands.
Qualitative Study

Recruitment and Study Procedures

Participants were recruited from the Wageningen Food and Biobased Research consumer database. This database consists of consumers who are interested in participating in nutrition and health research and live in the Wageningen region. An email invitation to participate in this study was sent to a subsample of the panel (750 consumers) using random selection. Inclusion criteria were age between 18 and 60 years and familiarity with smartphone and app use. A total of 62 participants signed up for the study, of which 48 (77%) were invited to participate. There were 3 dropouts during the home-use test and 5 no-shows at the FGDs; therefore, a total of 40 participants completed the study.

Study participants first took part in a home-use test. In total, 6 commercially available, free nutrition apps in which food intake could be tracked were selected for this test: MyFitnessPal, FatSecret, Lifesum, Mijn Eetmeter, FoodProfiler, and SamenGezond. The apps were selected based on a short literature search to identify the prerequisites of successful mHealth apps and their differences in BCTs (goal setting, goal tracking, monitoring, feedback, rewards, social support, identification, game elements, and personalization) and other app functionalities (prompts, synchronization with other apps and devices, and costs). The apps were used as a tool to start the conversation on user experiences and critical app elements; the aim was not to test or rate these specific apps. Participants were asked to download and use 1 of these 6 apps for a period of 3 weeks. Some participants had previous experience with 1 of the apps used in the test. In that case, they were assigned to a different app that was new to them because we also wanted to include their first experience of using the app. After 3 weeks of app use, 6 semistructured FGDs (1 per included app) of 1.5 hours were organized at the Wageningen University & Research campus. The discussions were led by a professional focus group moderator. A focus group guide was designed and used during the discussion to ensure the comparability of the 6 FGDs. The main objective of the discussions was to identify, from a user perspective, what were the critical elements for successfully monitoring and supporting healthy eating behaviors. Another objective was to explore possible reasons to quit using the specific app. In each session, 6 to 8 consumers participated, who all tested the same nutrition app before their session. The 3 main topics addressed in the FGDs were general smartphone use, use of health and nutrition apps, and user experiences with the tested nutrition app. The latter topic was discussed extensively. Participants were asked to describe their positive and negative experiences and how often they had used the app.

Subsequently, the app functionalities were discussed and evaluated regarding their usefulness. The functionalities differed per app, but in all focus groups, both predefined intervention components of the app (BCTs such as goal setting, feedback, reward, social support, and knowledge) and the implementation of these components (eg, use aspects such as reminders, chat, synchronization with other devices, and gamification element) were discussed. Audio recordings were conducted, and minutes were recorded for each session. Upon completion of the study, the participants received an incentive of €50 (conversion rate at the time of the study: €1=US $1.12) for their time investment.

Analyses

As a first step, the minutes and recordings of the discussions were analyzed by creating a descriptive matrix per question to identify common themes. Through this matrix, the reasons for discontinuation were identified. The model shown in Figure 1 was built using a bottom-up approach. On the basis of the app evaluation, user quotes from the participants were translated into the app properties. For example, the user quote “I would use the products that were placed under the dinner category at other moments” was translated into the key app property: “logical product categories.” Thus, all user quotes related to the tested app were translated, resulting in a list of 46 properties (Table S1 in Multimedia Appendix 1). These app properties were then assigned to 10 different categories (also called “user-centric app aspects”; Table S1 in Multimedia Appendix 1). These categories were partly derived from the predefined list of BCTs and other app properties in the focus group guide (eg, “Monitoring”) and partly from topics participants came up with themselves in the discussion (eg, “Database”). In this manner, the model with 10 different user-centric aspects and 46 app properties was built. In the analysis, it was not about the frequency of the quotes but about their unicity, as the aim was to generate a complete overview of user experiences.

The 3 different phases of app use were identified as the final step. Some of the user-centric app aspects particularly occurred when the user installed the app and during the first (few) time(s) of use, the start phase. Some aspects typically occurred during daily use, the usephase. Most participants reached a point where the app would be abandoned or used permanently, the end phase. This was related to a combination of aspects in the 2 earlier phases and the continuous engagement of the user. The phases were placed in the outer ring of the model.

The analyses of all 6 FGDs were performed by the same professional focus group moderator who had led the discussions. At least 1 of the researchers was present at each focus group session, and afterward, the minutes and analyses of the results were reviewed by the researcher.
Figure 1. Overview of the 3 phases of nutrition app use subdivided into 10 “user-centric app aspects.”

Quantitative Study

Sampling and Study Procedures
A web-based survey was conducted in a representative sample of the Dutch adult population (>18 years), familiar with the use of smartphone apps and either with or without experience regarding the use of nutrition apps. The survey was administered by a professional market research agency (MSI-ACI Europe Ltd). Quota sampling was applied to obtain a representative sample for age, gender, level of education, region, and income. Participants were approached by email to fill out a web-based self-administered survey and received an incentive in the form of credits for a personal saving system.

The survey included questions on nutrition app use, reasons for using and for not using nutrition apps, and the importance of 46 nutrition app functionalities that resulted from the FGDs. In total, 1500 participants completed the survey. During data cleaning, 80 participants were removed from the analyses because they showed no dispersion in their answers on the importance of app functionalities, suggesting that they did not fill out this part of the survey in earnest.

Measures

Nutrition App Use
Respondents were asked to indicate whether they make use of nutrition apps or made use of nutrition apps in the past. On the basis of their responses, they were categorized into former users, previous users, and nonusers. Subsequently, they were asked to indicate their reasons for (not) using nutrition apps, for example, “Because I want to lose weight” or “I never heard of nutrition apps.” Former users were asked what was their reason or were their reasons for quitting the use of the app, for example, “It cost me too much time.” Respondents could select multiple options from a predefined list of reasons or fill in an open answer.

Nutrition App Functionalities
The 46 nutrition app functionalities that resulted from the FGDs (Table S1 in Multimedia Appendix 1) were included in the survey. For each app functionality (eg, “A quick and easy entry of food products”), participants were asked how important they thought this functionality was to include in a nutrition app. The items were randomized into 4 subsets and assessed on 7-point Likert scales ranging from 1 (very unimportant) to 7 (very important).

Demographics
Age, gender, and education level were included in the survey to analyze the sample on sociodemographic characteristics.

Statistical Analysis
Categorical variables were displayed as frequencies and percentages, and numeric variables were displayed as mean (SD). Respondents were categorized into users and nonusers.
according to their nutrition app use behavior. The group of users consisted of current users and former users. The number of participants in each group and the percentage of the total study population were calculated. The mean (SD) scores were calculated for the importance ratings of each nutrition app functionality. The top 3 most important app functionalities per phase were created based on these mean ratings. The 10 user-centric app aspects included multiple app functionalities. Per user-centric app aspect, mean (SD) scores were calculated, combining all app functionalities within the user-centric app aspects (refer to Table S1 in Multimedia Appendix 1 for an overview). One-way ANOVA was used to compare the means of the 3 different groups (nonusers, current users, and former users). The Brown-Forsythe ANOVA with Games-Howell post hoc tests was applied to account for unequal samples and variances. Statistical significance was set at P<.001 for all analyses. Statistical analyses were performed using SPSS software (version 25.0; IBM Corp).

Results

Qualitative Study

Phases of App Use and User-Centric App Aspects

A total of 40 participants (8 male individuals and 32 female individuals, with a mean age of 40.9, SD 14.1 years) participated in the FGDs. None of the participants had a low education level, 15% (6/40) of the participants had a medium education level, and 85% (34/40) of the participants had a high education level. The FGDs revealed that users go through 3 different phases when using a nutrition app: start, use, and end. Each phase includes a range of key aspects or categories. In total, 10 such “user-centric app aspects” were identified (Figure 1). Each of these aspects includes a total of 46 different key app functionalities (refer to Table S1 in Multimedia Appendix 1 for a complete overview).

App Functionalities

In the starting phase, the purpose (user-centric app aspect 1, Figure 1) of the app should be clear immediately, and a clear introduction (user-centric app aspect 2, Figure 1) to the different functionalities of the app should be present (user: “A tutorial that you can view optionally would be helpful”). The next aspect is personalization (user-centric app aspect 3, Figure 1) of the app by entering personal data and goals (user: “When you create your own list of recipes, you only have to fill it in once, which is convenient”). In addition, certain other app functionalities must be adjustable according to personal wishes, such as how often notifications appear. During the use phase, users go through several aspects of the app, either sequentially or simultaneously. First, user-friendliness (user-centric app aspect 4, Figure 1) is of great importance in this phase, especially a quick and easy daily food intake entry (user: “Efficient entry is important. I am very impatient”). Moreover, the product database (user-centric app aspect 5, Figure 1) in the app must be of good quality and not be contaminated with duplicate products or incorrect nutritional information (user: “There is no added value of having so many similar products in the list”). Furthermore, the information (user-centric app aspect 6, Figure 1) or advice provided by the app should educate the user (user: “I didn’t know almonds contained so many calories.”). In addition, the user must gain sufficient insight into their own dietary behavior and progress by monitoring (user-centric app aspect 7, Figure 1) functions in the app (user: “I adjusted my behaviour based on the daily overview of what I ate”). Visualizing progress toward achieving personal goals can be helpful. Users prefer to receive positive feedback (user: “I liked the encouraging tone of voice of the feedback messages”; user-centric app aspect 8, Figure 1), a variety of different feedback messages, or a game element as a way to provide feedback. In addition, a reward system where, for example, credits can be earned by keeping up with entering food intake daily has a stimulating effect on continued use of the app. Furthermore, some appreciate the possibility of communication (user-centric app aspect 9, Figure 1) with other users (via a community, forum, or social media) or with a web-based coach (user: “I entered a goal to eat more vegetable and the coach would give tips”). In the end phase, continuous engagement (user-centric app aspect 10, Figure 1) of the user is particularly important (user: “It took forever to fill the app. That really demotivated me”). In addition, the app should continuously offer new and relevant information to keep users interested and engaged.

Reasons to Quit Use

Entering Food Intake and the Database

Most participants in the home-use test discontinued the use of the nutrition app prematurely. Although some participants did mention a few advantages, such as an increased awareness of personal food intake and dietary habits, most participants experienced too many disadvantages. The poor user-friendliness of the app made the time investment too high for most users. This was mainly linked to the time-consuming task of registering daily food intake. If entering food products could not be achieved quickly and easily, this was a big barrier (user: “I had to type in the same food products over and over again”). In some apps, users could add their own food products to the food product database. This caused contamination of the database, with too many details and options (user: “Full-fat yoghurt had so many entries, with all different amounts of calories.”). In contrast, sometimes the database was too limited or incomplete for specific product categories (user: “There were five different options for chocolate milk, but only one type of cheese”). These issues sometimes caused the user to not trust the content of the database (user: “The app showed very different calorie amounts for different apples, it made me question the reliability”).

Feedback and Advice

In some cases, the way feedback and advice were framed caused the user’s continuous engagement to decline. Some apps used a patronizing tone of voice (user: “I want to be aware of what I eat, but don’t be judged through the advice given.”) or were too rigid in the feedback provided (user: “One calorie too much and you are in the red zone. That’s too abrupt”). For an app to remain relevant and triggering for a longer period, it needs to constantly offer new information to the user. Some users indicated that the advice or tips were too repetitive or already known (user: “The app tells me nuts are healthy. I know that
already, so I deliberately entered that I ate nuts just to get rid of this notification.”). Some participants indicated that continued use of a nutrition app would be unlikely for them. In the beginning, there can be a steep learning curve because, as a new user, you become aware of your dietary pattern and learn about the macronutrient composition of products and healthier product alternatives. In this phase, a nutrition app can have a lot to offer, and the time and effort to track food intake daily pays off in insights, support, and suggestions to improve the diet. However, after a certain amount of time, when certain behaviors might have been adapted and the learning curve flattens, the necessity and relevance of a nutrition app diminishes (user: “You have to use these type of apps to teach yourself good behaviour. And then you have to put them away”). Still, some users think it is a good idea if the app would notify or email them after a couple of months to remind them of their goals and increase their awareness.

Quantitative Study

Nutrition App Functionalities

A total of 1420 participants were included in the final analyses. The sample was nearly equally distributed in terms of gender, with 49% (696/1420) of male individuals and a mean age of 45.7 (SD 16.5) years, with an age range of 18 to 79 years. The majority had a middle (626/1420, 44%) or high (579/1420, 41%) level of education. The sample was representative for the Dutch population regarding age and gender. Respondents with a low education level were somewhat underrepresented, and respondents with a high education level were overrepresented. Almost all app functionalities (43 out of 46) were rated with a mean score above the neutral score of 4. The possibility of linking the nutrition app with social media (mean 3.8, SD 1.9), a gamification element in the app (mean 3.8, SD 1.9), and the possibility of being in touch with other users through social media platforms (mean 3.5, SD 1.8) were the only functionalities rated with a mean score <4. The complete list of mean ratings per app functionality can be obtained from Table S2 in Multimedia Appendix 1. Table 1 shows the mean importance ratings for the 10 user-centric app aspects, which all include multiple app functionalities (refer to Table S1 in Multimedia Appendix 1 for the associated functionalities). The user-centric app aspects of purpose, introduction, user-friendliness, database, and information received the highest mean ratings (all ≥5).

In Table 2, the top 3 most important app functionalities per use phase and the user-centric app aspect to which they belong are displayed (refer to Table S2 in Multimedia Appendix 1 for the full list of app functionality ratings). In the starting phase, the top 3 app functionalities include a clear introduction and the purpose of the app. Furthermore, flexibility in food tracking is important. In the use phase, app functionalities relating to the product database and the user-friendliness of the app were rated as particularly important. In the end phase, the most important app functionalities were the possibility of setting achievable goals, setting new personal goals, and offering new information to the user continuously.

Table 3 shows the mean importance ratings for the 10 user-centric app aspects per user group (current users, former users, and nonusers). Significant differences between the groups were found in the following app aspects: personalization (P<.001), user-friendliness (P<.001), database (P<.001), and monitoring (P<.001). Regarding personalization, user-friendliness, and monitoring, current users gave significantly higher ratings than nonusers. Regarding the database, former users gave significantly higher ratings than nonusers. Although the differences between these groups were significant, the mean ratings for all 3 user groups were still very close to each other (ranging from a 0.2 to 0.7 difference on a 7-point Likert scale).

Table 1. Mean importance rating per user-centric app aspect (n=1420).

<table>
<thead>
<tr>
<th>Phase and user-centric app aspect</th>
<th>Values, mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Start</strong></td>
<td></td>
</tr>
<tr>
<td>Purpose</td>
<td>5.1 (1.2)</td>
</tr>
<tr>
<td>Introduction</td>
<td>5.2 (1.2)</td>
</tr>
<tr>
<td><strong>Use</strong></td>
<td></td>
</tr>
<tr>
<td>Personalization</td>
<td>4.9 (1.1)</td>
</tr>
<tr>
<td>User-friendliness</td>
<td>5.2 (1.1)</td>
</tr>
<tr>
<td>Database</td>
<td>5.4 (1.2)</td>
</tr>
<tr>
<td>Information</td>
<td>5.0 (1.2)</td>
</tr>
<tr>
<td>Monitoring</td>
<td>4.7 (1.2)</td>
</tr>
<tr>
<td>Feedback</td>
<td>4.4 (1.3)</td>
</tr>
<tr>
<td>Communication</td>
<td>4.4 (1.2)</td>
</tr>
<tr>
<td><strong>End</strong></td>
<td></td>
</tr>
<tr>
<td>Continuous engagement</td>
<td>4.9 (1.2)</td>
</tr>
</tbody>
</table>

*a Measured on a 7-point Likert scale (1=very unimportant and 7=very important).*

https://mhealth.jmir.org/2023/1/e39515
Table 2. Top 3 most important nutrition app functionalities per use phase and the corresponding user-centric app aspect (n=1420).

<table>
<thead>
<tr>
<th>Phase and app functionalitya</th>
<th>Values, mean (SD)</th>
<th>User-centric app aspect</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Start</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Immediately clear how app should be used</td>
<td>5.45 (1.32)</td>
<td>Introduction</td>
</tr>
<tr>
<td>The app has a clear purpose</td>
<td>5.40 (1.40)</td>
<td>Purpose</td>
</tr>
<tr>
<td>Possibility to track food intake at own time</td>
<td>5.33 (1.45)</td>
<td>Personalization</td>
</tr>
<tr>
<td><strong>Use</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Complete and reliable product database</td>
<td>5.58 (1.41)</td>
<td>Database</td>
</tr>
<tr>
<td>Easy navigation through the app</td>
<td>5.56 (1.36)</td>
<td>User-friendliness</td>
</tr>
<tr>
<td>Limited advertisements in free version</td>
<td>5.53 (1.51)</td>
<td>User-friendliness</td>
</tr>
<tr>
<td><strong>End</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Possibility to set realistic and achievable goals</td>
<td>5.23 (1.44)</td>
<td>Continuous engagement</td>
</tr>
<tr>
<td>Possibility to set new personal goals</td>
<td>5.13 (1.45)</td>
<td>Continuous engagement</td>
</tr>
<tr>
<td>New and relevant information is continuously offered</td>
<td>4.88 (1.44)</td>
<td>Continuous engagement</td>
</tr>
</tbody>
</table>

aMeasured on a 7-point Likert scale (1=very unimportant and 7=very important).

Table 3. Mean importance rating per user-centric app aspect, comparing 3 different user groups (current, former, and nonusers).

<table>
<thead>
<tr>
<th>Phase and user-centric app aspect</th>
<th>Current users (n=276), mean (SD)</th>
<th>Former users (n=38), mean (SD)</th>
<th>Nonusers (n=1106), mean (SD)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Start</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Purpose</td>
<td>5.35 (0.90)</td>
<td>5.22 (0.84)</td>
<td>5.09 (1.26)</td>
<td>.004</td>
</tr>
<tr>
<td>Introduction</td>
<td>5.31 (1.00)</td>
<td>5.11 (0.97)</td>
<td>5.21 (1.30)</td>
<td>.40</td>
</tr>
<tr>
<td><strong>Use</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Personalization</td>
<td>5.21 (0.81)a</td>
<td>5.11 (0.67)b</td>
<td>4.77 (1.16)b</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>User-friendliness</td>
<td>5.34 (0.87)a</td>
<td>5.57 (0.69)b</td>
<td>5.10 (1.10)b</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Database</td>
<td>5.57 (0.95)a,b</td>
<td>5.94 (0.76)a</td>
<td>5.34 (1.22)b</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Information</td>
<td>5.21 (1.00)</td>
<td>5.16 (0.98)</td>
<td>4.91 (1.25)</td>
<td>.001</td>
</tr>
<tr>
<td>Monitoring</td>
<td>5.02 (1.01)a</td>
<td>4.66 (1.14)a,b</td>
<td>4.68 (1.28)b</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Feedback</td>
<td>4.65 (1.25)</td>
<td>4.33 (1.32)</td>
<td>4.38 (1.26)</td>
<td>.005</td>
</tr>
<tr>
<td>Communication</td>
<td>4.59 (1.24)</td>
<td>4.16 (1.20)</td>
<td>4.35 (1.23)</td>
<td>.007</td>
</tr>
<tr>
<td><strong>End</strong></td>
<td></td>
<td></td>
<td></td>
<td>.001</td>
</tr>
<tr>
<td>Continuous engagement</td>
<td>5.17 (0.98)</td>
<td>5.17 (0.90)</td>
<td>4.88 (1.26)</td>
<td></td>
</tr>
</tbody>
</table>

a,bCells with the same letters indicate no significant difference following the post hoc analysis.

**Nutrition App Use and Reasons to Quit**

Approximately one-fifth (314/1420, 22.1%) of the respondents had experience using a nutrition app, either in the past or at the time of filling out the survey. The majority (1106/1420, 77.9%) never made use of a nutrition app. Within the group of users, a distinction could be made between current users (276/1420, 19.4%) and former users (38/1420, 2.7%).

Table 4 shows the most important reasons to make use of a nutrition app, as filled out by current users. The most important reasons were gaining insight into their own dietary pattern (113/276, 40.9%), losing weight (112/276, 40.6%), and maintaining body weight (96/276, 34.8%). More specific goals such as gaining insight into a specific meal moment (56/276, 20%), gaining insight into healthier alternatives for specific food products (50/276, 18%), or aiming to reduce snacking (48/276, 17%) seem less relevant.

Table 5 shows the most important reasons to stop using a nutrition app, according to former users. The following reasons were not selected in the survey and are therefore left out of the table: “App could not be personalized to my needs”; “Too many advertisements”; “It was difficult to keep track of personal progress”; and “It was unclear how to use the app.” The most frequently mentioned reason was that using the app required too much time (14/38, 36.8%). Other frequently mentioned reasons were that the goal for which the app was installed was not important anymore (6/38, 15.8%) or that the app was not providing new information any longer (5/38,
13.2%). Remarkably, quitting the use because the database was not reliable (1/38, 3%) was mentioned by only 1 participant. The fact that the app could not be personalized to the users’ needs or that it was difficult to keep track of personal progress were both not mentioned. The same holds for too many advertisements in the app or that it is unclear how the app works. Table 6 shows the most important reasons for not using a nutrition app, as answered by the group of nonusers. The most frequently mentioned reasons were no need to gain insight into dietary pattern (379/1106, 34%), followed by not seeing the need to use a nutrition app (360/1106, 30%), or having never heard of nutrition apps (235/1106, 21%). Moreover, in this group, the time investment seems to be a barrier because 16.6 (184/1106) of the participants mentioned not having time to use a nutrition app. Privacy does not seem to be an important barrier because being afraid that the data will not be treated confidentially was only mentioned by a relatively small part of the group (108/1106, 10%).

Table 4. Most important reasons to use a nutrition app in current users (n=276).a

<table>
<thead>
<tr>
<th>Reason</th>
<th>Values, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaining insight into own dietary pattern</td>
<td>113 (40.9)</td>
</tr>
<tr>
<td>Losing weight</td>
<td>112 (40.6)</td>
</tr>
<tr>
<td>Maintaining body weight</td>
<td>96 (34.8)</td>
</tr>
<tr>
<td>Gaining insight into macronutrient intake, for example, protein</td>
<td>91 (33.0)</td>
</tr>
<tr>
<td>Aiming to eat healthier</td>
<td>85 (30.8)</td>
</tr>
<tr>
<td>Improving my health</td>
<td>85 (30.8)</td>
</tr>
<tr>
<td>Gaining insight into specific products and nutrients</td>
<td>78 (28.3)</td>
</tr>
<tr>
<td>Gaining insight into dietary pattern and physical activity</td>
<td>78 (28.3)</td>
</tr>
<tr>
<td>Gaining insight into a specific meal moment</td>
<td>56 (20.3)</td>
</tr>
<tr>
<td>Gaining insight into healthier alternatives for specific products</td>
<td>50 (18.1)</td>
</tr>
<tr>
<td>Aiming to reduce snacking</td>
<td>48 (17.4)</td>
</tr>
<tr>
<td>Other reasons</td>
<td>2 (0.8)</td>
</tr>
</tbody>
</table>

*aParticipants could indicate multiple reasons; therefore, percentages do not add up to 100%.

Table 5. Most important reasons to quit using a nutrition app in former users (n=38).a

<table>
<thead>
<tr>
<th>Reason</th>
<th>Values, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>It costs too much time</td>
<td>14 (36.8)</td>
</tr>
<tr>
<td>Goal for which I installed the app was not important anymore</td>
<td>6 (15.8)</td>
</tr>
<tr>
<td>The app was not providing new information anymore</td>
<td>5 (13.2)</td>
</tr>
<tr>
<td>I reached the goal for which I installed the app</td>
<td>3 (7.9)</td>
</tr>
<tr>
<td>App was not user-friendly</td>
<td>3 (7.9)</td>
</tr>
<tr>
<td>Too little or inappropriate feedback on dietary intake</td>
<td>2 (5.3)</td>
</tr>
<tr>
<td>Functionality of the app were too limited</td>
<td>1 (2.6)</td>
</tr>
<tr>
<td>Database with food products was not reliable</td>
<td>1 (2.6)</td>
</tr>
<tr>
<td><strong>Other reasons</strong></td>
<td><strong>5 (13.2)</strong></td>
</tr>
<tr>
<td>No space for it on my phone</td>
<td>1 (2.6)</td>
</tr>
<tr>
<td>The app triggered unhealthy/obsessed behaviors</td>
<td>2 (5.3)</td>
</tr>
<tr>
<td>I had to monitor physical exercise</td>
<td>1 (2.6)</td>
</tr>
<tr>
<td>I did not achieve the desired result</td>
<td>1 (2.6)</td>
</tr>
</tbody>
</table>

*aParticipants could indicate multiple reasons; therefore, percentages do not add up to 100%.
Table 6. Most important reasons for not using a nutrition app in nonusers (n=1106)∗

<table>
<thead>
<tr>
<th>Reason</th>
<th>Values, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No need to gain insight in own dietary pattern</td>
<td>379 (34.2)</td>
</tr>
<tr>
<td>Do not see the point in using a nutrition app</td>
<td>329 (29.7)</td>
</tr>
<tr>
<td>Never heard of it</td>
<td>235 (21.2)</td>
</tr>
<tr>
<td>No time to use a nutrition app</td>
<td>184 (16.6)</td>
</tr>
<tr>
<td>Not involved in eating differently or healthier</td>
<td>165 (14.9)</td>
</tr>
<tr>
<td>Do not feel like learning how a nutrition app works</td>
<td>156 (14.1)</td>
</tr>
<tr>
<td>Afraid that data will not be treated confidentially</td>
<td>108 (9.7)</td>
</tr>
<tr>
<td><strong>Other reasons</strong></td>
<td></td>
</tr>
<tr>
<td>User-unfriendliness or other obstacles</td>
<td>35 (2.5)</td>
</tr>
<tr>
<td>Sufficient knowledge on healthy nutrition</td>
<td>26 (1.8)</td>
</tr>
<tr>
<td>No need to use a nutrition app</td>
<td>31 (2.2)</td>
</tr>
<tr>
<td>Not possible owing to illness, age, or specific diet</td>
<td>11 (0.8)</td>
</tr>
<tr>
<td><strong>Other</strong></td>
<td>13 (0.9)</td>
</tr>
</tbody>
</table>

∗Participants could indicate multiple reasons; therefore, percentages do not add up to 100%.

Discussion

Principal Findings

In our study, we found that there are numerous functionalities in nutrition apps that contribute to consumers’ intentions to use and maintain using these tools. In total, 3 different phases of app use, 10 user-centric app aspects, and 46 associated app functionalities were identified. We found that consumers encounter several difficulties and barriers in using nutrition apps for a longer period. The qualitative study provided insights into the needs, perceptions, and opinions on app aspects that are important to consider in developing effective nutrition apps. Both by users and nonusers, these aspects were considered as important to include in nutrition apps, and no large differences between the groups were found. Our findings undermine the importance of a participatory approach when designing mHealth interventions, ensuring that the intervention addresses the target user’s needs and that the applied technology is easy to use to be successfully implemented in real life. This shows the relevance of not only evaluating the effectiveness of mHealth interventions by assessing health outcomes (eg, what does the use of a nutrition app do with nutritional behavior) but also by including user evaluations of various app aspects for effective implementation (eg, what is important for users to be engaged with nutrition apps) [31].

Comparison With Prior Work and Recommendations

Overview

To the best of our knowledge, this study is the first to identify the different phases of nutrition app use, including user-centric app aspects and key app functionalities. We add to the literature by providing a complete overview of which app functionalities are important in each phase of app use, according to both users and nonusers. Several other studies have examined consumers’ preferences and barriers to using diet and nutrition apps. Here, the findings of these studies will be described and compared with our findings.

Findings Per Use Phase

In the starting phase, personalization of different nutrition app features seems to be a promising strategy for user engagement. App features should therefore be customizable and tailored to individual needs and goals, which is also described in the review by König et al [29]. Their findings are in accordance with our survey results, in which we found that especially personalization of the food tracking feature (eg, the possibility to track food intake at a convenient time) was important in the starting phase. Furthermore, we showed the importance of a clear purpose and introduction in the starting phase. A study by Dennison et al [32] evaluating mHealth app use found that participants want to be made fully aware of what the app can do before use. However, users are unlikely to read lengthy instructions and terms and conditions [32]. This emphasizes the importance of a clear and short introduction (eg, a tutorial) when setting up the app.

In the use phase, we found that user-friendliness and the food product database were among the most important app aspects. In a large web-based survey among European consumers, Vasiloglou et al [25] found that one of the primary criteria for selecting nutrition apps was ease of use. An app was less likely to be selected in case of issues with the food product database, such as incorrect nutritional information, a database that does not include local foods, or a database that omits major foods [25]. Several issues relating to the food database were mentioned in the FGDs, ranging from too detailed information and too many options for 1 product to questioning the reliability of the nutritional information provided. Issues with the food database can have consequences for nutrition app selection by consumers [25]. Other studies confirmed that the reliability and quality of the food database are common issues in nutrition apps and that
the accuracy of nutrient information is sometimes questionable [33-36].

Although the current state of evidence supports that gamification can have a positive impact on changing health behaviors [37], including a gamification element in a nutrition app received one of the lowest ratings in our survey, meaning that consumers did not see the need to include this functionality in a nutrition app. Another functionality that received a low rating was interaction through social media. This was also found in the review by Snizay et al [38] on engagement with mHealth apps. They found that social support factors (social media and social competition) are not universally useful and might even cause disengagement by triggering negative emotions.

In the end phase, the ability to set new and achievable goals was one of the most important elements of the survey according to users. In the literature, achievable goal setting is identified as a promising facilitator for achieving behavior change [39]. Snizay et al [38] showed that goal setting was related to sustained engagement with mHealth and well-being apps. Incorporating a way to set daily and achievable goals, therefore, seems promising to keep users engaged in the final phase. In addition, nutrition apps should continuously offer new information, facts, and advice to keep users interested and engaged over a longer period.

The user-centric app aspects that arose from our qualitative study included several other validated BCTs such as monitoring and providing feedback. Broadly, the app elements that we identified are on the one hand elements that relate to these BCTs, such as factual information on nutrient intake (information), a visual progress overview (monitoring), and feedback messages (feedback), and on the other hand, the more technical design aspect of the app, such as a tutorial and a reliable database. Our study adds to the literature by showing that, for users, not only these technical aspects but also the way BCTs are implemented are important app elements. This suggests that the BCT mechanisms are not only considered as effective theoretical interventions to include in mHealth apps by health psychologists [13-16] but are, next to technical design aspects, also considered as critical elements from the user perspective.

Differentiating between the phases of use is a relevant approach to changing health behavior. There are several other theoretical models in the field of health behavior change that make a distinction between different stages, such as the Transtheoretical Model. This model describes stage-specific characteristics for behavior change and suggests that behavioral change is a dynamic process, comprising the precontemplation, contemplation, preparation, action, and maintenance stages [40]. Our 3 phases of nutrition app use overlap with the preparation (start), action (use), and maintenance (continuation) stages of the Transtheoretical Model. A user typically goes through the start phase, the use phase, and the end phase, where they reach a point where the app will be used permanently or occasionally or will not be used anymore. The decision for continued use is interlinked with the aspects mentioned in the earlier phases of use. The precontemplation and contemplation phases are lacking in our research. In these phases, awareness and intention are created to start performing a certain behavior. Because in our study participants were required to use a nutrition app as a home-use test and did not start using the app out of their own intrinsic motivation, we cannot make any statements about what app elements are important to create the intention to start using the app. Our starting phase starts when the app is installed and a user starts to navigate through the app, but obviously, in practice, this is preceded by an “intention to start” phase. The Unified Theory of Acceptance and Use of Technology sheds some light on this intention phase and distinguishes 4 factors that are important in this phase: performance expectancy (eg, the belief that a nutrition app will help), effort expectancy (eg, the expectancy that the app will be easy to use), social influence (eg, the beliefs of others who are important), and facilitating conditions (eg, the degree to which a user believes that an infrastructure exists to support use of the system) [41]. Future research is needed to obtain a better understanding of app requirements that are crucial to get users to install and open the app in the first place.

**Quit or Start Nutrition App Use**

The high time investment that consumers perceived as one of the main barriers was also one of the main reasons for quitting nutrition app use in the survey. The fact that using a nutrition app is perceived as time-consuming can be a result of several issues, such as poor user-friendliness or bad quality of the food product database. Poor user-friendliness is indeed a common issue for nutrition apps [29]. According to a study by Zečević et al [26], technical issues can also be a barrier in this regard. Therefore, nutrition app developers should pay particular attention to a complete and trustworthy food database and the user-friendliness of the app.

Finally, in our qualitative study, we found that nutrition apps can be specifically helpful for new users and that the learning curve is steepest in the beginning. A recent study by Samoggia et al [42] shows that a nutrition-information app is indeed mostly effective among consumers with limited knowledge. One of the main reasons to use a nutrition app that emerged from our survey was to gain more insight into one’s dietary pattern. Lowe et al [43] also suggest that nutrition app use can help increase nutrition knowledge and awareness of consumption practices. Losing and maintaining body weight were other frequently mentioned reasons to use a nutrition app. This is in line with the findings of the review by König et al [29]: the main goals of using nutrition apps were related to food tracking, diet improvement, and weight management. Several review studies show the effectiveness of nutrition apps in reducing body weight in different consumer groups [7,44,45]. Therefore, given their magnitude, low cost, and easy accessibility, nutrition apps are promising tools for consumers with limited knowledge to adopt healthier eating behaviors and to lose or maintain body weight.

**Limitations and Future Research**

Our study has some limitations that need to be addressed. First, in both studies, a relatively large number of higher-educated consumers and, in the qualitative study, consumers interested in nutrition apps participated, which might have biased our results. However, these groups are probably also the ones that make use of nutrition apps in real life; therefore, we expect that the results might in fact be quite representative for...
implementation in real life. mHealth apps seem to be mostly designed to help a group of higher-educated and motivated consumers, which can be considered a limitation of these types of tools. This means that for unmotivated or lower-educated consumers, other types of interventions might be more suitable, which should be tested in future research. In this qualitative study, free versions of the 6 nutrition apps were included. It might be possible that the paid upgrades of the apps included better or additional features. Furthermore, the consumers who participated in the FGDs had no clear goal when using the app during the home-use test because we asked them to install the app for our study. The fact that they had no clear personal goal with the app, combined with the poor user-friendliness of some of the apps, might have caused early discontinuation by some users. In the survey, all 46 nutrition app functionalities were assessed on 7-point Likert scales and rated on importance. The rating of these 46 functionalities might have caused fatigue; however, we did include motivational messages in between questions, and respondents with no variability in their answers were removed from the analyses. The top 3 most important app functionalities per use phase were based on mean scores. This approach was chosen because we aimed to validate all user-centric app aspects and functionalities that we found in the FGDs. Including all of them in a ranking task or choice-based experiment was not feasible. This method may have caused consumers to rate almost all aspects as important, as they were not forced to make a choice. This made it difficult to draw conclusions on which specific elements are most important to include in nutrition apps. Therefore, a choice-based experiment with a selection of nutrition app functionalities is recommended, making it possible to uncover the trade-offs between different app functionalities. Another limitation is that we examined consumers’ intentions and preferences, and we did not study the effect of nutrition app functionalities on actual dietary behavior. Such an intervention would be recommended for future research.

Finally, in both studies, we mainly focused on the elements and functionalities in the nutrition app itself. However, user characteristics and characteristics of the eating context could also influence consumers’ intentions to use nutrition apps. The framework of König et al [29] highlights that besides technological reasons, the characteristics of the potential user, the interplay between user and technology, and the social environment also impact whether a nutrition app is used. In addition, Flaherty et al [46] stress the increasing importance of situational involvement and individual characteristics in engagement with mHealth apps.

Conclusions
Nutrition apps should be supportive in all 3 phases of use (start, use, and end) to increase consumers’ intentions to start and maintain the use of these apps and achieve a change in dietary behavior. In the starting phase, a clear purpose, introduction, and personalization are important functionalities. In the use phase, a high-quality, credible food product database and user-friendliness are particularly important. In the end phase, the app should continuously offer new information and the possibility of setting new personal goals. High time investment is an important reason to quit the use of a nutrition app. Several other issues with nutrition apps (ie, poor user-friendliness and not offering new information anymore) need to be addressed first before long-term use can be achieved. Because almost all app functionalities in our study were considered as important by both users and nonusers, a choice-based experiment with different nutrition apps is recommended as a next step.

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Authors’ Contributions
SvdH, IR, and SM designed and executed the qualitative study in collaboration with Canvas Concepting. SvdH, MCDV, and SM designed the quantitative study. SM executed the quantitative study, in collaboration with MSI-ACI Europe Ltd. SM and SvdH analyzed the data of both the qualitative and quantitative study, with support from Canvas Concepting for the analyses of the focus group discussions. SvdH drafted the paper as first author. IR, MCDV, and SM reviewed the paper and contributed to paper discussions.

Conflicts of Interest
None declared.

Multimedia Appendix 1
Supplementary tables and figures.
[DOCX File, 24 KB - mhealth_v11i1e39515_app1.docx ]

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Abbreviations

BCT: behavior change technique
FGD: focus group discussion
mHealth: mobile health

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Original Paper

The Effectiveness of a Traditional Chinese Medicine–Based Mobile Health App for Individuals With Prediabetes: Randomized Controlled Trial

Hsueh-Wen Chung1, MS; Chen-Jei Tai2,3, MD, PhD; Polun Chang4, PhD; Wen-Lin Su5,6, MD, PhD; Li-Yin Chien7, MPH, ScD

1Department of Nursing, College of Nursing, National Yang Ming Chiao Tung University, Taipei City, Taiwan
2Tai’s Traditional Chinese Medicine Clinic, Taipei City, Taiwan
3Department of Obstetrics and Gynecology, School of Medicine, College of Medicine, Taipei Medical University, Taipei City, Taiwan
4Institute of Biomedical Informatics, National Yang Ming Chiao Tung University, Taipei City, Taiwan
5Division of Pulmonary and Critical Care Medicine, Department of Internal Medicine, Taipei Tzu Chi Hospital, Buddhist Tzu Chi Medical Foundation, New Taipei City, Taiwan
6School of Medicine, Tzu Chi University, Hualien, Taiwan
7Institute of Community Health Care, College of Nursing, National Yang Ming Chiao Tung University, Taipei City, Taiwan

Corresponding Author:
Li-Yin Chien, MPH, ScD
Institute of Community Health Care
College of Nursing
National Yang Ming Chiao Tung University
No. 155, Sec. 2 Linong Street, Beitou District
Taipei City, 11221
Taiwan
Phone: 886 2 2826 7000 ext 7142
Fax: 886 2 2826 7142
Email: lychien@nycu.edu.tw

Abstract

Background: Traditional Chinese medicine (TCM) theories assert that body constitution and meridian energy lay the foundation for disease prevention. TCM-based health concepts have not yet been incorporated into mobile health (mHealth) apps for individuals with prediabetes.

Objective: The aim of this study was to examine the effectiveness of a TCM mHealth app for individuals with prediabetes.

Methods: This randomized controlled trial recruited 121 individuals with prediabetes at a teaching hospital in New Taipei City between February 2020 and May 2021. The participants were randomly assigned to the TCM mHealth app group (n=42), ordinary mHealth app group (n=41), or control group (n=38). All participants received the usual care that included 15-20 minutes of health education about the disease, along with healthy diet and exercise encouragement. The ordinary mHealth app included physical activity (PA), diet, and disease education, along with individual records. The TCM mHealth app additionally included qi and body constitution information, along with constitution-based PA and diet advice. The control group received the usual care alone and did not have access to any app. Data were collected at baseline, at the end of the 12-week intervention, and 1 month after the intervention. Body constitution, including yang-deficiency, yin-deficiency, and phlegm-stasis, was measured according to the Body Constitution Questionnaire, with higher scores indicating a greater deficiency. Body energy was examined using the Meridian Energy Analysis Device. The Short-Form 36 questionnaire was used to evaluate health-related quality of life (HRQOL), which yielded physical component scores and mental component scores, with higher scores indicating better physical and mental aspects of HRQOL, respectively.

Results: Compared to the control group, the TCM mHealth app group showed greater improvement in hemoglobin A1c (HbA1c), yang-deficiency and phlegm-stasis body constitution, and BMI; however, no significant differences were found in these outcomes between the TCM mHealth app and ordinary mHealth app groups. The TCM mHealth app group showed better improvement in body energy and mental component scores than the ordinary mHealth app group. There were no significant differences in fasting
plasma glucose, yin-deficiency body constitution, Dietary Approaches to Stop Hypertension dietary behavior, and total PA among the three groups after the intervention.

**Conclusions:** Use of either the ordinary or TCM mHealth app improved HRQOL among individuals with prediabetes. Compared to the outcomes of controls not using any app, use of the TCM mHealth app was effective at improving HbA1c, BMI, yang-deficiency and phlegm-stasis body constitution, and HRQOL. Moreover, using the TCM mHealth app seemed to improve the body energy and HRQOL more than when using the ordinary mHealth app. Further studies with a larger sample size and longer follow-up period may be necessary to determine whether the differences favoring the TCM app are clinically meaningful.

**Trial Registration:** ClinicalTrials.gov NCT04096989; https://clinicaltrials.gov/ct2/show/NCT04096989

**KEYWORDS**
mHealth app; prediabetes; traditional Chinese medicine; health-related quality of life; body constitution; meridian energy

**Introduction**

Prediabetes is a subhealth condition characterized by higher than normal blood sugar levels, but not yet at a sufficiently high level to warrant a diagnosis of type 2 diabetes mellitus (T2DM) [1]. The American Diabetes Association proposes a diagnosis of prediabetes according to a fasting plasma glucose (FPG) level in the range of 100-125 mg/dL, hemoglobin A1c (HbA1c) in the range of 5.7%-6.4%, or 2-hour postprandial blood glucose level after the 75-g oral glucose test in the range of 140-199 mg/dL [2]. The prevalence of prediabetes among adults has been estimated to be 34.5% [3], with approximately 5%-10% of those diagnosed with prediabetes ultimately developing T2DM within 1 year [4].

The Centers for Disease Control and Prevention Diabetes Prevention Program (DPP) has been shown to effectively delay or prevent the development of T2DM among individuals diagnosed with prediabetes [5-7]. To reduce the cost and promote DPP-based lifestyle interventions, a technology-assisted DPP intervention is advised to be adopted with mobile and web-based apps and text messaging. Using a smartphone and computer could be ideal techniques to create widely available, easy-to-use diabetes prevention tools [8,9]. A randomized controlled trial (RCT) showed that mobile-delivered DPP achieved significant weight and BMI reductions compared with usual care. However, the intervention does not appear to be effective in controlling HbA1c [10]. Another RCT developed a fully automated algorithm-driven behavioral intervention delivered via the web, internet, mobile phone, and automated phone calls, demonstrating that the intervention group had significantly decreased FPG and HbA1c, and increased physical activity (PA) and vegetable consumption [11,12].

People’s lifestyles and behaviors have close associations with their sociocultural background [13]. Body constitution and meridian energy are fundamental concepts in traditional Chinese medicine (TCM). Body constitution represents the individual’s body condition that makes them susceptible to certain diseases but not others [14]. Body constitution forms the basis for disease treatment and prevention in TCM [15]. Meridians are channels that form a network in the body through which qi and blood (vital energy) flow [16,17]. The energy flow throughout the body via the 12 meridians is referred to as the meridian energy [18]. A high mean meridian energy (the average of the 12 meridian energies or body energy) usually means that qi and blood flow are strong and move smoothly throughout the meridians [19].

Several measures use different types of classifications for body constitution [20-23]. Nevertheless, yang-deficiency, yin-deficiency, and phlegm-stasis body constitution are common features that are prevalent in patients with chronic diseases [24,25]. Yang-deficiency refers to an insufficiency of qi. Individuals with this deficiency may experience symptoms such as fatigue, shortness of breath, chills, loose stool, and a large volume of urine. Yin-deficiency reflects an insufficiency in blood and interstitial fluids, and thus patients with yin-deficiency may experience symptoms such as being constantly thirsty, experiencing hot flushes, hard stool, and a low volume of urine. Phlegm is a viscous and turbid pathological factor formed due to an imbalance in body fluid. Phlegm-stasis refers to the accumulation of phlegm in the body as a form of condensation, which results in dizziness, chest tightness, and numbness in the limbs [26]. These TCM concepts of blood, phlegm, and fluids are not equivalent to the Western uses of these terms, but are instead used to represent energetic qualities. For example, in TCM, blood is considered a vehicle for qi and blood flow are strong and move smoothly throughout the meridians [27].

Previous studies showed that individuals with prediabetes or diabetes were more deficient in the body constitutions of yang-deficiency, yin-deficiency, and phlegm-stasis, and also had lower meridian energy [20,21,32]. In addition, body constitution is related to an unhealthy lifestyle, in which yang-deficiency and phlegm-stasis are related to physical inactivity and smoking, respectively [33]. Despite high heterogeneity in the contents of available interventions, TCM lifestyle programs typically involve body constitution-based TCM health education, Chinese dietary therapy, and traditional Chinese exercises [34-38]. These programs were designed to stimulate the qi-blood circulation and regulate Zang-Fu to enhance quality of life. Previous studies have shown that TCM lifestyle programs improve body constitution [34], dietary behavior [35], and PA [36], while helping to lower blood sugar [37,38]. According to TCM theory, an improved body constitution could decrease the susceptibility to chronic diseases [14]. Increased body energy would manifest in better stamina through TCM lifestyle programs [17]. Therefore, we...
hypothesized that body constitution and body energy could be improved by body constitution and TCM-based lifestyle modification through *Qigong* (a type of PA) and a healthy dietary regimen, and thus help to achieve blood sugar control and enhance health.

To the best of our knowledge, no study has been conducted to identify whether TCM-based health concepts could be incorporated into a mobile health (mHealth) app for individuals with prediabetes. The need for incorporating TCM body constitutions is based on two key factors: (1) as a sociocultural appropriate method to contextualize PA and diet, and (2) as possible mediation variables for blood sugar control such as HbA$_1c$ and FBG. Accordingly, the aim of this study was to develop a TCM mHealth app and examine its effectiveness on blood sugar control, body constitution, body energy, and health-related quality of life (HRQOL) as primary outcomes, as well as on BMI, dietary behavior, and PA as secondary outcomes among individuals with prediabetes. The hypothesis was that the TCM mHealth app would improve overall health through modifying health behavior and BMI. Therefore, the primary outcomes were overall health indicators (including body constitution and meridian energy) and the secondary outcomes were BMI and health behaviors.

**Methods**

**Study Design**

This study was an open-label, parallel-group RCT (ClinicalTrials.gov NCT04096989) with a three-group design. We cooperated with the health examination center and outpatient clinics at a teaching hospital in northern Taiwan to recruit individuals diagnosed with prediabetes from February 2020 to May 2021. The inclusion criteria were (1) having been diagnosed with prediabetes (according to an HbA$_1c$ of 5.7%-6.4% or an FPG level of 100-125 mg/dL [2]); (2) aged 20 years and above; (3) not having cardiopulmonary disease, cancer, or other major diseases; and (4) provision of informed consent. Those who had used hypoglycemic agents, β-blockers, thiazide diuretics, nicotinic acid, or steroids within the past 3 months were excluded.

Participants were randomly assigned to three groups: TCM mHealth app, ordinary mHealth app, or control group. A statistician drew up a computer-generated randomization list. The allocation sequence was kept in an opaque, sealed, and stapled envelope, and a staff member in the outpatient clinic who was not involved in the study held the sealed envelopes. After the participants agreed to participate in the study, the researcher opened the envelope to reveal their group assignment.

The informed consent form was signed by all participants before enrollment in the study. The informed consent form stated that the risk of participation in this study was low. If the participants felt physically or mentally unwell due to their participation, they had to contact the researchers and had the right to withdraw at any time. No adverse events were reported during the study period.

**Ethics Approval**

This study was approved by the institutional review board at Taipei Tzu Chi Hospital (approval no. 08-X-026).

**Participants**

The required sample size was calculated on the basis of repeated-measures ANOVA ($\alpha=.05$, power=.80, effect size=0.3) with three repeated measurements as per a previous study [37]. G-power software indicated that the required sample size was 31 per group. To account for 30% attrition [39], we recruited 121 participants in the study.

Figure 1 presents a flow diagram of participant allocation to the three groups. A total of 212 individuals with prediabetes were assessed for eligibility, 52 of whom did not meet the eligibility criteria and 39 of whom declined to participate. A total of 121 participants were randomly assigned to the TCM mHealth app group (n=42), ordinary mHealth app group (n=41), or control group (n=38).

All participants received the usual care at the study hospital when they received the diagnosis of prediabetes. The usual care was 15-20 minutes of health education by family medicine physicians, including disease explanation, healthy diet advice, and exercise encouragement. The control group received usual care only without the use of any app.
Figure 1. Participant flow diagram. mHealth: mobile health; T1: baseline; T2: end of the intervention; T2DM: type 2 diabetes mellitus; T3: 1 month after the intervention; TCM: traditional Chinese medicine.

**Intervention**

An expert team that included nursing researchers, TCM doctors, Western medicine doctors, and app developers was formed to guide the development of the intervention app. The team decided that the content embedded in the app would be developed in accordance with the DPP [40,41] and a review of the literature [34,37,42]. The experts sketched, shared, and discussed potential app versions and developed prototypes. To gather user feedback on the prototypes, qualitative interviews with seven experts and five individuals were conducted, with an aim to determine user preference for the prototype and what could be improved in the app. We used the feedback to revise and finalize the mHealth app. We invited five individuals with prediabetes to use the TCM mHealth app for 30 minutes. Subsequently, a short questionnaire was administered to determine app usability and satisfaction. The participants reported positive experiences. They all agreed with the statements "I found the TCM mHealth app easy to use" and "I would recommend the TCM mHealth app to my friends and others."

The mHealth app (both the ordinary and TCM versions) included four modules: health diary, health education, milestone, and chatroom. The “health diary” tracked the participant’s weight, BMI, blood sugar level, dietary diary, and PA over time. “Health education” provided information about specific topics such as learning about prediabetes, Dietary Approaches to Stop Hypertension (DASH) diet, and PA. The TCM mHealth app additionally included health education topics on body constitution, meridian energy, and advice on a body constitution–based diet (such as foods to avoid and foods that are recommended) and PA such as videos, pictures, and descriptive illustrations of types of Qigong (ie, Baduanjin and belly breath). A text message was sent to the participants to remind them to read the topics every week. Milestones were added for the participants to review their goals so that they could make adjustments to reach their monthly goals. For example, if the participants set a goal of an FPG level of 60-99 mg/dL, when this goal was achieved, a window would pop up to show the achievement. The participants could also check bar and line charts over 1 week or 1 month to compare the discrepancy between the actual and desired values as well as actual and ideal
behaviors at different time points so that they could adjust their expected goal as needed.

In the “chatroom,” personal and group chat rooms were set up using the LINE app (Naver Corp, Gyeonggi Province, South Korea). The researchers sent text messages to the participants in the personal chat room, provided feedback on the results, and encouraged participants to share their experiences in the group chat room. The participants collected virtual gold by completing questionnaires and quizzes and by achieving the set goals. The participants could use the virtual gold to claim actual prizes from the researchers. Gamification elements were added to encourage engagement with the mHealth app. Screenshots and descriptions of the ordinary and TCM mHealth apps are presented in Multimedia Appendix 2. The taxonomy of behavior change techniques [43] used in the apps is presented in Multimedia Appendix 3.

The participants in the TCM and ordinary mHealth app groups received a face-to-face education session on how to use the mHealth app and create a user account. Both mHealth app groups received information about prediabetes and evidence-based methods to decrease the possibility of progression to T2DM (eg, moderate-intensity PA of ≥150 minutes/week, DASH diet, and disease health education). The TCM mHealth app group additionally received body constitution and qi energy information, as well as constitution-based PA and diet advice (see Multimedia Appendix 2). Participants who were assigned to the TCM mHealth app group filled out the Body Constitution Questionnaire (BCQ) [20-22] at the beginning of the study. Tailored TCM diet and PA advice based on the individual’s body constitution as determined by their BCQ results was incorporated into the TCM mHealth app.

The researchers monitored logins and log file analysis at least once every week at the mHealth app backend. If the participants did not use the app, complete the diary, or watch health education, additional text messages were sent to the participants. The CONSORT-EHEALTH guidelines [44] were followed in reporting this study (see Multimedia Appendix 4).

**Data Collection**

Data were collected at baseline (T1), at the end of the 12-week intervention (T2), and 1 month after the intervention (T3). Sociodemographic characteristics (age, gender, marital status, education level, and employment status), clinical characteristics (history of chronic disease and use of TCM), and lifestyle factors (smoking and alcohol drinking) were collected by a structured questionnaire at baseline. Primary outcome measures, including blood sugar control (FPG and HbA1c levels), body constitution, meridian energy, and HRQOL, were collected at T1, T2, and T3.

Body constitution was assessed by the BCQ [20-22], which measures the presence and severity of symptoms in the most recent 7 days. The BCQ consists of 44 symptom ratings rated on a 5-point Likert-type scale ranging from 1 (not at all) to 5 (very severe). The items were summed and categorized into three types of body constitutions: 19 items for yang-deficiency, 19 for yin-deficiency, and 16 for phlegm-stasis. A higher score indicates a higher level of deficiency in the body constitution type [45]. The reliability and validity of the BCQ have been supported by the results of previous studies [20-22].

Meridian energy was measured using the Meridian Energy Analysis Device (MEAD) ME-PRO 6.1.1 (Medpex Enterprise Ltd, Taichung, Taiwan). The level of meridian energy was assessed using the MEAD values for the 24 acupoints (Ryodoraku points) along the 12 meridians ranging from 0 to 200 µA [16,46]. The participants were required to take nothing by mouth for at least 8 hours; remove their shoes, socks, and metal materials that may cause a disturbance; and sit in the room for 10-15 minutes before the meridian energy checkup [47]. Body energy was yielded by the average of the energy flows through the 24 acupoints along the 12 meridians, which serves as an indicator for the fluency of qi and blood moving throughout the body. Individuals with prediabetes have a lower level of body energy [32]. A low level of body energy indicates that the meridians are blocked and thus the qi and blood circulation are not smooth. A lower level of body energy thus indicates worse stamina.

HRQOL was measured by the Medical Outcome Survey Short Form (SF-36) Taiwan version. SF-36 is composed of 36 items, which form two summary scales, namely the physical component score (PCS) and the mental component score (MCS). Higher scores on the PCS and MCS indicate a better physical and mental aspect of HRQOL, respectively [48,49]. The reliability and validity of the SF-36 Taiwan version have been well-established [50,51].

The secondary outcomes in this study were BMI, dietary behavior, and PA. Dietary behavior was assessed by the dietary behavior questionnaire, which consisted of 14 items based on a 4-point Likert scale, ranging from 1 (never) to 4 (always). The scores ranged from 14 to 56, with higher scores indicating a better correspondence to the DASH diet [42]. PA was assessed by the International Physical Activity Questionnaire Taiwan version, which contained 7 questions about the frequency, duration, and intensity of PA in the last 7 days. The results could be further classified into mild, moderate, and vigorous PA and quantified into metabolic equivalents (MET), expressed as MET-minutes/week [52].

**Statistical Analysis**

The statistical analyses were performed using IBM SPSS Statistics for Windows, version 23.0 (IBM Corp, Armonk, NY, USA). We analyzed the data using an intention-to-treat analysis. For participants with incomplete or missing data, we used the maximum-likelihood method for imputation [53].

Descriptive characteristics are presented as percentages or as means and SD, as appropriate. We used the paired t-test to examine the changes in outcome variables within groups. One-way ANOVA was used for comparisons among groups with the Scheffe posthoc test for pairwise comparisons. Finally, we used generalized estimating equations (GEEs) to estimate the intervention effects after adjusting for age, gender, and baseline value of the outcome variables.
Results

Participant Characteristics
The characteristics of the three groups are shown in Table 1.

Table 1. Characteristics of the participants in the three groups.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Total (N=121)</th>
<th>CG(^a) (n=38)</th>
<th>OMG(^b) (n=41)</th>
<th>TCMG(^c) (n=42)</th>
<th>(\chi^2) or (F^d) (df)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years), mean (SD)</td>
<td>58.08 (10.21)</td>
<td>60.14 (10.83)</td>
<td>56.93 (10.88)</td>
<td>57.34 (8.81)</td>
<td>1.15 (2)</td>
<td>.32</td>
</tr>
<tr>
<td>Sex, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2.11 (2)</td>
<td>.35</td>
</tr>
<tr>
<td>Female</td>
<td>64 (52.9)</td>
<td>18 (47.4)</td>
<td>20 (48.8)</td>
<td>26 (61.9)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>57 (47.1)</td>
<td>20 (52.6)</td>
<td>21 (51.2)</td>
<td>16 (38.1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Currently married, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.69 (2)</td>
<td>.43</td>
</tr>
<tr>
<td>No</td>
<td>28 (23.1)</td>
<td>6 (15.8)</td>
<td>11 (26.8)</td>
<td>11 (26.2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>93 (76.9)</td>
<td>32 (84.2)</td>
<td>30 (73.2)</td>
<td>31 (73.8)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education level, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>3.61 (4)</td>
<td>.46</td>
</tr>
<tr>
<td>Elementary school or below</td>
<td>10 (8.3)</td>
<td>5 (13.2)</td>
<td>2 (4.9)</td>
<td>3 (7.1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Junior and senior high school</td>
<td>48 (39.7)</td>
<td>12 (31.6)</td>
<td>16 (39.0)</td>
<td>20 (47.6)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>University or above</td>
<td>63 (52.1)</td>
<td>21 (55.3)</td>
<td>23 (56.1)</td>
<td>19 (45.2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment status, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.18 (2)</td>
<td>.55</td>
</tr>
<tr>
<td>Unemployed</td>
<td>49 (40.5)</td>
<td>18 (47.4)</td>
<td>16 (39.0)</td>
<td>15 (35.7)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed</td>
<td>72 (59.5)</td>
<td>20 (52.6)</td>
<td>25 (61.0)</td>
<td>27 (64.3)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>History of chronic disease, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.03 (2)</td>
<td>.60</td>
</tr>
<tr>
<td>No</td>
<td>13 (10.7)</td>
<td>3 (7.9)</td>
<td>6 (14.6)</td>
<td>4 (9.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>108 (89.3)</td>
<td>35 (92.1)</td>
<td>35 (85.4)</td>
<td>38 (90.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Smoking status, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>6.81 (4)</td>
<td>.15</td>
</tr>
<tr>
<td>Never</td>
<td>97 (80.2)</td>
<td>29 (76.3)</td>
<td>30 (73.2)</td>
<td>38 (90.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quit</td>
<td>20 (16.5)</td>
<td>8 (21.1)</td>
<td>10 (24.4)</td>
<td>2 (4.8)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Current smoker</td>
<td>4 (3.3)</td>
<td>1 (2.6)</td>
<td>1 (2.4)</td>
<td>2 (4.8)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alcohol drinking, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>5.82 (4)</td>
<td>.21</td>
</tr>
<tr>
<td>Never</td>
<td>106 (87.6)</td>
<td>32 (84.2)</td>
<td>35 (85.4)</td>
<td>39 (92.9)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quit</td>
<td>4 (3.3)</td>
<td>2 (5.3)</td>
<td>0 (0.0)</td>
<td>2 (4.8)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Current drinker</td>
<td>11 (9.1)</td>
<td>4 (10.5)</td>
<td>6 (14.6)</td>
<td>1 (2.4)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(^a\)CG: control group.
\(^b\)OMG: ordinary mobile health app group.
\(^c\)TCMG: traditional Chinese medicine mobile health app group.
\(^d\)F and \(\chi^2\) are the respective values of one-way ANOVA and Pearson \(\chi^2\) test.

Overall Intervention Effects
The crude effects of the intervention on the outcomes are shown in Figures 2 and 3 (details are shown in Multimedia Appendix 5). Of the outcomes included, there were significant differences in yang-deficiency and phlegm-stasis body constitution among the three groups, with the TCM mHealth app group scoring higher than the control group (Figure 2). In addition, the ordinary mHealth app group reported the highest amount of PA among the three groups (Figure 3). For body constitution and PA, GEE results are preferred over the crude results given baseline differences. There were no significant differences in other outcomes between the groups at preintervention. Net effects of the intervention on the outcomes are shown in Table 2 (full model results are shown in Multimedia Appendix 6) using the control group as the reference. To explicitly compare the effects between the TCM and ordinary mHealth groups, Table 3 shows the results using the ordinary mHealth group as the reference (full model results are shown in Multimedia Appendix 7).
Figure 2. Changes in primary outcomes. (A) Fasting plasma glucose. (B) HbA1c. (C) Yang deficiency body constitution. (D) Ying deficiency body constitution. (E) Phlegm stasis body constitution. (F) Body energy. (G) Physical component score. (H) Mental component score. Within-group across-time comparisons were made from a paired t test with T1 as the reference. Between-group comparisons were based on one-way ANOVA with the Scheffe posthoc test, with the results presented below graphs. mHealth: mobile health; T1: baseline; T2: end of the intervention; T3: 1 month after the intervention; TCM: traditional Chinese medicine. *P<.05, #P<.001.

Figure 3. Changes in secondary outcomes. (A) BMI. (B) DASH dietary behavior. (C) Total physical activity. Within-group across-time comparisons were made from a paired t test with T1 as the reference. Between-group comparisons were based on one-way ANOVA with the Scheffe posthoc test, with the results presented below the graph in (C). mHealth: mobile health; T1: baseline; T2: end of the intervention; T3: 1 month after the intervention; TCM: traditional Chinese medicine. *P<.05, #P<.001.
Table 2. Generalized estimating equation models to compare the differences among the three groups, using the control group as the reference.\(^a\)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>OMG(^c)×T2(^b), (\beta) (95% CI)</th>
<th>OMG×T3(^d), (\beta) (95% CI)</th>
<th>TCMG(^e)×T2, (\beta) (95% CI)</th>
<th>TCMG×T3, (\beta) (95% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FPG(^f)</td>
<td>-1.18 (-5.92 to 3.56)</td>
<td>3.17 (-2.22 to 8.56)</td>
<td>-2.52 (-7.39 to 2.35)</td>
<td>-0.37 (-5.61 to 4.86)</td>
</tr>
<tr>
<td>HbA(_1c)(^g)</td>
<td>-0.06 (-0.15 to .04)</td>
<td>-0.05 (-0.14 to .04)</td>
<td>-0.08 (-0.18 to .02)</td>
<td>-0.11 (-0.21 to -0.01)</td>
</tr>
<tr>
<td>Yang-deficiency BC(^h)</td>
<td>-0.81 (-3.16 to 1.53)</td>
<td>-0.46 (-2.73 to 1.81)</td>
<td>-3.15 (-6.09 to -2.21)</td>
<td>-2.37 (-5.04 to .29)</td>
</tr>
<tr>
<td>Yin-deficiency BC</td>
<td>-0.02 (-2.56 to 2.52)</td>
<td>0.03 (-2.08 to 2.13)</td>
<td>-2.29 (-5.28 to .70)</td>
<td>-1.62 (-4.21 to .96)</td>
</tr>
<tr>
<td>Phlegm-statis BC</td>
<td>-1.36 (-4.16 to 1.44)</td>
<td>-1.88 (-4.38 to .63)</td>
<td>-3.45 (-6.49 to -1.42)</td>
<td>-3.30 (-6.01 to -5.58)</td>
</tr>
<tr>
<td>Body energy</td>
<td>-1.16 (-11.23 to 10.91)</td>
<td>-5.84 (-17.68 to 6.01)</td>
<td>8.60 (-1.91 to 19.11)</td>
<td>7.81 (-3.36 to 18.98)</td>
</tr>
<tr>
<td>PCS(^i)</td>
<td>2.56 (-.44 to 5.56)</td>
<td>2.90 (-.07 to 5.89)</td>
<td>4.93 (1.97 to 7.89)</td>
<td>4.89 (1.92 to 7.87)</td>
</tr>
<tr>
<td>MCS(^j)</td>
<td>4.63 (.91 to 8.35)</td>
<td>2.68 (-1.16 to 6.51)</td>
<td>8.11 (3.82 to 12.40)</td>
<td>7.26 (3.35 to 11.17)</td>
</tr>
<tr>
<td>BMI</td>
<td>-0.03 (-.34 to .29)</td>
<td>-0.24 (-.61 to .13)</td>
<td>-0.12 (-.43 to .20)</td>
<td>-0.37 (-.73 to -0.02)</td>
</tr>
<tr>
<td>DASH(^k) dietary behavior</td>
<td>.22 (-1.42 to 1.86)</td>
<td>-0.51 (-2.49 to 1.48)</td>
<td>1.21 (-.62 to 3.06)</td>
<td>.99 (-1.05 to 3.04)</td>
</tr>
<tr>
<td>Total physical activity</td>
<td>236.33 (-231.76 to 704.43)</td>
<td>213.18 (-360.50 to 786.86)</td>
<td>248.59 (-191.18 to 688.37)</td>
<td>122.74 (-459.22 to 704.71)</td>
</tr>
</tbody>
</table>

\(^a\)Interaction effects were examined after adjustments for age and gender, and the baseline value of the outcome variable; baseline and control group served as references.

\(^b\)OMG: ordinary mobile health app group.

\(^c\)T2: end of the intervention.

\(^d\)T3: 1 month after the intervention.

\(^e\)TCMG: traditional Chinese medicine mobile health app group.

\(^f\)FPG: fasting plasma glucose.

\(^g\)HbA\(_1c\): hemoglobin A\(_1c\).

\(^h\)BC: body constitution.

\(^i\)PCS: physical component score.

\(^j\)MCS: mental component score.

\(^k\)DASH: Dietary Approaches to Stop Hypertension.
Table 3. Generalized estimating equation models to compare the outcomes between the TCM mHealth app group (n=42) and ordinary mHealth app group (n=41).a

<table>
<thead>
<tr>
<th>Parameter</th>
<th>TCGM×T2, β (95% CI)</th>
<th>TCGM×T3, β (95% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FPGe</td>
<td>-1.82 (-6.30 to 2.66)</td>
<td>3.96 (-9.91 to 1.99)</td>
</tr>
<tr>
<td>HbA1c f</td>
<td>-0.2 (-12 to .09)</td>
<td>-0.06 (-15 to .04)</td>
</tr>
<tr>
<td>Yang-deficiency BCg</td>
<td>-2.26 (-5.12 to .61)</td>
<td>-1.96 (-4.83 to .92)</td>
</tr>
<tr>
<td>Yin-deficiency BC</td>
<td>-2.16 (-5.00 to .68)</td>
<td>-1.40 (-4.20 to 1.41)</td>
</tr>
<tr>
<td>Phlegm-stasis BC</td>
<td>-2.4 (-5.19 to .70)</td>
<td>-1.55 (-4.03 to .94)</td>
</tr>
<tr>
<td>Body energy</td>
<td>8.65 (-2.11 to 19.41)</td>
<td>12.30 (1.31 to 23.30)</td>
</tr>
<tr>
<td>PCS h</td>
<td>2.32 (-58 to 5.22)</td>
<td>2.24 (-87 to 5.35)</td>
</tr>
<tr>
<td>MCS i</td>
<td>3.14 (-82 to 7.10)</td>
<td>4.29 (.27 to 8.31)</td>
</tr>
<tr>
<td>BMI</td>
<td>-10 (-41 to .21)</td>
<td>-14 (-49 to .20)</td>
</tr>
<tr>
<td>DASHj dietary behavior</td>
<td>1.06 (-48 to 2.60)</td>
<td>1.44 (-45 to 3.33)</td>
</tr>
<tr>
<td>Total physical activity</td>
<td>4.99 (-535.31 to 545.30)</td>
<td>-82.67 (-708.14 to 542.80)</td>
</tr>
</tbody>
</table>

aInteraction effects were examined after adjustments for age and gender and the baseline value of the outcome variable; baseline and ordinary mobile health group served as references.  
bTCMG: traditional Chinese medicine mobile health app group.  
cT2: end of the intervention.  
dT3: 1 month after the intervention.  
eFPG: fasting plasma glucose.  
fHbA1c: hemoglobin A1c.  
gBC: body constitution.  
hPCS: physical component score.  
iMCS: mental component score.  
jDASH: Dietary Approaches to Stop Hypertension.

Primary Outcomes

Blood Sugar Control
There were no significant differences in the FPG and HbA1c among the three groups at the three time points. FPG did not change significantly at postintervention and 1 month after the intervention as compared to the preintervention (baseline) levels for all three groups. However, HbA1c decreased significantly over time for all three groups (Figure 2; Multimedia Appendix 5).

The GEE analyses revealed no significant group differences in FPG. The HbA1c levels decreased significantly in the TCM mHealth app group at T3 and were significantly different than those in control group, but there were no significant differences between the ordinary mHealth app and control groups (Table 2; Multimedia Appendix 6).

Body Constitution
The TCM mHealth app group scored the highest in yang-deficiency and phlegm-stasis body constitution at T1, with significant differences between the TCM and control groups. There were no significant differences in body constitution of the three groups at T2 and T3. All three types of body constitutions improved significantly at T3 for the TCM group, but no such improvements were observed in the ordinary mHealth app and control groups (Figure 2; Multimedia Appendix 5).

The GEE analyses indicated that the TCM mHealth app group showed significant improvements in yang-deficiency body constitution at T2 compared to that in the control group. Furthermore, greater improvement in phlegm-stasis body constitution was found compared to that in the control group, and the effect persisted until 1 month after the intervention. However, no effect on yin-deficiency body constitution was observed (Table 2; Multimedia Appendix 6). There were no significant differences in body constitution between the TCM and ordinary mHealth app groups (Table 3; Multimedia Appendix 7).

Body Energy
There were no significant differences in body energy among the three groups at the three time points. Body energy increased significantly from T1 to T2 and from T1 to T3 in the TCM mHealth app group, but remained unchanged in the ordinary mHealth app and control groups (Figure 2; Multimedia Appendix 5).

The GEE results indicated that the TCM mHealth app group showed a significant increase in body energy at T3 compared to that in the ordinary mHealth group (Table 3; Multimedia Appendix 7).
**Health-Related Quality of Life**

There were no significant differences in the PCS among the three groups at the three time points. The TCM mHealth app group had a significant increase in the PCS from T1 to T2 and from T1 to T3. The ordinary mHealth app group also had a significant increase in the PCS from T1 to T3 (Figure 3; Multimedia Appendix 5).

With regard to the MCS, the TCM mHealth app group had a significantly higher score at T2 compared with that of the control group \((P=.02)\), as did the ordinary mHealth app group \((P=.03\); Figure 2; Multimedia Appendix 5\). The TCM mHealth app group showed a significant increase in the MCS from T1 to T2 and from T1 to T3. Moreover, the ordinary mHealth app group had a significant increase in the MCS from T1 to T2 and from T1 to T3 (with borderline significance; \(P=.04\) and \(P=.05\), respectively).

The GEE results indicated that the TCM mHealth app group had a significant increase in the PCS and MCS at T2 and T3 compared with that of the control group (Table 2; Multimedia Appendix 6). In addition, the increase in the MCS in the TCM mHealth app group from T1 to T3 appeared to be higher than that in the ordinary mHealth app group (Table 3; Multimedia Appendix 7). The ordinary mHealth app group had a significant increase in the MCS at T2 compared to that of the control group (Table 2; Multimedia Appendix 6).

**Secondary Outcomes**

**BMI**

There were no significant differences in BMI among the three groups at the three time points (Figure 3; Multimedia Appendix 5). The BMI in the TCM and ordinary mHealth app groups decreased significantly from T1 to T2 and from T1 to T3. However, the BMI of the control group remained unchanged.

The GEE results indicated that the TCM mHealth app group showed a significant decrease in BMI at T3 compared to that in the control group (Table 2; Multimedia Appendix 6). However, there were no significant differences in the change in BMI between the TCM and ordinary mHealth app groups (Table 3; Multimedia Appendix 7).

**Dietary Behavior**

There were no significant differences in the DASH dietary behavior among the three groups at the three time points (Figure 3; Multimedia Appendix 5). The DASH dietary behavior improved significantly in all three groups from T1 to T2 and from T1 to T3. The GEE results showed no significant differences in the DASH dietary behavior among the three groups over time (Tables 2 and 3; Multimedia Appendices 6 and 7).

**Physical Activity**

The ordinary mHealth app group had a significantly higher PA level than that of the other two groups across all three time points (Figure 3; Multimedia Appendix 5). The PA increased significantly from T1 to T3 in all three groups. The GEE results showed no significant differences in the total PA among the three groups over time (Tables 2 and 3; Multimedia Appendices 6 and 7).

**Discussion**

**Principal Findings**

This RCT found that the TCM mHealth group showed better HbA\(_{1c}\), yang-deficiency body constitution, phlegm-stasis body constitution, physical aspect of HRQOL, mental aspect of HRQOL, and BMI than the control group. When the TCM and ordinary mHealth app groups were compared, the TCM mHealth app group showed higher body energy and mental aspect scores of the HRQOL at 1 month after intervention than the ordinary mHealth app group. These results suggest that the TCM mHealth app helps to effectively control blood sugar, decrease yang-deficiency and phlegm-stasis body constitution, and improve body energy and HRQOL. Incorporating TCM body constitution and meridian energy concepts into an mHealth app appears plausible and can improve health for individuals with prediabetes. According to TCM theory, an improved body constitution could decrease susceptibility to chronic diseases [14] and increased body energy would manifest in better stamina [17]. Therefore, improved body constitution and increased body energy could explain the effectiveness of the TCM mHealth app for improving HbA\(_{1c}\) and HRQOL. Further studies are needed to examine the interrelationships among these outcomes.

Previous studies showed that using an mHealth app improved HbA\(_{1c}\), dietary behavior, PA, and BMI compared to those of controls [10-12]. However, we did not find such an effect for the ordinary mHealth app group when compared with the control group in this study. It was noted that all participants in the study had received 15-20 minutes of health education about the disease, healthy diet, and exercise encouragement when they were diagnosed with prediabetes in the study hospital. Possibly owing to this health education, we found that the HbA\(_{1c}\), DASH dietary behavior, and PA improved over time for all three groups. Such universal improvement in health behavior may be the reason for the lack of significant effect on these outcomes when the ordinary mHealth app group was compared to the controls.

The TCM dietary and PA advice used in the TCM mHealth app is mainly based on the types of foods/PA to avoid and those to consume/practice based on the individual’s body constitution. Qigong, including belly breathing and Baduanjin, was recommended for all participants since these exercises can improve qi and are appropriate for all types of body constitutions. The recommended types of foods consumed differed according to the individual’s body constitution. We found that the TCM dietary and PA principles do not conflict with the principles of the DASH diet and recommended PA amount, except that individuals with a yin-deficiency body constitution were advised to avoid vigorous PA.

When compared to the ordinary mHealth app group, the TCM mHealth app group did not differ significantly in improving body constitution and HbA\(_{1c}\). However, the TCM mHealth app group showed better improvement in the mental aspect of HRQOL and in increasing body energy than the ordinary
mHealth app group. These results imply that using the TCM mHealth app can better improve body energy and HRQOL in individuals with prediabetes compared to the ordinary mHealth app. This may be because people who practice TCM consider that health conditions can improve with sufficient qi. The importance of these indicators across cultures needs to be examined in future studies.

Our study showed that both the TCM and ordinary mHealth app groups exhibited a significant improvement in HbA1c and HRQOL with time. This finding is consistent with a previous meta-analysis that reported a positive effect of a lifestyle intervention on HbA1c in individuals with prediabetes [54]. Another meta-analysis reported positive effects of Qigong in improving the HRQOL [55]. Another study demonstrated that individuals with prediabetes who achieved moderate-intensity PA (≥150 minutes/week) have higher levels of HRQOL than inactive people [56]. Therefore, the mHealth app can be used to assist individuals with prediabetes to increase their PA and HRQOL, while decreasing their HbA1c.

This study showed effectiveness of the intervention in HbA1c but not FPG. The insignificant FPG results may be explained as follows. First, various factors can influence FPG, such as emotional state, drugs, and stress hormones [57]. Thus, FPG is not a stable estimate of glycemic exposure [58]. Second, although we encouraged the participants to fast for at least 8 hours, we are unsure if they followed these instructions. In future studies, we suggest that more than two tests should be used to enhance diagnostic accuracy.

In this study, we found that the TCM mHealth app effectively improved the yang-deficiency and phlegm-stasis body constitution in individuals with prediabetes, but could not improve the yin-deficiency body constitution. More research is needed to develop effective interventions to improve the yin-deficiency body constitution among individuals with prediabetes.

Finally, the TCM mHealth app group did show significant improvements in body constitution and body energy in our study, while the other two groups did not show changes in these factors over time. These results suggest that medical practitioners could provide the TCM mHealth app to individuals with prediabetes, through which Qigong and a Chinese dietary regimen can improve body energy, body constitution, and HRQOL. Studies with a larger sample size and longer follow-up period are needed to compare the effectiveness of the two different approaches.

Limitations
This study has several limitations. First, most participants were from an outpatient department and had chronic conditions. Therefore, this sample may have had more complex health problems than present in people with prediabetes alone. The participants may be more homogeneous since they were from one single center. Second, the sample size was small. The limited sample size may be the reason for some statistically insignificant results when comparing between groups. Third, the study was an open-label trial where participants were aware of their group assignments; thus, performance bias was possible. Fourth, the study used a 12-week intervention and a 1-month follow-up period according to previous TCM lifestyle programs [35,37]. A follow-up period from 12 to 24 months may be preferred in future studies. Fifth, the use of the mHealth apps in the follow-up period was not monitored. In addition, during the intervention period, the participants were reminded to use the apps, but the time spent on app use varied, suggesting that the participation level may be different. Lastly, this study included three types of body constitutions. There are many other types of body constitutions that could be considered in future studies.

Conclusion
We developed a TCM mHealth app to incorporate TCM concepts into an mHealth app for individuals with prediabetes. Compared to controls not using the app, the TCM mHealth app appeared to be effective in improving HbA1c, BMI, yin-deficiency and phlegm-stasis body constitution, and HRQOL. Compared to individuals using the ordinary mHealth app, individuals using the TCM mHealth app showed higher body energy and mental aspects of the HRQOL 1 month after the intervention. The TCM mHealth app was not effective in improving FPG, yin-deficiency body constitution, DASH dietary behavior, and total PA. The study results suggest that individuals with prediabetes could use the TCM mHealth app to improve their body energy and HRQOL. Further studies with a larger sample size and a longer follow-up period are warranted to verify whether the differences favoring the TCM app are clinically meaningful.

Acknowledgments
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Data Availability
All data generated or analyzed during this study are included in this published article and its supplementary information files.

Conflicts of Interest
None declared.
Multimedia Appendix 1  
Definitions of terms in traditional Chinese medicine.  
[PDF File (Adobe PDF File), 96 KB - mhealth_v11i1e41099_app1.pdf]

Multimedia Appendix 2  
Screenshots of the ordinary and TCM mHealth apps.  
[PDF File (Adobe PDF File), 1813 KB - mhealth_v11i1e41099_app2.pdf]

Multimedia Appendix 3  
Taxonomy of the behavior change techniques used in the mHealth app.  
[PDF File (Adobe PDF File), 210 KB - mhealth_v11i1e41099_app3.pdf]

Multimedia Appendix 4  
CONSORT-EHEALTH checklist.  
[PDF File (Adobe PDF File), 270 KB - mhealth_v11i1e41099_app4.pdf]

Multimedia Appendix 5  
Comparison of the primary and secondary outcomes among the TCM mHealth app, ordinary mHealth app, and control groups (N=121).  
[PDF File (Adobe PDF File), 159 KB - mhealth_v11i1e41099_app5.pdf]

Multimedia Appendix 6  
Generalized estimating equation models to compare the differences among the three groups, using the control group as the reference.  
[PDF File (Adobe PDF File), 253 KB - mhealth_v11i1e41099_app6.pdf]

Multimedia Appendix 7  
Generalized estimating equation models to compare the outcomes between the TCM mHealth app (n=42) and ordinary mHealth app groups (n=41).  
[PDF File (Adobe PDF File), 239 KB - mhealth_v11i1e41099_app7.pdf]

References


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Abbreviations

BCQ: Body Constitution Questionnaire
DASH: Dietary Approaches to Stop Hypertension
DPP: Diabetes Prevention Program
FPG: fasting plasma glucose
GEE: generalized estimating equation
HbA1c: hemoglobin A1c
HRQOL: health-related quality of life
MCS: mental component score
MEAD: Meridian Energy Analysis Device
MET: metabolic equivalent
mHealth: mobile health
PA: physical activity
PCS: physical component score
RCT: randomized controlled trial
SF-36: Medical Outcome Survey Short-Form
T2DM: type 2 diabetes mellitus
TCM: traditional Chinese medicine

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The Effectiveness of a Mobile Phone–Based Physical Activity Program for Treating Depression, Stress, Psychological Well-Being, and Quality of Life Among Adults: Quantitative Study

Hyungsook Kim1,2,3, PhD; Kikwang Lee4, PhD; Ye Hoon Lee5, PhD; Yoonjung Park6, PhD; Yonghyun Park1, PhD; Yeonwoo Yu4, BA; Jaeyoung Park5, BA; Sihyeon Noh5, BA

1Hanyang Digital Healthcare Center, Hanyang University, Seoul, Republic of Korea
2Department of Cognitive Sciences, School of Intelligence, Hanyang University, Seoul, Republic of Korea
3Graduate School of Public Policy, Hanyang University, Seoul, Republic of Korea
4Department of Sport, Health, and Rehabilitation, College of Physical Education, Kookmin University, Seoul, Republic of Korea
5Division of Global Sport Industry, Hankuk University of Foreign Studies, Gyeonggi-do, Republic of Korea
6Department of Health & Human Performance, University of Houston, Houston, TX, United States

Corresponding Author:
Ye Hoon Lee, PhD
Division of Global Sport Industry
Hankuk University of Foreign Studies
81, Oedae-ro, Mohyeon-eup, Cheoin-gu
Gyeonggi-do, 17035
Republic of Korea
Phone: 82 31 330 4986
Email: lee_ye22@o365.hufs.ac.kr

Abstract

Background: Depression is a substantial global health problem, affecting >300 million people and resulting in 12.7% of all deaths. Depression causes various physical and cognitive problems, leading to a 5-year to 10-year decrease in life expectancy compared with the general population. Physical activity is known to be an effective, evidence-based treatment for depression. However, people generally have difficulties with participating in physical activity owing to limitations in time and accessibility.

Objective: To address this issue, this study aimed to contribute to the development of alternative and innovative intervention methods for depression and stress management in adults. More specifically, we attempted to investigate the effectiveness of a mobile phone–based physical activity program on depression, perceived stress, psychological well-being, and quality of life among adults in South Korea.

Methods: Participants were recruited and randomly assigned to the mobile phone intervention or waitlist group. Self-report questionnaires were used to assess variables before and after treatment. The treatment group used the program around 3 times per week at home for 4 weeks, with each session lasting about 30 minutes. To evaluate the program’s impact, a 2 (condition) × 2 (time) repeated-measures ANOVA was conducted, considering pretreatment and posttreatment measures along with group as independent variables. For a more detailed analysis, paired-samples 2-tailed t tests were used to compare pretreatment and posttreatment measurements within each group. Independent-samples 2-tailed t tests were conducted to assess intergroup differences in pretreatment measurements.

Results: The study included a total of 68 adults aged between 18 and 65 years, who were recruited both through web-based and offline methods. Of these 68 individuals, 41 (60%) were randomly assigned to the treatment group and 27 (40%) to the waitlist group. The attrition rate was 10.2% after 4 weeks. The findings indicated that there is a significant main effect of time (F1,60=15.63; P=.003; ηp2=.21) in participants’ depression scores, indicating that there were changes in depression level across time. No significant changes were observed in perceived stress (P=.25), psychological well-being (P=.35), or quality of life (P=.07). Furthermore, depression scores significantly decreased in the treatment group (from 7.08 to 4.64; P=.03; Cohen d=0.50) but not in the waitlist group (from 6.72 to 5.08; P=.20; Cohen d=0.36). Perceived stress score of the treatment group also significantly decreased (from 2.95 to 2.72; P=.04; Cohen d=0.46) but not in the waitlist group (from 2.82 to 2.74; P=.55; Cohen d=0.15).
Conclusions: This study provided experimental evidence that mobile phone–based physical activity program affects depression significantly. By exploring the potential of mobile phone–based physical activity programs as a treatment option, this study sought to improve accessibility and encourage participation in physical activity, ultimately promoting better mental health outcomes for individuals with depression and stress.

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KEYWORDS
depressive symptoms; mobile intervention; exercise; internet-based fitness; mental health

Introduction

Background
Depression is a mental health problem that affects >300 million people worldwide, accounting for 12.7% of all deaths [1]. Depression causes various types of physical and cognitive problems, such as the loss of appetite, sleep disturbances, helplessness, and suicidal thoughts and attempts [2]. Therefore, it has been reported that the mean life expectancy of people with depression is 5 to 10 years shorter than that of the general population [3]. Similar to the global trend, the number of people with depression in South Korea is increasing every year, and medical expenses are also gradually increasing. As the COVID-19 pandemic and social distancing continued in South Korea, 19.8% of the population was classified as a risk group for depression, and the number of people with depression has increased by >30% from approximately 750,000 in 2018 to 830,000 in 2020 [4]. Furthermore, according to the 2018 National Health and Nutrition Examination Survey [5], the stress awareness rate among adults in Korea was 29.1%, and it persisted at approximately 30% over the following 3 years. This means that 3 out of 10 adults feel very much or a lot of stress in their daily lives. Therefore, interest in intervention methods for managing depression in adults is increasing [6].

The traditional methods of preventing and treating depression include drug therapy, psychotherapy (eg, cognitive therapy and interpersonal therapy), and combinations of both [7]. Antidepressants—for example, selective serotonin reuptake inhibitors—are often used as the first-line treatment for depression because of their advantages of scalability and accessibility [8]. Despite the demonstrable biological underpinnings of the antidepressant mechanisms supporting the use of these drugs [7], it has been reported that only approximately 50% of individuals who take such medication achieve a statistically significant reduction in depressive symptoms [9]. In addition, previous literature has demonstrated the side effects and increased mortality associated with the difficulty of maintaining drug compliance, increased weight and diabetes risk, sexual dysfunction, and various diseases. Moreover, if antidepressants are stopped before recovery, symptoms seem to worsen rapidly, and it is difficult to continue drug treatment because of negative perceptions about drug consumption and dependency [10]. Thus, there is a need for alternative treatment methods that can overcome these issues.

Cognitive behavioral therapy is an alternative treatment that is widely recognized as one of the most effective evidence-based therapies for depression. Studies conducted worldwide have reported small to medium effects on mitigating depression [11]. However, despite the availability of effective treatments, a large proportion of people with depression do not seek or receive professional help, with studies reporting that up to 80% of adolescents with depression do not receive adequate treatment [12]. Barriers to treatment are reported to include prejudice, accessibility issues, and cost issues associated with psychiatric treatment [13]. These issues are not limited to specific regions or countries, as people worldwide often experience reluctance to seek treatment owing to the fear of stigma and high cost of therapy. Furthermore, cognitive behavioral therapy is often a weekly treatment for at least 10 sessions, which can be financially burdensome for many individuals. Therefore, alternative treatment methods that address or avoid these difficulties are needed [14].

Physical activity and exercise can be an effective alternative form of depression treatment [15]. They exert antidepressant effect through multiple biological and psychosocial pathways [16-18]. Kandola et al [7] conducted a review to explore the relationship between physical activity and depression, aiming to understand the mechanisms by which physical activity exerts its antidepressant effect. The review highlights the interdependent changes that occur in the brain owing to exercise, creating a protective environment against depression. These changes include increased levels of neurotrophins, improved brain structure, and enhanced functioning in areas implicated in depression and stress regulation. Exercise produces changes in the brain through various pathways, including neuroplasticity, which is disrupted in depression [19]. Studies have found that exercise can increase the volume of the hippocampus and cortical regions, and high levels of cardiorespiratory fitness are associated with large volumes in these areas [20-22]. In addition, exercise interventions can reduce chronic low-grade inflammation, decrease depressive symptoms, and mitigate oxidative stress, which can contribute to depression. Regular exercise may also help to dampen hypothalamic-pituitary-adrenal axis activity and cortisol sensitivity, leading to increased resilience to stress, and it may have a direct influence on the neuroendocrine system, helping to reduce cortisol levels in people with depression [23]. The review concludes that psychosocial factors, such as self-esteem and self-efficacy, also interact with biological changes to influence depression. Therefore, it is important to note that the mechanisms by which physical activity exerts its antidepressant effect are multifaceted and may vary depending on the individual. Several meta-analyses have found that exercise can reduce the symptoms of depression with a moderate to large effect size and that exercise can be a useful addition to pharmacotherapy and psychotherapy [24-30].
Recently, the COVID-19 pandemic has increased the need for mental health and well-being management in non–face-to-face environments [31]. Depression is strongly associated with social phobias [32], which limit people’s ability to exercise in spaces with other people, such as fitness centers. Therefore, easy-to-access and easy-to-use internet-based or mobile phone–based physical activity apps can be good alternatives for people with depression. Mobile phone–based physical activity programs have the potential to provide significant benefits as an adjunct to professional treatment for depression. These benefits include increased convenience, adherence, personalization, social support, and cost-effectiveness [33]. By enabling individuals to engage in physical activity regularly, mobile phone–based programs with reminder and tracking features can increase adherence to physical activity interventions [34]. Furthermore, these programs can be tailored to an individual’s specific needs and preferences, potentially increasing motivation and engagement. Social support features, such as web-based communities or peer support, are also common in mobile phone–based programs and may help individuals to stay motivated and engaged in the program [35]. Finally, mobile phone–based programs may be more cost-effective than traditional in-person interventions, making them more accessible to individuals who may not have the financial resources for traditional treatment [36]. Numerous studies have demonstrated the effectiveness of mobile phone–based physical activity programs at home for adults in treating depression [37-40].

In light of the increasing demand for non–face-to-face mental health management during the COVID-19 pandemic, there has been a surge in the development and evaluation of technology-based physical activity interventions [36]. However, despite their potential benefits, there is a lack of studies exploring the effectiveness of web-based physical activity interventions in reducing depression and improving mental health outcomes such as perceived stress [41], psychological well-being [42], and quality of life [36,43]. Moreover, the existing studies have produced mixed outcomes, and many have not included control groups [36], highlighting the need for further studies to examine the mental health outcomes of web-based physical activity interventions.

Objective

To address this issue, we investigated the effectiveness of a mobile phone–based physical activity program among adults in South Korea by examining various mental health indicators such as depression, perceived stress, psychological well-being, and quality of life. Specifically, we hypothesized that the mobile phone–based physical activity program will lead to significant improvement in depression, perceived stress, psychological well-being, and quality of life in the intervention group compared to the control group. We hope that this study of mobile phone–based physical activity programs, which can be easily accessed by people with depression at home, will contribute to mitigating the negative impact of mental health issues. It is our aspiration that this study will provide more comprehensive guidelines for decision makers to promote and execute mobile phone–based exercise interventions for individuals with depression and stress.

Methods

Participants

The participants were recruited through various channels, including the Hanyang Digital Healthcare Center website [44], the Hanyang Happiness Dream Counseling Center, and the related blog [45]. In addition, recruitment efforts included the distribution of posters, flyers, and local newsletters in the community. Participants were recruited from the first week of March 2022 to the third week of April 2022 through the web-based and offline advertisements. Participants completed the baseline questionnaire in the fourth week of April 2022 and the posttest questionnaire in the first week of June 2022. The study enrolled adults who were aged between 18 and 65 years, were fluent in Korean, had basic knowledge about the internet, and could attend the 3 in-person appointments at the project locations (ie, Hanyang Digital Healthcare Center). To be eligible, they needed to have access to the internet and pass the Physical Activity Readiness Questionnaire.

Sample Size Calculation

To calculate the sample size, the G*power 3 program was used, with power set to 95% and significance level of .01 for precise testing. The study measured the degree of depression relief in the fourth week using the sixth week’s measurement from a previous study. The effect size was determined to be 1.1957131, and the minimum number of study participants required was calculated to be 54, with 27 participants per group. Given that the study was on the general public who felt depressed for 8 weeks, a dropout rate of 20% was set, and a total of 65 study participants were recruited.

Procedure

Following the randomization process, participants in the intervention group were shown the mobile phone–based physical activity program during their initial appointment and were provided with instructions about how to access and use it at home. To ensure that participants in the treatment group completed the exercise program as intended, we provided them with a set of instructions and guidelines and a calendar to track their progress. We also asked them to complete a Google Form after each exercise session to confirm that they had completed the exercise and to report any issues or concerns. By using the Google Form to collect data about participant compliance, this study minimized any potential bias that could arise from direct contact with participants. Participants in the study were compensated for their time and effort with a monetary reward of KRW ₩100,000 (US $75.76) for the treatment group and KRW ₩50,000 (US $37.88) for the control group at the end of the study. Participants were informed about the compensation at the beginning of the study and were reminded about the amount and timing of payment before the last session. The monetary reward was intended to incentivize participation and improve retention rates.

Ethics Approval and Informed Consent

This study was approved by the Hanyang University (the first authors’ institution) institutional review board (HYUIRB-202203-010-2). We obtained the necessary approvals.
before starting the study to ensure that ethical standards were met, and the rights of the participants were protected. The purpose and procedure of the study were explained before starting of the study, and only those who provided written informed consent and voluntarily participated were included.

**Instrument**

**Overview**

The Korean versions of the Patient Health Questionnaire—9 (PHQ-9), Perceived Stress Scale, and World Health Organization (WHO)—5 Well-Being Index were used in this study. These scales have been previously validated in the literature [46]. Translation and cultural adaptation were conducted using established guidelines, including forward and backward translations and cultural adaptation by a team of bilingual experts [47]. The quality-of-life instrument underwent a rigorous translation process, which involved independent translations, review and discussion of discrepancies, back translation, comparison with the original scales, and pilot-testing with Korean-speaking individuals. The translations were revised as needed based on their feedback. The study requested that participants complete paper-and-pencil research surveys at 2 different points in time—at baseline and week 4. The surveys were conducted at the intervention location (ie, Hanyang Digital Healthcare Center).

**Depression**

As a measurement tool for depression, this study used PHQ-9 [48]. The PHQ-9 is divided into 9 categories of responses to the question, “How often have you suffered from depression-related problems in the past 2 weeks?” The categories are discomfort, depressed feelings, changes in sleep patterns, fatigue, changes in appetite, guilt or worthlessness, poor concentration, restlessness, and suicidal thoughts. High scores calculated by summing the measured scores indicate high degrees of depressive symptoms or high severity of depression.

**Perceived Stress**

The Korean version of the Perceived Stress Scale [49] was used to measure the perceived stress of the participants. The Perceived Stress Scale has 10 items rated on a 5-point Likert scale (1=“not at all” to 5=“very much”), and it is composed of 2 subfactors of positive perception and negative perception according to the way stress is perceived. To measure the perceived stress levels, positive perception factors were reverse scored and summed with negative perception factors to calculate the total score on the scale.

**Psychological Well-Being**

To measure psychological well-being, this study used the WHO-5 Well-Being Index developed by WHO [50], which consists of 5 items. The tool is structured to respond to the following five questions on a 6-point scale ranging from 0=“never” to 5=“always” in the past 2 weeks: (1) “I felt pleasant and happy,” (2) “I was calm and relaxed,” (3) “I was active and energetic,” (4) “I woke up refreshed in the morning after sleeping,” and (5) “My daily life was full of interesting things.” Therefore, possible well-being scores range from 0 to 25, with high scores indicating high levels of psychological well-being.

**Quality of Life**

To measure quality of life, this study used the quality-of-life scale [51]. The tool consists of 4 items, and each item is answered on a 5-point Likert scale ranging from 1=“strongly disagree” to 5=“strongly agree.” High scores indicate high quality-of-life self-ratings. Sample items are “I am satisfied with my life” and “I try to keep developing myself.”

**Mobile Phone–Based Physical Activity Program**

The physical activity program used in this study is mobile based and aims to improve physical fitness factors associated with depression. The program features a series of animated and video demonstrations of exercises that involve repetitive movements, designed to engage and challenge various muscle groups. These movements are performed rhythmically and in a coordinated manner to enhance muscular strength and cardiorespiratory endurance. The program’s exercises are repeated several times during each sequence, and 3D animated images display movements designed to enhance coordination and balance by integrating hand and leg movements in different ways. The program’s movements challenge the hands, feet, and trunk and are designed to improve muscular strength and cardiorespiratory endurance.

More specifically, the program is composed of 6 therapeutic movement sequences, each incorporating specific fitness elements (as shown in Figure 1). The first and second sequences were designed to proceed more quickly and include mostly arm exercises. Some specific examples of exercises in these sequences include movements such as alternating arm and leg raises while standing on 1 leg. These exercises require participants to use their core muscles to stabilize their bodies while moving their limbs. In addition, the combination of upper and lower body movements can help to improve cardiovascular fitness by increasing the heart rate and respiratory rate.

The third and fourth sequences in the program focus on coordinated movements of both the arms and legs. The exercises are aimed at expanding the range of motion around the body’s center of gravity and enhancing muscular endurance and balance. It involves standing with the feet hip-width apart and lifting both arms up and out to the sides of the body, reaching toward the sky. The palms of the hands may face each other or be turned outward. The chest and head are lifted upward to create an expansive posture. This movement is often associated with a feeling of openness and energy, as it stretches and opens the chest, shoulders, and arms. By coordinating the movements of both the arms and legs, participants are required to use multiple muscle groups simultaneously, which can help to improve overall body strength and coordination.

The fifth sequence involves walking and running in place to improve cardiorespiratory capacity. This sequence is specifically designed to improve cardiorespiratory capacity or the ability of the body’s cardiovascular and respiratory systems to efficiently deliver oxygen and nutrients to the muscles during physical activity. To perform this sequence, the participant simply walks or runs in place, lifting their feet off the ground and moving their arms back and forth in a natural rhythm. Walking and running in place can be modified to increase the intensity of the...
exercise by incorporating variations such as high knees, heel kicks, or lateral shuffles. These variations can challenge the cardiovascular and respiratory systems by increasing the intensity and demand of the exercise.

The sixth sequence is designed to enhance coordination between the arms and legs, with the aim of increasing the range of motion around joints. For example, one exercise involves lunging forward with 1 leg while simultaneously extending the arm out in front of the body and then alternating sides. Another exercise involves standing with the feet shoulder-width apart and lifting both arms straight up above the head while simultaneously bending the knees and lowering the body into a squat position. Participants may then return to the standing position while lowering the arms to the sides of the body.

In addition, the program’s movement exercises consist of actions with characteristics similar to gestures associated with the expression of positive emotions (joy and happiness). The body motions associated with expressions of joy and happiness have the characteristics of expansiveness, wherein the upper extremities and upper body move upward, with the arms extending laterally [52-55]. This typically involves raising both arms and reaching them outward to the sides of the body while also lifting the chest and head upward to create an expansive, uplifting posture. This upward stretching of the hands also has a stress-reducing effect [56,57]. The participants follow the movements of positive emotional expression while upbeat music plays in the background, which can also reduce depression. Moving in rhythm requires the user to engage in active behavior as opposed to psychomotor retardation, which is a behavioral trait associated with depression.

Only participants in the treatment group were instructed to engage in physical activity while watching videos with physical activity content 5 times a week for 4 weeks. The videos consisted of a total of approximately 20 minutes of physical activity content and were delivered to the participants’ mobile devices through a YouTube link at the same time every day. The researchers did not provide additional treatment or counseling related to the program content.

Data Analysis
To evaluate the effectiveness of the mobile-based physical activity program for the treatment group and the waitlist group, the self-report questionnaire scores were compared and analyzed using SPSS Statistics for Windows (version 22.0; IBM Corp). To evaluate the impact of the program, we first conducted a 2 (condition) × 2 (time) repeated-measures ANOVA with pretreatment and posttreatment measures and group as independent variables. Following this analysis, we conducted paired-samples 2-tailed t tests to compare pretreatment and posttreatment measurements within each group, to gain a more detailed understanding of the data.

Results
Recruitment
Figure 2 shows the CONSORT (Consolidated Standards of Reporting Trials) diagram, which illustrates the participant flow throughout the study. Of the 68 initial participants, 41 (60%) were assigned to the treatment group and 27 (40%) were assigned to the waitlist group. Overall, 88% (36/41) of the participants completed the follow-up assessment in the treatment group, and 93% (25/27) of the participants completed it in the waitlist group.

The participants of this study were 68 adults aged between 18 and 65 years, who voluntarily expressed their intentions to participate. The selected participants were randomly divided into a treatment group (41/68, 60%) and a waitlist group (27/68,
40%). The treatment and waitlist groups were not balanced in terms of participant numbers because most participants expressed their intention to participate voluntarily on the premise that they would be assigned to the intervention group. Overall, 12% (5/41) of participants in the treatment group and 7% (2/27) of participants in the waitlist group dropped out owing to personal reasons. Thus, a total of 61 participants were included in the final data analysis (Table 1). Specifically, of the total 61 participants, the treatment group consisted of 36 (59%) participants, ranging in age from 20 to 54 years, including 17 (47%) male participants and 19 (53%) female participants. Among these 36 participants, 25 (69%) were unmarried and 11 (31%) were married. Regarding educational background, the 36 participants were distributed as follows: 10 (28%) had completed high school, 10 (28%) were college graduates, and 10 (28%) had graduate degrees, with the lowest number of participants having a high school diploma (n=6, 17%). In terms of occupation, of the 36 participants, 16 (44%) were students, 14 (39%) were regular workers, and 3 (8%) were nonregular workers. The waitlist group consisted of a total of 41% (25/61) participants, ranging in age from 19 to 49 years, including 56% (14/25) male participants and 44% (11/25) female participants. Among the 25 participants, 24 (96%) were unmarried and 1 (4%) was divorced. Regarding educational background, of the 25 participants, the most common level had 13 (52%) participants with a high school diploma, followed by 10 (40%) participants with graduate school or higher education, and 2 (8%) participants with a college degree.

Figure 2. Study flow diagram.
Table 1. Baseline participant characteristics.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>All participants (N=68), n (%)</th>
<th>Intervention group (n=41), n (%)</th>
<th>Waitlist group (n=27), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td>33 (49)</td>
<td>19 (46)</td>
<td>14 (52)</td>
</tr>
<tr>
<td>Female</td>
<td>35 (51)</td>
<td>22 (54)</td>
<td>13 (48)</td>
</tr>
<tr>
<td>Marital status</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single</td>
<td>55 (81)</td>
<td>29 (71)</td>
<td>26 (96)</td>
</tr>
<tr>
<td>Married</td>
<td>12 (18)</td>
<td>12 (29)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Divorce</td>
<td>1 (1)</td>
<td>0 (0)</td>
<td>1 (4)</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High school graduation</td>
<td>6 (9)</td>
<td>6 (15)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>College</td>
<td>27 (40)</td>
<td>12 (29)</td>
<td>15 (56)</td>
</tr>
<tr>
<td>Graduation from university</td>
<td>13 (19)</td>
<td>11 (27)</td>
<td>2 (7)</td>
</tr>
<tr>
<td>Graduate student</td>
<td>22 (32)</td>
<td>12 (29)</td>
<td>10 (37)</td>
</tr>
<tr>
<td>Employment</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Student</td>
<td>35 (51)</td>
<td>19 (46)</td>
<td>16 (59)</td>
</tr>
<tr>
<td>Not working</td>
<td>3 (4)</td>
<td>3 (7)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Full time</td>
<td>19 (28)</td>
<td>16 (39)</td>
<td>3 (9)</td>
</tr>
<tr>
<td>Part time</td>
<td>11 (16)</td>
<td>3 (7)</td>
<td>8 (30)</td>
</tr>
<tr>
<td>Monthly income (KRW ₩ [US $])</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No income</td>
<td>15 (23)</td>
<td>7 (17)</td>
<td>8 (30)</td>
</tr>
<tr>
<td>&lt;500,000 (&lt;$380.6)</td>
<td>10 (15)</td>
<td>5 (12)</td>
<td>5 (19)</td>
</tr>
<tr>
<td>510,000-1,000,000 (388.22-761.21)</td>
<td>6 (9)</td>
<td>3 (7)</td>
<td>3 (11)</td>
</tr>
<tr>
<td>1,010,000-1,500,000 (768.82-1141.81)</td>
<td>7 (10)</td>
<td>7 (17)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>1,510,000-2,000,000 (1149.43-1522.42)</td>
<td>5 (7)</td>
<td>2 (5)</td>
<td>3 (11)</td>
</tr>
<tr>
<td>2,010,000-2,500,000 (1503.03-1903.02)</td>
<td>7 (10)</td>
<td>2 (5)</td>
<td>5 (19)</td>
</tr>
<tr>
<td>2,510,000-3,000,000 (1910.63-2283.63)</td>
<td>3 (4)</td>
<td>1 (2)</td>
<td>2 (7)</td>
</tr>
<tr>
<td>3,010,000-4,000,000 (2291.24-3044.84)</td>
<td>5 (7)</td>
<td>5 (12)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>&gt;4,000,000 (&gt;3052.45)</td>
<td>10 (15)</td>
<td>9 (22)</td>
<td>1 (3)</td>
</tr>
</tbody>
</table>

Changes Observed in the Treatment Group and Waitlist Group

First, Tables 2 and 3 summarize the changes (in the treatment and waitlist groups, respectively) in the investigated variables between baseline and after the implementation of the mobile phone–based physical activity program developed for this study. In the treatment group, the mean depression score significantly decreased from 7.08 (SD 5.49) to 4.64 (SD 4.07; \(t_{70}=2.14, \ P=.03; \) Cohen \(d=0.50\)). The mean depression score of the waitlist group also decreased (from 6.72, SD 5.43 to 5.08, SD 3.4), but this change was not statistically significant (\(t_{48}=1.27, \ P=.20; \) Cohen \(d=0.36\)). There was significant decrease in the mean perceived stress score of the treatment group (from 2.95, SD 0.51 to 2.72, SD 0.5; \(t_{70}=1.99, \ P=.04; \) Cohen \(d=0.46\)). In the waitlist group, the mean perceived stress score decreased from 2.82 (SD 0.58) to 2.74 (SD 0.45), but this change was not statistically significant (\(t_{48}=0.59, \ P=.55; \) Cohen \(d=0.15\)). The mean psychological well-being score of the treatment group increased from 2.63 (SD 0.80) to 2.96 (SD 0.92) between baseline and after the treatment, but this change was not statistically significant (\(t_{70}=-1.63, \ P=.10; \) Cohen \(d=0.38\)). In the waitlist group, there was slight increase in the mean psychological well-being score from 2.91 (SD 0.80) to 3.04 (SD 0.62; \(t_{48}=-0.63, \ P=.53; \) Cohen \(d=0.18\)). Finally, the mean quality-of-life scores increased from 2.89 (SD 0.92) to 3.27 (SD 0.88) and from 3.12 (SD 0.85) to 3.33 (SD 0.79) in the treatment and waitlist groups, respectively, between baseline and after the treatment. However, neither of these increases was statistically significant (\(t_{70}=-1.76, \ P=.08; \) Cohen \(d=0.42\) for the treatment group; \(t_{48}=-0.89, \ P=.37; \) Cohen \(d=0.25\) for the waitlist group).

Figure 3 shows the changes in the treatment and waitlist groups, between baseline and program completion, according to repeated-measures ANOVA of the depression, perceived stress, psychological well-being, and quality-of-life scores. As shown...
in Table 3, none of the evaluated changes were statistically significant in association with the mobile phone–based exercise. However, accounting for all participants (irrespective of group), depression levels ($F_{1,60}=15.63; P=.001; \eta^2=0.21$) decreased significantly after treatment relative to baseline. However, according to the ANOVA, overall, there were no significant changes between baseline and after treatment in perceived stress ($F_{1,60}=7.58; P=.25; \eta^2=0.04$), psychological well-being ($F_{1,60}=6.97; P=.35; \eta^2=0.03$), or quality of life ($F_{1,60}=3.56; P=.06; \eta^2=0.10$).

Table 2. Mean differences between pretreatment and posttreatment scores in the treatment group.

<table>
<thead>
<tr>
<th></th>
<th>Pretreatment score, mean (SD)</th>
<th>Posttreatment score, mean (SD)</th>
<th>t test (df)</th>
<th>P value</th>
<th>Cohen d</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depression</td>
<td>7.08 (5.49)</td>
<td>4.64 (4.07)</td>
<td>2.14 (70)</td>
<td>.03</td>
<td>0.50</td>
</tr>
<tr>
<td>Perceived stress</td>
<td>2.95 (0.51)</td>
<td>2.72 (0.49)</td>
<td>1.99 (70)</td>
<td>.04</td>
<td>0.46</td>
</tr>
<tr>
<td>Psychological well-being</td>
<td>2.63 (0.80)</td>
<td>2.96 (0.92)</td>
<td>-1.63 (70)</td>
<td>.10</td>
<td>0.38</td>
</tr>
<tr>
<td>Quality of life</td>
<td>2.89 (0.92)</td>
<td>3.27 (0.88)</td>
<td>-1.76 (70)</td>
<td>.08</td>
<td>0.42</td>
</tr>
</tbody>
</table>

*2-tailed t test.

Table 3. Mean differences between pretreatment and posttreatment scores in the waitlist group.

<table>
<thead>
<tr>
<th></th>
<th>Pretreatment score, mean (SD)</th>
<th>Posttreatment score, mean (SD)</th>
<th>t test (df)</th>
<th>P value</th>
<th>Cohen d</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depression</td>
<td>6.72 (5.43)</td>
<td>5.08 (3.4)</td>
<td>1.27 (48)</td>
<td>.20</td>
<td>0.36</td>
</tr>
<tr>
<td>Perceived stress</td>
<td>2.82 (0.58)</td>
<td>2.74 (0.45)</td>
<td>0.59 (48)</td>
<td>.55</td>
<td>0.15</td>
</tr>
<tr>
<td>Psychological well-being</td>
<td>2.91 (0.80)</td>
<td>3.04 (0.62)</td>
<td>-0.63 (48)</td>
<td>.53</td>
<td>0.18</td>
</tr>
<tr>
<td>Quality of life</td>
<td>3.12 (0.85)</td>
<td>3.33 (0.79)</td>
<td>-0.89 (48)</td>
<td>.37</td>
<td>0.25</td>
</tr>
</tbody>
</table>

*2-tailed t test.

Figure 3. Interaction analysis results. PHQ-9: Patient Health Questionnaire–9; WHO-5: World Health Organization–5.

Second, independent-samples 2-tailed t tests were performed on the pretreatment results to evaluate the differences between the treatment group and the waitlist group at baseline. Table 4 summarizes the characteristics of the participants in the treatment group and the waitlist group. Regarding the negative well-being indicators, the level of depression was higher in the treatment group (mean 7.08, SD 5.49) than in the waitlist group (mean 6.72, SD 5.43). Perceived stress was also higher in the treatment group (mean 2.95, SD 0.51) than in the waitlist group (mean 2.82, SD 0.58). However, there were no statistically significant differences between the groups in terms of depression ($t_{59}=-0.25, P=.79$; Cohen $d=0.06$) or perceived stress ($t_{59}=-0.92, P=.36$; Cohen $d=0.23$). Regarding the pretreatment positive well-being indicators, psychological well-being (mean 2.91, SD 0.80) and quality of life (mean 3.12, SD 0.85) were higher in the waitlist group than in the treatment group (mean 2.63, SD 0.80 for psychological well-being; mean 2.89, SD 0.92 for quality of life), but these differences were not statistically significant ($t_{59}=1.33, P=.18$; Cohen $d=0.35$ for psychological well-being; $t_{59}=0.96, P=.34$; Cohen $d=0.26$ for quality of life).

Finally, Table 5 summarize the posttreatment intergroup comparisons. The mean scores of the waitlist group for all variables—depression (mean 5.08, SD 3.45), perceived stress (mean 2.74, SD 0.45), psychological well-being (mean 3.04, SD 0.62), and quality of life (mean 3.33, SD 0.79)—were higher than those of the treatment group (mean 4.64, SD 4.07 for depression; mean 2.72, SD 0.49 for perceived stress; mean 2.96, SD 0.92 for psychological well-being; and mean 3.27, SD 0.88 for quality of life). However, none of the posttreatment intergroup differences were statistically significant ($t_{59}=0.44, P=.66$; Cohen $d=0.12$ for depression; $t_{59}=0.12, P=.90$; Cohen $d=0.06$ for perceived stress; $t_{59}=0.12, P=.90$; Cohen $d=0.06$ for psychological well-being; and $t_{59}=0.12, P=.90$; Cohen $d=0.06$ for quality of life).
Recent years, digital physical activity applications have gained popularity, with fitness tracking apps such as MyFitnessPal, Fitbit, and Strava being actively developed. These apps use sensors to track users’ physical activity, including steps taken, distance traveled, and calories burned. They also allow users to set goals and track progress over time. Virtual reality fitness games, such as RingFit, Beat Saber, and BoxVR, are another area of ongoing development in digital physical activity applications. These games use virtual reality technology to create immersive environments that users can interact with through physical activity. The gamification of physical activity is also an area of ongoing development through apps such as Pokémon Go and Zombies, Run! This study is particularly important, as it demonstrates the effectiveness of a home-based physical activity program for reducing depressive symptoms and perceived stress among adults in South Korea. The cost-effectiveness of this treatment program adds to its potential as a means of promoting mental health and physical activity in populations with limited access to traditional mental health services. Therefore, this study provides an important foundation for further studies into the efficacy of digital physical activity programs as a means of promoting mental health and physical activity, particularly in populations experiencing high levels of stress and depression.

Recently, especially since the onset of the COVID-19 pandemic, many studies have been conducted to investigate the effectiveness of mobile phone–based health apps in promoting physical activity, and it is evident that such apps are promising tools for promoting physical activity [58]. The mobile phone–based physical activity program evaluated in this study was shown to be effective; thus, our results concur with previous evidence showing that physical activity is associated with improvements in depression and perceived stress. Our mobile phone–based exercise program facilitated a combination of muscular strength training and aerobic training, which has been previously shown to be effective. Although there is robust evidence for the beneficial effects of exercise on mental health, various studies have supported different types and modes of

### Table 4. Pretreatment results of the treatment and waitlist groups.

<table>
<thead>
<tr>
<th></th>
<th>Treatment group score, mean (SD)</th>
<th>Waitlist group score, mean (SD)</th>
<th>t test (df)&lt;sup&gt;a&lt;/sup&gt;</th>
<th>P value</th>
<th>Cohen d</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depression</td>
<td>7.08 (5.49)</td>
<td>6.72 (5.43)</td>
<td>−0.25 (59)</td>
<td>.79</td>
<td>0.06</td>
</tr>
<tr>
<td>Perceived stress</td>
<td>2.95 (0.51)</td>
<td>2.82 (0.58)</td>
<td>−0.92 (59)</td>
<td>.36</td>
<td>0.23</td>
</tr>
<tr>
<td>Psychological well-being</td>
<td>2.63 (0.80)</td>
<td>2.91 (0.80)</td>
<td>1.33 (59)</td>
<td>.18</td>
<td>0.35</td>
</tr>
<tr>
<td>Quality of life</td>
<td>2.89 (0.92)</td>
<td>3.12 (0.85)</td>
<td>0.96 (59)</td>
<td>.34</td>
<td>0.26</td>
</tr>
</tbody>
</table>

<sup>a</sup>2-tailed t test.

### Table 5. Posttreatment results of the treatment and waitlist groups.

<table>
<thead>
<tr>
<th></th>
<th>Treatment group score, mean (SD)</th>
<th>Waitlist group score, mean (SD)</th>
<th>t test (df)&lt;sup&gt;a&lt;/sup&gt;</th>
<th>P value</th>
<th>Cohen d</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depression</td>
<td>4.64 (4.07)</td>
<td>5.08 (3.45)</td>
<td>0.44 (59)</td>
<td>.66</td>
<td>0.12</td>
</tr>
<tr>
<td>Perceived stress</td>
<td>2.72 (0.49)</td>
<td>2.74 (0.45)</td>
<td>0.12 (59)</td>
<td>.90</td>
<td>0.04</td>
</tr>
<tr>
<td>Psychological well-being</td>
<td>2.96 (0.92)</td>
<td>3.04 (0.62)</td>
<td>0.34 (59)</td>
<td>.73</td>
<td>0.10</td>
</tr>
<tr>
<td>Quality of life</td>
<td>3.27 (0.88)</td>
<td>3.33 (0.79)</td>
<td>0.26 (59)</td>
<td>.79</td>
<td>0.07</td>
</tr>
</tbody>
</table>

<sup>a</sup>2-tailed t test.
exercise; for example, 16 weeks of aerobic exercise (dance, jump, and traditional games) improved the depressive symptoms of adults with depression [59], and 8 weeks of high-intensity strength training (at 80% of the 1-repetition maximum) was beneficial in the treatment of older adults with depression [60]. However, regardless of the type and mode of exercise, physical activity is beneficial for mental health. Therefore, any type of exercise using mobile phone–based physical activity is recommended for mental health.

Regular physical activity and exercise are effective therapies for most chronic diseases, including mental disorders [15,61]. For example, a recent meta-analysis by Pearce et al [24], which included 15 studies and 2,110,588 person-years, demonstrated that participants accumulating half the recommended amount of physical activity had an 18% lower risk of depression than adults without physical activity. Furthermore, adults accumulating the recommended volume of 8.8 marginal metabolic equivalent task hours per week had a 25% lower risk of diminishing potential benefits. Several systematic reviews have found that exercise can reduce the symptoms of depression with a moderate to large effect size and can be a useful addition to pharmacotherapy and psychotherapy [25-30]. Exercise has been shown to counteract reductions in the secretion of neurotransmitters, such as dopamine and serotonin, thus having a positive effect on emotions and reducing the severity of psychological symptoms, such as anxiety and depression. He et al [62] reported that 10 weeks of voluntary running exercise significantly increased serotonin, dopamine, and norepinephrine levels in the hippocampus, which had been reduced in rats with chronic mild stress.

The results of this study indicate that the mobile phone–based physical activity program developed for this study led to a significant decrease in perceived stress among participants in the treatment group, whereas the waitlist group showed no significant change. The significant reduction in perceived stress observed in the treatment group suggests that mobile phone–based physical activity programs could be a viable option for individuals seeking to reduce stress levels [63]. There are several potential underlying mechanisms that may explain the significant effect of the mobile phone–based physical activity program on perceived stress. First, physical activity has been shown to stimulate the release of endorphins, which are natural chemicals that can improve mood and reduce feelings of stress and anxiety. These endorphins can counteract the negative feelings associated with stress and promote a sense of well-being. Second, engaging in physical activity may help individuals to divert their mind from stressful thoughts or situations, providing a temporary escape and reducing overall levels of perceived stress. In other words, when individuals engage in physical activity, they may shift their attention away from the stressors or negative thoughts that are causing stress. This can provide a temporary break from stress, allowing the individual to clear their mind and return to their stressors with a renewed focus and sense of calmness. The theoretical implications of this study are also important. According to the stress and coping theory [64], stress is a result of the relationship between an individual and their environment and the way in which they perceive and cope with stressors. This theory suggests that stress can be managed through the development of effective coping strategies, such as engaging in physical activity. The findings of this study support the stress and coping theory, as the mobile phone–based physical activity program was found to be effective in reducing perceived stress levels among participants. Furthermore, the results of this study provide support for the use of digital interventions in mental health treatment. The use of mobile phone–based physical activity programs is an example of how technology can be leveraged to improve mental health outcomes. This study adds to the growing body of research on the effectiveness of digital interventions for mental health [65,66]. The use of mobile phone–based physical activity programs could be a useful addition to the mental health treatment landscape, particularly in populations with limited access to traditional mental health services.

On the basis of the results of this study, it appears that the mobile phone–based physical activity program did not have significant effect on perceived stress, psychological well-being, or quality of life among participants. Although there was slight increase in the mean scores for psychological well-being and quality of life in both the treatment and waitlist groups, these increases were not statistically significant. It is possible that the lack of significant findings in this study could be owing to various factors. For example, the duration and frequency of the program may not have been sufficient to produce significant changes in mental health outcomes. In addition, individual differences in adherence to the program and motivation to engage in physical activity could have influenced the results.

Despite the lack of significant findings, the use of mobile phone–based physical activity programs as a cost-effective and accessible alternative for the treatment of depression and perceived stress among adults should not be dismissed [67]. It is important to continue exploring and refining such programs to maximize their potential benefits for mental health. Moreover, the nonsignificant changes in quality of life and psychological well-being in the waitlist group suggest that simply being enrolled in the program could have a positive effect on these outcomes. Future studies should explore the potential placebo effect of simply being enrolled in a program and the potential benefits of combining mobile phone–based physical activity programs with other interventions such as cognitive behavioral therapy or medication.

**Practical Implications**

On the basis of the findings of this study, practitioners can suggest mobile phone–based physical activity programs as a cost-effective and accessible alternative for the treatment of depression and perceived stress among adults. These programs can be easily implemented at home and can help individuals overcome time and accessibility barriers associated with physical activity.

For example, a practitioner working in a mental health clinic can recommend a mobile phone–based physical activity program to their patients who are experiencing symptoms of depression or perceived stress. The program can be used as a complement to their existing treatment or as a stand-alone intervention. The practitioner can provide guidance about how to use the program.
monitor the patient’s progress, and adjust the treatment plan accordingly. The expected outcomes of using such a program can be a significant decrease in depressive symptoms and perceived stress levels, leading to improved mental and physical well-being. Patients may also experience increase in motivation, self-efficacy, and overall quality of life. However, it is important to note that the program may not have a significant effect on other variables such as psychological well-being or quality of life, as observed in this study.

Furthermore, a community center or gym can offer a mobile phone–based physical activity program to members who are unable to attend in-person exercise classes. This can help make physical activity more accessible to individuals who may have difficulty in traveling to a gym or attending a class during scheduled times. In addition, the program can be offered at a lower cost than that of in-person classes, making it a more affordable option for those with a tight budget.

Finally, an employer can provide a mobile phone–based physical activity program to their employees as part of a workplace wellness program. This can help employees manage stress and improve their mental health, which could lead to increased productivity and job satisfaction. In addition, offering such a program can demonstrate that the employer values employee well-being and is committed to promoting a healthy work environment.

**Limitations and Future Research Directions**

The limitations of this study were as follows. First, the treatment period of 4 weeks was short, and it limited the confirmation of the prevention effect over time. Therefore, more rigorous evaluations of the effectiveness of such programs—via randomized controlled trials in which participants are randomly assigned to treatment and waitlist groups—should be conducted, and such trials should be conducted over sufficient treatment periods of at least 3 months.

Second, the participants of this study consisted of members of the general public with low levels of depressive symptoms. Thus, it cannot be generalized that findings apply to adults with high levels of depressive symptoms. Although it is worthwhile to investigate the effectiveness of digital applications for this type of sample in an attempt to prevent severe depression, the program may need to target patients who have mild to severe depressive symptoms for treatment purposes.

Third, although the mobile phone–based physical activity program was modified and supplemented through preliminary studies, many factors need to be corrected in the course of the implementation of the program. Moreover, considering the feedback of the participants who completed 4 weeks of the program, it is possible that the lack of graphical detail in the content composition and errors in the program acted as factors that lowered the motivation of the participants. Therefore, there is a need to improve participation levels by further supplementing and improving the treatment program based on the feedback of the study participants.

Finally, although this study did not find significant changes in psychological well-being or quality of life among participants, the potential benefits of mobile phone–based physical activity programs for mental health should not be overlooked. Further studies are needed to identify optimal program characteristics and implementation strategies to maximize their efficacy in improving psychological well-being and quality of life.

**Conclusions**

In conclusion, this study investigated the effects of mobile phone–based physical activity programs on depression, perceived stress, psychological well-being, and quality of life. The findings indicated that 4 weeks of training using the program significantly reduced the participants’ levels of depression and perceived stress. This study suggests that practitioners can recommend mobile phone–based physical activity programs as a cost-effective and accessible alternative for treating depression and perceived stress among adults. Practitioners can offer guidance to patients about how to use the program and monitor their progress while adjusting their treatment plan accordingly. This program can be used as a complement to existing treatment or as a stand-alone intervention. Expected outcomes may include significant reduction in depressive symptoms and perceived stress levels, increased motivation and self-efficacy, and improved overall quality of life. However, practitioners should be aware that the program may not have significant effect on other variables such as psychological well-being or quality of life. Community centers or gyms can also offer such programs to members who are unable to attend in-person classes, making physical activity more accessible and affordable. Employers can also provide these programs as part of a workplace wellness program, thus promoting a healthy work environment and improving employee productivity and job satisfaction.

**Acknowledgments**

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**Conflicts of Interest**

None declared.

Multimedia Appendix 1

CONSORT-eHEALTH checklist (V 1.6.1).
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**Abbreviations**

**CONSORT:** Consolidated Standards of Reporting Trials
PHQ-9: Patient Health Questionnaire–9
WHO: World Health Organization

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Feasibility, Acceptability, and Potential Impact of a Novel mHealth App for Smokers Ambivalent About Quitting: Randomized Pilot Study

Jennifer B McClure1,2, PhD; Jaimee L Heffner3, PhD; Chloe Krakauer1, PhD; Sophia Mun1, MPH; Predrag Klasnja4, PhD; Sheryl L Catz5, PhD

1Kaiser Permanente Washington Health Research Institute, Seattle, WA, United States
2Kaiser Permanente Bernard J Tyson School of Medicine, Pasadena, CA, United States
3Cancer Prevention Program, Public Health Sciences Division, Fred Hutchinson Cancer Center, Seattle, WA, United States
4School of Information, University of Michigan, Ann Arbor, MI, United States
5Betty Irene Moore School of Nursing, University of California, Davis, Sacramento, CA, United States

Abstract

Background: Most smokers are ambivalent about quitting—they want to quit someday, but not now. Interventions are needed that can engage ambivalent smokers, build their motivation for quitting, and support future quit attempts. Mobile health (mHealth) apps offer a cost-effective platform for such interventions, but research is needed to inform their optimal design and assess their acceptability, feasibility, and potential effectiveness.

Objective: This study aims to assess the feasibility, acceptability, and potential impact of a novel mHealth app for smokers who want to quit smoking someday but are ambivalent about quitting in the near term.

Methods: We enrolled adults across the United States who smoked more than 10 cigarettes a day and were ambivalent about quitting (n=60). Participants were randomly assigned to 1 of 2 versions of the GEMS app: standard care (SC) versus enhanced care (EC). Both had a similar design and identical evidence-based, best-practice smoking cessation advice and resources, including the ability to earn free nicotine patches. EC also included a series of exercises called experiments designed to help ambivalent smokers clarify their goals, strengthen their motivation, and learn important behavioral skills for changing smoking behavior without making a commitment to quit. Outcomes were analyzed using automated app data and self-reported surveys at 1 and 3 months post enrollment.

Results: Participants who installed the app (57/60, 95%) were largely female, White, socioeconomically disadvantaged, and highly nicotine dependent. As expected, key outcomes trended in favor of the EC group. Compared to SC users, EC participants had greater engagement (mean sessions 19.9 for EC vs 7.3 for SC). An intentional quit attempt was reported by 39.3% (11/28) of EC users and 37.9% (11/29) of SC users. Seven-day point prevalence smoking abstinence at the 3-month follow-up was reported by 14.7% (4/28) of EC users and 6.9% (2/29) of SC users. Among participants who earned a free trial of nicotine replacement therapy based on their app usage, 36.4% (8/22) of EC participants and 11.1% (2/18) of SC participants requested the treatment. A total of 17.9% (5/28) of EC and 3.4% (1/29) of SC participants used an in-app feature to access a free tobacco quitline. Other metrics were also promising. EC participants completed an average of 6.9 (SD 3.1) out of 9 experiments. Median helpfulness ratings for completed experiments ranged from 3 to 4 on a 5-point scale. Finally, satisfaction with both app versions was very good (mean 4.1 on a 5-point Likert scale) and 95.3% (41/43) of all respondents would recommend their app version to others.
Conclusions: Ambivalent smokers were receptive to the app-based intervention, but the EC version, which combined best-practice cessation advice with self-paced, experiential exercises, was associated with greater use and evidence of behavior change. Further development and evaluation of the EC program is warranted.

Trial Registration: ClinicalTrials.gov NCT04560868; https://clinicaltrials.gov/ct2/show/NCT04560868

(JMIR Mhealth Uhealth 2023;11:e46155) doi:10.2196/46155

KEYWORDS
ambivalence; app; digital health intervention; mHealth intervention; mHealth; motivation; nicotine; smoking; smoking cessation; tobacco

Introduction

Tobacco use is responsible for over 8 million deaths per year worldwide [1]. The health risks of smoking are widely known and well documented, but the addictive properties of nicotine make quitting smoking difficult [2]. This explains why the majority of people who smoke want to quit someday but are not yet ready to commit to giving up tobacco anytime soon. This finding holds true across time, cultures, and countries [3-7].

When people are ready to quit smoking, effective, evidence-based treatment is widely available. This includes a combination of quit advice, supportive counseling, and pharmacotherapy [8,9]. However, to meaningfully reduce population smoking rates worldwide, a broader public health approach is required. Specifically, interventions are needed for those who want to quit smoking someday but are not yet ready to commit to change or to take action. These people are typically not eligible for cessation treatments (such as counseling or pharmacotherapy), which are largely limited to those who are ready to stop smoking.

While some may assume that people who are ambivalent about quitting smoking are not interested in an intervention, research has shown these individuals will enroll in smoking-focused intervention trials [10-14]. This illustrates that they are open to receiving information and assistance, despite their ambivalence about quitting smoking in the near term. A recent meta-analysis of 22 studies also found that interventions in this population can be as effective as interventions targeted to people who are ready to quit; however, the cost of intervention is substantially higher [13]. For example, the pooled cost per quit among smokers who are not yet ready to quit was US $19,510 for pharmacological interventions, US $11,416 for behavioral interventions, and US $14,662 for combined pharmacological and behavioral interventions compared to estimated costs per quit among smokers who were ready to quit, which ranged from US $1807 to US $3326 for behavioral interventions and US $2655 to US $3108 for combination therapy [13]. This cost is a prohibitive barrier for many health care providers, health care systems, and public health agencies, which is why provision of smoking cessation services is typically limited to people who are ready to quit and not offered to those who are ambivalent about quitting. However, this means the majority of smokers are excluded from intervention opportunities, even though they could benefit from them. To further reduce smoking prevalence, new intervention strategies that are both effective and cost-effective are needed for people who are ambivalent about quitting smoking.

We contend that mobile health (mHealth) apps offer a promising platform for intervening with people who are ambivalent about quitting. App-based interventions can have wide population-level reach with relatively little per-person intervention cost. From a user standpoint, they are also convenient and accessible. These benefits have helped drive the ballooning demand for and availability of digital health therapeutics and mHealth apps in recent years [15,16]. Yet, to our knowledge, there are no publicly available mHealth apps at this time that are designed specifically for smokers who are not ready to quit smoking.

It remains an open question whether ambivalent smokers would use an app-based smoking intervention if they are not ready to quit. Although, they would be interested in using an app to help them change their smoking behavior [17-19], especially if the app is responsive to their goals, such as reducing how much they smoke, and if they are not asked to commit to quitting. To date, only 1 published trial has evaluated app-delivered intervention in this population [20]. This study tested a comprehensive intervention that combined daily text messages (motivational support and quizzes) with financial incentives, encouragement to use 1 or more self-selected relaxation and distraction apps, motivational phone support from a tobacco treatment specialist, and precessation use of nicotine replacement therapy (NRT). While the 3-week intervention significantly enhanced quit rates at 6-month follow-up, more research is needed to confirm ambivalent smokers’ interest in using app-based smoking interventions and to inform their optimal design.

The primary objective of this randomized pilot study was to evaluate the feasibility and acceptability of using an mHealth app called GEMS to motivate and support smoking behavior change among smokers who want to quit smoking someday but have not yet. Two versions of GEMS were evaluated, each using a similar, but not identical, graphical user interface and content. The standard care (SC) version offered best-practice cognitive behavioral advice and other resources recommended for people who are ready to quit smoking, including access to cessation counseling and pharmacotherapy. The enhanced care (EC) version included this same content plus a series of specific cognitive and behavioral exercises designed to build motivation and enhance self-efficacy to reduce smoking or quit, and to promote quit attempts and cessation. We hypothesized that participants would use both versions of the app, but the EC version would have greater program use and, in turn, better support change in motivation, self-efficacy, and smoking behavior. However, this pilot study was not powered to detect...
statistically significant differences in cognitive or behavioral outcomes between the 2 app versions. Instead, findings will inform the need for further evaluation of the GEMS app and could inform the design of similar app-based interventions targeting smokers who are ambivalent about quitting smoking.

Methods

Ethics Approval
All research activities were conducted at the Kaiser Permanente Washington (KPWA) Health Research Institute and approved by the KPWA Institutional Review Board (#2020). Data were collected between December 2020 and October 2021. The study is registered with ClinicalTrials.gov (NCT04560868).

Study Design
The study used a parallel, 2-arm design. Participants were randomly assigned to the SC or EC version of the app using an automated, block-stratified randomization scheme (≥15 cigarettes per day vs 10-14 cigarettes). This scheme ensured balanced representation of lighter versus heavier smokers between intervention arms since this could impact users’ motivation or ability to change their smoking behavior. Participants were followed for 3 months post enrollment and completed self-report surveys at 1 and 3 months post enrollment. Consistent with the purpose of a pilot trial [21], the goal of this work is to provide proof of concept for the app’s feasibility and acceptability.

Recruitment, Eligibility, and Randomization
Participants were recruited through social media ads and screened for eligibility by phone. Individuals were eligible if they met the following criteria: 18 years of age or older; could read and speak in English; smoked at least 100 lifetime cigarettes; smoked in the past week; smoked at least ten cigarettes a day; wanted to quit smoking someday, but not in the next month; reported daily smartphone use; self-reported they could read text on their phone screen; were willing to install the app within 3 days were offered assistance. Those who failed to install the app during the 3-month study period were deactivated app access and ceased app usage tracking. Both versions of the app (SC and EC) had a similar design and identical content, except for the addition of the novel experiments in the EC version. This design meant that both groups received an active intervention and provided data useful to assessing the concept of offering an app-based intervention to people who were ambivalent about quitting, while also allowing us to assess differences that might be attributed to the additional features in the EC version. Shared and unique features of each app version are described below.

SC Content and Features Common to Both App Versions
The SC content was based on evidence-based treatment grounded in the US Public Health Service Guidelines for Treatment of Nicotine Dependence [9] and standard cognitive behavioral therapy for smoking cessation [22], with additional content and features informed by user-centered design work conducted by our team [17,18,23]. Messaging acknowledged users were not ready to stop smoking, but content focused on how to stop smoking, as per usual care treatment for smoking cessation. For example, the main feature of this program version was a Quit Guide that included advice on how to quit smoking: didactic information (eg, what is nicotine withdrawal, how does pharmacotherapy work); and a 6-step guide on how to quit (eg, how to choose and use stop-smoking medicines, how to set a quit date, how to prepare for your quit date, what to do on your quit date, and how to stay the course and prevent relapse). Participants could also call a nationwide tobacco quitline from within the app to enroll in free counseling available to all US residents. Other content included a calculator for estimating how much money could be saved by quitting smoking, a daily cigarette tracker, and 2 sets of narrative peer advice presented through short testimonials: 1 set offering motivational encouragement for quitting smoking and 1 modeling how to talk back to common excuses people give for smoking or not quitting. Finally, participants could keep notes on their quitting progress using an in-app journal.

Participants earned badge rewards (gems—hence the app name) for using app features (eg, saving calculator, daily cigarette tracker) and for viewing psychoeducational content (eg, each Quit Guide step). Participants were asked to actively indicate when they read key content by clicking a “Mark as Read” button on each page. Participants using the SC version of the app could earn up to 10 usage badges. After 6 badges were earned, users in both groups could request a free 2-week trial of NRT to help them stop smoking.

Intervention Design, Content, and Functionality

General Overview
Both app versions were called GEMS. The name was chosen based on user feedback. Ambivalent smokers liked the name because it did not suggest the app was smoking related, making it more confidential and more appealing than a name implying the app was focused on smoking cessation.

After installing the app and setting up a user account, participants viewed a welcome screen, which explained the program’s purpose and a brief tutorial and orientation to the app’s features. Content could then be accessed ad-lib until completion of the 3-month follow-up survey, which concluded study participation. At this point, the study team remotely deactivated app access and ceased app usage tracking. Both versions of the app (SC and EC) had a similar design and identical content, except for the addition of the novel experiments in the EC version. This design meant that both groups received an active intervention and provided data useful to assessing the concept of offering an app-based intervention to people who were ambivalent about quitting, while also allowing us to assess differences that might be attributed to the additional features in the EC version. Shared and unique features of each app version are described below.
Experimental App Content and Unique Features

The EC app version mirrored the SC’s design, content, and functionality with 3 key exceptions. First, the home page of the EC version included, as the main content, a series of 9 cognitive and behavioral exercises called experiments. Each experiment was designed to help users clarify their values, build and strengthen their motivation for reducing or quitting smoking, and enhance their self-efficacy for changing smoking behavior by learning specific skills that could help them manage cravings and resist the urge to smoke (Table 1). Unless EC users opted to block text reminders, they also received reminder prompts to initiate or complete experiments. Second, in the EC version, the Quit Guide was in the resource toolbox, accessible from the home page, but it was less prominent than in the SC version, where it occupied the home page. Third, EC participants could earn up to 19 total badges: 9 for completing each of the experiments and 10 for viewing the program content common with the SC version.

The theoretical rationale for the experiments, an overview of their design and flow, and preliminary formative research testing their acceptability and potential impact with smokers ambivalent about quitting have been previously reported [19]. Briefly, the EC intervention is grounded in empirically validated recommendations for treating nicotine dependence [9] and several complementary motivation and behavior change theories (eg, the PRIME theory of motivation [24,25], cognitive behavioral therapy, acceptance and commitment therapy, and social cognitive theory [26-28]). The experiments’ design was further informed by Fogg’s model of persuasive design [29], which suggests that when people have low motivation for change (as is the case with smokers ambivalent about quitting), the behaviors they are expected to engage in should be simple (ie, require low ability) and coupled with extrinsic triggers to prompt engagement (ie, reminder prompts). The specific behavioral goals and skills targeted in each experiment are summarized in Table 1 and an example is depicted in Figure 1.

With the exception of the first experiment, which could be completed in a few minutes, each exercise was designed to be practiced for a 24-hour period, after which participants were prompted to return and report what they learned by answering a brief series of reflective questions. Emphasis was placed on trying and learning from each exercise, as opposed to mastery or success, to avoid creating a sense of failure if participants did not complete or master the experiment. The experiments also built on one another, so lessons and skills learned in earlier experiments were designed to support success with later experiments.

To encourage sequential completion and forward progress, each experiment unlocked after completion of the previous experiment. If an experiment was started but not completed, the next experiment automatically unlocked after several days.

### Table 1. Enhanced care experiments’ targeted skills and goals.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Targeted skills and goals</th>
</tr>
</thead>
<tbody>
<tr>
<td>One</td>
<td>Clarify personal values and health goals. Explore how smoking fits with these.</td>
</tr>
<tr>
<td>Two</td>
<td>Identify personal reasons for quitting. Build motivation for change.</td>
</tr>
<tr>
<td>Three</td>
<td>Identify high-risk situations for smoking. Inform future problem-solving and preparation for quitting.</td>
</tr>
<tr>
<td>Four</td>
<td>Learn deep breathing as a tool for stress reduction and craving management. Build self-efficacy for managing cravings and motivation for quitting.</td>
</tr>
<tr>
<td>Five</td>
<td>Mindful acceptance. Learn to let urges pass without smoking. Enhance self-efficacy for managing cravings and motivation for quitting. Create positive outcome expectations.</td>
</tr>
<tr>
<td>Six</td>
<td>Stimulus control. Learn to reduce the reinforcing effects of smoking. Enhance self-efficacy and motivation for quitting.</td>
</tr>
<tr>
<td>Seven</td>
<td>Cognitive restructuring. Reframe not smoking as a positive choice, not a deprivation. Support self-efficacy and create positive outcome expectations for quitting.</td>
</tr>
<tr>
<td>Nine</td>
<td>Put all skills into practice with a 24-hour “practice” quit. Enhance self-efficacy, motivation, and positive outcome expectations.</td>
</tr>
</tbody>
</table>
Key Outcomes and Baseline Measures

Sources

Self-report surveys were completed on the internet at baseline, 1 month, and 3 months post enrollment. Participants received a US $25 electronic gift card for completing each survey.

App use and qualitative postexperiment ratings were assessed with automated, time-stamped data.

Key Outcomes of Interest

As a pilot study, we examined a range of primary and secondary outcomes to inform the feasibility, acceptability, and potential impact of the EC version relative to the SC version of GEMS.

A key outcome was whether people would install the app. Among those who did, primary outcomes of interest, each assessed at 3-month follow-up, were total number of user sessions, presence of a self-reported quit attempt lasting at least 24 hours, and a self-report of no smoking for the past 7 days (7-day point prevalent abstinence [PPA]).

Secondary outcomes used to assess program use and engagement included total duration of app usage calculated as number of days between installation and last use; total number of usage badges earned; number of participants who earned enough usage badges to request free NRT; proportion of those earning NRT who requested it; the proportion of participants who clicked on the Call Now button to access free quitline counseling; and the number of people who used each app feature.

Secondary outcomes used to assess program use and engagement included total duration of app usage calculated as number of days between installation and last use; total number of usage badges earned; number of participants who earned enough usage badges to request free NRT; proportion of those earning NRT who requested it; the proportion of participants who clicked on the Call Now button to access free quitline counseling; and the number of people who used each app feature.

Satisfaction was assessed based on users’ overall satisfaction with their assigned program’s content and advice. All ratings used a 5-point Likert scale from “not at all” to “extremely.” In the EC arm, users also rated the helpfulness of each experiment using a 5-point Likert scale from “not helpful” to “very helpful.” Ratings were made in real time following the completion of each experiment.

Additional secondary outcomes included motivation and self-efficacy for both smoking fewer cigarettes a day and quitting smoking, each assessed as cognitive intermediaries of behavior change at the 1-month follow-up using 10-point Likert scales ranging from “not at all” to “extremely.” Other secondary indices of behavior change included a self-reported quit attempt lasting at least 24 hours, assessed at 1 month; self-reported 7-day PPA at 1 month; and the proportion of participants who reported a 50% or greater reduction in smoking from baseline to the 3-month follow-up.

Baseline assessment measures included participant demographics, use of smartphones and smoking apps, tobacco and e-cigarette use, and self-reported lifetime diagnosis or treatment for depression, anxiety, bipolar disorder, schizophrenia, alcohol use disorder, or drug use (assessed as a single yes or no for any of the listed conditions). Nicotine dependence was assessed with the Fagerström Test of Nicotine Dependence (FTND) [30]. Problem drinking was assessed with the Alcohol Use Disorders Identification Test-Consumption (AUDIT-C) [31]. Frequency of cannabis use was assessed with a single item from the Cannabis Use Disorder Identification Test-Revised (CUDIT-R) [32]. Response options for this item were never, monthly or less, 2-4 times a month, 2-3 times a week, or 4 or more times a week. Finally, we assessed participants’ outcome expectations that the help received from the study would be a key factor in either their smoking less or their quitting smoking. Each was assessed with a 5-point Likert scale ranging from 1=“strongly disagree” to 5=“strongly agree” and was modified from a similar item previously shown to predict cessation [33].

Data and Programming Issues

Two programming issues are worth noting. First, due to a REDCap programming error, some participants who self-reported 7-day PPA at 3 months were not flagged by the system. As a result, biochemical confirmation was not obtained from these individuals as originally planned. Since these individuals made up a high proportion of individuals who self-reported 7-day PPA at 3 months, only self-reported smoking outcomes were analyzed. Second, due to a code issue, 4 EC participants were allowed to cycle through some of the experiments after a 15-minute practice period instead of the planned 24-hour period. This issue was caught early and corrected, so these individuals were retained in the analyses.
**Data Analyses**

As defined a priori, outcomes are based on 2 subsets of participants. We first report on the total number of individuals who agreed to join the study and who installed the study app, as an initial indicator of study acceptability. All other analyses used a modified intent-to-treat approach and included all randomized participants who installed the app, regardless of subsequent app usage. Participants who failed to install the app were excluded from this cohort because the goal of these analyses was to assess metrics of feasibility, acceptability, and potential impact of app content among individuals who installed and used the intervention. Everyone in this analytic sample contributed automated app usage data; however, self-reported data at 1 and 3 months post enrollment were subject to missingness. Comparisons of satisfaction ratings for specific app features were restricted to participants who both self-reported use of the feature and whose automated data confirmed this use. Per convention, missing smoking outcomes were conservatively imputed as smoking. For consistency, we used a similar approach when analyzing 24-hour quit attempts (ie, missing data were imputed as not making a quit attempt). As determined a priori, secondary sensitivity analyses were also conducted for these 2 behavioral outcomes using (1) complete cases only and (2) multiple imputation by chained equation with 10 imputed data sets created with logistic regression imputation and Barnard-Rubin adjusted degrees of freedom [34,35]. For all other outcomes, analyses used complete cases without imputation.

Descriptive statistics were used to characterize the baseline sample and outcomes of interest. To compare outcomes across groups at follow-up, regression models were fitted using generalized estimating equations with robust standard errors and an exchangeable working correlation. When applicable, the model was simultaneously fitted to outcomes collected at 1 and 3 months post enrollment. For binary outcomes, we estimated relative risks (RR) of the outcome with the EC version relative to the SC version using a Poisson regression model. When events were too rare to obtain estimates of relative risks, linear regression models were used to estimate risk differences instead. Linear regression models were fitted to continuous outcomes to estimate mean differences between arms.

When applicable, to allow for separate reporting of comparisons at 1 and 3 months post baseline, time of survey collection and the interaction between follow-up time and assigned app version were included as covariates. For precision, we adjusted for the number of cigarettes smoked per day at baseline and, when applicable, baseline values of the outcome. Because groups differed at baseline by the proportion who reported a history of mental health or substance use disorder, risky drinking based on AUDIT-C scores, and household income, and these variables are known to affect cessation outcomes, we also adjusted for these potential confounders in sensitivity analyses. Point estimates are presented with 95% CIs and P values are from 2-sided Wald tests. All analyses were conducted in R version 4.0.2 [36].

**Sample Size**

The total enrolled sample (n=60) and final analytic sample (n=57) exceed the range of 24 to 50 participants commonly recommended for pilot studies [37,38]. Smaller samples are deemed appropriate when the goal is to assess intervention feasibility and acceptability as opposed to intervention efficacy or effectiveness. The study was not powered to detect minimal clinically meaningful differences between groups with statistical significance.

**Results**

**Participants**

A total of 60 participants consented and enrolled in the study. Of these, most participants (57/60, 95%) installed the app and were included in the analytic sample (Figure 2). Demographic characteristics of this group are presented in Table 2. These participants were largely female, White, and socioeconomically disadvantaged. One-third of participants (19/57, 33.3%) had previously used health-related apps, but only 7% (4/57) had ever used a smoking cessation app. Participants smoked nearly a pack a day on average (mean 18.1 cigarettes a day) and most (36/57, 63.2%) had FTND scores indicative of “high” or “very high” nicotine dependence. Nearly one-third (18/57, 31.6%) reported using cannabis 2 or more times a week, and a similar proportion (21/57, 36.8%) self-reported previous diagnosis or treatment for either depression, anxiety, bipolar disorder, schizophrenia, alcohol use disorder, or drug use. At baseline, motivation for quitting smoking someday was moderately high (mean 6.2 out of 10, SD 1.2) and self-efficacy for quitting was moderately low (mean 4.1 out of 10, SD 1.8).
Figure 2. CONSORT (Consolidated Standards of Reporting Trials) flow diagram.
Table 2. Baseline descriptive characteristics.

<table>
<thead>
<tr>
<th></th>
<th>Overall (N=57)</th>
<th>Standard care (n=29)</th>
<th>Enhanced care (n=28)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female, n (%)</td>
<td>41 (71.9)</td>
<td>22 (75.9)</td>
<td>19 (67.9)</td>
</tr>
<tr>
<td>White, n (%)</td>
<td>47 (82.5)</td>
<td>24 (82.8)</td>
<td>23 (82.1)</td>
</tr>
<tr>
<td>Hispanic, n (%)</td>
<td>0 (0)</td>
<td>0 (0)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Employed, n (%)</td>
<td>29 (50.9)</td>
<td>14 (48.3)</td>
<td>15 (53.6)</td>
</tr>
<tr>
<td>Annual household income &lt;US $45,000, n (%)</td>
<td>33 (57.9)</td>
<td>13 (44.8)</td>
<td>20 (71.4)</td>
</tr>
<tr>
<td>No college degree, n (%)</td>
<td>41 (71.9)</td>
<td>23 (79.3)</td>
<td>18 (64.3)</td>
</tr>
<tr>
<td>Mental health or substance use disorder (Yes)(^{ab}), n (%)</td>
<td>21 (36.8)</td>
<td>9 (31)</td>
<td>12 (42.9)</td>
</tr>
<tr>
<td>Age (years), mean (SD)</td>
<td>47.5 (10.3)</td>
<td>47.1 (9.1)</td>
<td>47.9 (11.5)</td>
</tr>
<tr>
<td>Cigarettes per day, mean (SD)</td>
<td>18.1 (7.8)</td>
<td>17 (6.6)</td>
<td>19.2 (8.8)</td>
</tr>
<tr>
<td>FTND(^{c}) (nicotine dependence)(^{d}), mean (SD)</td>
<td>6.1 (1.9)</td>
<td>5.9 (2)</td>
<td>6.4 (1.7)</td>
</tr>
<tr>
<td>Nicotine and tobacco, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Use tobacco other than cigarettes (Yes)</td>
<td>6 (10.5)</td>
<td>3 (10.3)</td>
<td>3 (10.7)</td>
</tr>
<tr>
<td>Use e-cigarettes (No)</td>
<td>47 (82.5)</td>
<td>23 (79.3)</td>
<td>24 (85.7)</td>
</tr>
<tr>
<td>Nicotine dependence: high or very high(^{d})</td>
<td>36 (63.2)</td>
<td>18 (62.2)</td>
<td>18 (64.3)</td>
</tr>
<tr>
<td>Substance and alcohol use, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cannabis use: 2 or more times/week(^{a})</td>
<td>18 (31.6)</td>
<td>9 (31)</td>
<td>9 (32.2)</td>
</tr>
<tr>
<td>Hazardous drinking levels(^{e})</td>
<td>16 (28.1)</td>
<td>10 (34.5)</td>
<td>6 (21.4)</td>
</tr>
<tr>
<td>App use, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ever downloaded health app (Yes)</td>
<td>19 (33.3)</td>
<td>10 (34.5)</td>
<td>9 (32.1)</td>
</tr>
<tr>
<td>Ever downloaded smoking app (Yes)</td>
<td>4 (7)</td>
<td>2 (6.9)</td>
<td>2 (7.1)</td>
</tr>
<tr>
<td>Motivation(^{f}), mean (SD)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reducing smoking</td>
<td>5.5 (1.1)</td>
<td>5.5 (1.1)</td>
<td>5.6 (1.2)</td>
</tr>
<tr>
<td>Quitting smoking</td>
<td>6.2 (1.2)</td>
<td>6.1 (1.3)</td>
<td>6.2 (1)</td>
</tr>
<tr>
<td>Self-efficacy(^{f}), mean (SD)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reducing smoking</td>
<td>3.8 (1.5)</td>
<td>4 (1.5)</td>
<td>3.5 (1.5)</td>
</tr>
<tr>
<td>Quitting smoking</td>
<td>4.1 (1.8)</td>
<td>4.2 (1.7)</td>
<td>3.9 (1.9)</td>
</tr>
<tr>
<td>Outcome expectation(^{g}), mean (SD)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Study app will help smoke less (Yes)</td>
<td>3.8 (0.9)</td>
<td>3.8 (0.9)</td>
<td>3.8 (0.8)</td>
</tr>
<tr>
<td>Study app will help quit smoking (Yes)</td>
<td>3.7 (0.8)</td>
<td>3.8 (0.9)</td>
<td>3.7 (0.8)</td>
</tr>
</tbody>
</table>

\(^{a}\)Missing responses: 2 did not provide annual household income; 4 did not answer question about cannabis use; and 2 did not answer questions about mental health or substance use disorders.

\(^{b}\)Self-reported diagnosis or treatment for depression, anxiety, bipolar disorder, schizophrenia, or alcohol use.

\(^{c}\)FTND: Fagerström Test of Nicotine Dependence.

\(^{d}\)Fagerström Test of Nicotine Dependence score. The range is from 0 to 10. Scores 6-7 indicate high dependence and 8-10 indicate very high dependence.

\(^{e}\)Alcohol Use Disorders Identification Test-Consumption score. Range from 0 to 12. Scores of 4 or above for men and 3 or above for women indicative of drinking levels that are hazardous to one’s health and safety.

\(^{f}\)Likert scale ranging from 1=“not at all” to 10=“extremely.”

\(^{g}\)Likert scale ranging from 1=“strongly disagree” to 5=“strongly agree.”

Indicators of Feasibility and Acceptability

General App Usage

A total of 3 enrolled participants failed to download the app. Among those who did install the app (57/60, 95%), usage differed significantly by group: EC participants averaged 19.9 (SD 16.2) total sessions compared to an average of 7.3 (SD 6.6) for SC users, yielding an average difference of 12.7 sessions (95% CI 6.23-18.93; \(P<.001\)).
Overall, duration of app usage was similar between arms but slightly favored the EC group. Mean days of use among EC users were 43 (SD 30.9) compared to 41.8 (SD 34.2) among SC users, yielding an average difference of 1.1 days (95% CI 15.65-17.85 days; \( P=.90 \)).

Most participants (53/57, 93%) earned at least one usage badge. However, EC users earned more badges (mean 10.1, SD 6.0) than SC users (mean 6.1, SD 3.5), yielding an average difference of 4.2 badges (95% CI 1.7-6.7; \( P=.001 \)). EC users were also more likely to earn the requisite 6 badges needed to request free NRT: 78.6% (22/28) of EC users met this bar compared to 62.1% (18/29) of SC users (RR 1.28, 95% CI 0.91-1.79; \( P=.16 \)). Interpretation of the results was unchanged in analyses adjusting for baseline differences (data not shown).

### Use of App Content and Features

SC and EC had similar use of the content and features common to both app versions, with 2 notable exceptions: SC users were twice as likely to indicate that they had read all of the content in the Quit Guide subsections compared to EC users, and EC users were 45% more likely to view the journal compared to SC users (see Table 3).

**Table 3.** Use of features common to both app versions.

<table>
<thead>
<tr>
<th>App feature</th>
<th>Overall (N=57), n (%)</th>
<th>Standard care (n=29), n (%)</th>
<th>Enhanced care (n=28), n (%)</th>
<th>Relative risk (95% CI)(^a)</th>
<th>( P ) value(^b)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Quit Guide</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step 1(^c)</td>
<td>35 (61.4)</td>
<td>26 (89.7)</td>
<td>9 (32.1)</td>
<td>0.36 (0.21-0.62)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Step 2(^c)</td>
<td>36 (63.2)</td>
<td>26 (89.7)</td>
<td>10 (35.7)</td>
<td>0.40 (0.24-0.66)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Step 3(^c)</td>
<td>34 (59.6)</td>
<td>24 (82.8)</td>
<td>10 (35.7)</td>
<td>0.44 (0.26-0.72)</td>
<td>.001</td>
</tr>
<tr>
<td>Step 4(^c)</td>
<td>26 (45.6)</td>
<td>19 (65.5)</td>
<td>7 (25)</td>
<td>0.38 (0.20-0.74)</td>
<td>.005</td>
</tr>
<tr>
<td>Step 5(^d)</td>
<td>25 (43.9)</td>
<td>18 (62.1)</td>
<td>7 (25)</td>
<td>0.41 (0.20-0.81)</td>
<td>.01</td>
</tr>
<tr>
<td>Cigarette tracker(^d)</td>
<td>24 (42.1)</td>
<td>13 (44.8)</td>
<td>11 (39.3)</td>
<td>0.88 (0.48-1.62)</td>
<td>.69</td>
</tr>
<tr>
<td>Savings calculator(^e)</td>
<td>25 (43.9)</td>
<td>13 (44.8)</td>
<td>12 (42.9)</td>
<td>0.96 (0.54-1.71)</td>
<td>.90</td>
</tr>
<tr>
<td>Peer testimonials(^f)</td>
<td>21 (36.8)</td>
<td>11 (37.9)</td>
<td>10 (35.7)</td>
<td>0.95 (0.49-1.86)</td>
<td>.88</td>
</tr>
<tr>
<td>Peer advice(^g)</td>
<td>18 (31.6)</td>
<td>10 (34.5)</td>
<td>8 (28.6)</td>
<td>0.84 (0.39-1.80)</td>
<td>.65</td>
</tr>
<tr>
<td>Journal(^h)</td>
<td>48 (84.2)</td>
<td>20 (69)</td>
<td>28 (100)</td>
<td>1.45 (1.14-1.85)</td>
<td>.003</td>
</tr>
<tr>
<td>More Help(^i)</td>
<td>38 (66.7)</td>
<td>19 (65.5)</td>
<td>19 (67.9)</td>
<td>1.05 (0.73-1.49)</td>
<td>.80</td>
</tr>
</tbody>
</table>

\(^a\)Relative risk (95% CI) of using that component of the app in the enhanced care arm relative to the standard care arm, adjusting for cigarettes per day at baseline. Standard care arm is the referent group.

\(^b\)2-sided Wald test for the null of no difference in risk between arms.

\(^c\)Based on completion of quit guide step content as defined by user marking all content in section as read.

\(^d\)Based on use of tracker to log smoking on at least one day.

\(^e\)Based on use of savings calculator to estimate cost savings of quitting smoking.

\(^f\)Based on event data showing each peer testimonial modeling how to talk back to common excuses for not quitting was opened and viewed.

\(^g\)Based on event data showing each vignette providing motivational support and advice was opened and viewed.

\(^h\)Based on event data showing the Journal was opened at least one time, whether or not an entry was created.

\(^i\)Based on opening the More Help page at least one time to access tobacco quitline referral and other information on where to get help quitting smoking.

### Overall Satisfaction Ratings

Self-reported satisfaction with participants’ assigned app version was similar in both groups. At 3-month follow-up, most respondents reported they would recommend the app to others (19/20, 95% EC users vs 22/23, 95.7% SC users; RR 1.03, 95% CI 0.89-1.19; \( P=.70 \)). Among respondents who earned at least one usage badge by 3 months post enrollment (n=43)—the minimum exposure threshold deemed adequate to evaluate the app content—respondents in both arms reported similarly high satisfaction with their assigned app’s overall content and advice. Mean satisfaction ratings in both arms were 4.1 out of 5 (SD 1.1). Similar results were observed at 1-month follow-up; mean satisfaction ratings were 3.6 (SD 1.2) among SC users and 3.8 (SD 1) among EC users (adjusted average difference 0.26, 95% CI –0.35 to 0.87; \( P=.40 \)).

### Experiment Engagement and Helpfulness

EC users completed an average of 6.14 (SD 3.31) and 6.89 (SD 3.08) experiments by 1- and 3-month follow-up, respectively. Completion rates across each of the 9 individual experiments ranged from 93% (26/28) to 61% (17/28) (Table 4).
Immediately after completing each experiment, EC users were asked to rate the helpfulness of the experiment. Median helpfulness scores ranged from 3 to 4 on a 5-point Likert scale (Table 4). Experiments receiving the highest median scores focused on learning to identify high-risk situations and triggers for smoking, reducing daily smoking, and making a practice quit attempt (median 4 for each). Exercises focused on learning deep breathing for stress reduction and reframing not smoking as a personal choice (as opposed to a deprivation) also received higher median scores (3.75).

Table 4. Portion of enhanced care participants completing each experiment and median helpfulness ratings.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>At 1-month follow-up&lt;sup&gt;a&lt;/sup&gt;, n (%)</th>
<th>At 3-month follow-up&lt;sup&gt;a&lt;/sup&gt;, n (%)</th>
<th>Helpfulness&lt;sup&gt;b&lt;/sup&gt;, median (IQR)</th>
<th>Range (minimum-maximum)&lt;sup&gt;b&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>One</td>
<td>25 (89)</td>
<td>26 (93)</td>
<td>3 (3-4)</td>
<td>1-5</td>
</tr>
<tr>
<td>Two</td>
<td>22 (79)</td>
<td>23 (82)</td>
<td>3 (2-4)</td>
<td>2-5</td>
</tr>
<tr>
<td>Three</td>
<td>21 (75)</td>
<td>23 (82)</td>
<td>4 (3-4.25)</td>
<td>1-5</td>
</tr>
<tr>
<td>Four</td>
<td>20 (71)</td>
<td>22 (79)</td>
<td>3.75 (2.25-4)</td>
<td>1-5</td>
</tr>
<tr>
<td>Five</td>
<td>20 (71)</td>
<td>22 (79)</td>
<td>3 (2.25-4)</td>
<td>1-5</td>
</tr>
<tr>
<td>Six</td>
<td>19 (68)</td>
<td>22 (79)</td>
<td>3.5 (3-4.75)</td>
<td>1-5</td>
</tr>
<tr>
<td>Seven</td>
<td>18 (64)</td>
<td>20 (71)</td>
<td>3.75 (2-4.08)</td>
<td>1-5</td>
</tr>
<tr>
<td>Eight</td>
<td>15 (54)</td>
<td>18 (64)</td>
<td>4 (3-4.83)</td>
<td>3-5</td>
</tr>
<tr>
<td>Nine</td>
<td>12 (43)</td>
<td>17 (61)</td>
<td>4 (3-5)</td>
<td>2-5</td>
</tr>
</tbody>
</table>

<sup>a</sup>The number and proportion of all enhanced care participants (n=28) who completed each experiment by 1- and 3-month postenrollment follow-up.

<sup>b</sup>Reflects the median (IQR), and range (minimum-maximum) of helpfulness ratings across all experimental participants who completed each in-app, postexperiment assessment. If a user completed the experiment more than once, the average of their ratings was used. Ratings could range from 1=“not at all” to 5=“extremely helpful.”

**Indicators of Intermediate Cognitive Change at 1 Month**

**Motivation**

Among participants still smoking at 1-month follow-up, mean self-reported motivation to quit was 8.2 (SD 2.1) for EC users compared to 7.1 (SD 2.6) for SC users (adjusted mean difference 0.54, 95% CI –0.49 to 1.57; P=.30). Motivation to smoke less at the 1-month follow-up averaged 8.3 (SD 1.7) for EC users compared to 7.4 (SD 2.5) among SC users (adjusted mean difference 0.92, 95% CI –0.07 to 1.92; P=.07). In both groups, indices of motivation increased from baseline (Table 2) to follow-up.

**Self-Efficacy**

Among participants still smoking at 1-month follow-up, mean self-efficacy for quitting smoking was 7.4 (SD 2.4) for EC users compared to 7.5 (SD 2.3) for SC users (adjusted mean difference 0.03, 95% CI –1.02 to 1.07; P=.96). Self-efficacy for smoking less at the 1-month follow-up averaged 6.3 (SD 2.2) for EC users compared to 7.7 (SD 2.5) for SC users (adjusted mean difference 0.06, 95% CI –0.97 to 1.09; P=.06). In both groups, indices of self-efficacy increased from baseline (Table 2) to follow-up.

**Indicators of Behavior Change at 3 Months**

**Requests for Free NRT**

Among the 40 participants who earned 6 usage badges and were eligible to request a free trial of NRT, 10 participants requested it (8/22, 36.4% EC users as compared to 2/18, 11.1% SC users; RR 3.18, 95% CI 0.77-13.17; P=.11).

**Call Now for Free Counseling**

At the 3-month follow-up, 17.9% (5/28) of EC participants and 3.4% (1/29) of SC participants had clicked on the Call Now button to connect with a free tobacco quitline counselor (RR 5.17, 95% CI 0.65-41.3; P=.12).

**Smoking Reduction**

At the 3-month follow-up, a similar proportion of participants using both app versions reported a significant reduction in their daily smoking rate: 28.6% (6/21) of EC users compared to 28% (7/25) of SC users (RR 0.01, 95% CI –0.25 to 0.27; P=.92) reported a 50% or greater reduction in their baseline daily smoking.

**Quit Attempts**

At the 3-month follow-up, 39.3% (11/28) of EC users and 37.9% (11/29) of SC users reported making an intentional quit attempt after joining the study, when missing values were imputed as not making a quit attempt (RR 1.01, 95% CI 0.55-1.85; P=.98). The interpretation of the results was unchanged in complete case and multiple imputation sensitivity analyses or analyses adjusting for baseline differences (results not shown).

**Smoking Abstinence**

At the 3-month follow-up, 14.7% (4/28) of EC users and 6.9% (2/29) of SC users reported not smoking, even a puff, in the last 7 days (risk difference 0.08, 95% CI –0.08 to 0.24; P=.35). The interpretation of the results was unchanged in complete case and multiple imputation sensitivity analyses or analyses adjusting for baseline differences (data not shown).
Discussion

Principal Findings

The primary objective of this randomized pilot study was to evaluate the feasibility and acceptability of the EC version of the GEMS app and to assess its potential to motivate and support smoking behavior change compared to a similar app that included SC content (SC version) but was not designed specifically for smokers who are ambivalent about quitting smoking. It is encouraging that 95% of the participants who agreed to enroll in the study installed the app. This provides an important initial signal of the intervention’s acceptability. However, because of the size and nature of the study, conclusions about the acceptability and impact of the intervention among participants who installed the app cannot be based on the statistical significance of the primary and secondary outcome comparisons. Instead, it is important to look at the trend and pattern of the point estimates at follow-up. Notably, in almost all cases, the observed outcomes trended in favor of the EC app version. This held true for both self-reported outcomes and those based on objective automated data.

As hypothesized, EC participants used the app more often (an average of 19.9 sessions vs 7.3 sessions for SC participants), and a greater proportion reported smoking abstinence at follow-up (14.7% of EC participants vs 6.9% of SC participants). This finding is consistent with previous research showing an association between greater program engagement, or adherence, and higher cessation rates [39,40]. The observed quit rate in the EC arm is similar to that observed from physician advice to quit and low-intensity counseling interventions (average 14%-16%) [9].

Additionally, EC participants earned an average of 4 more usage badges. Notably, EC participants had the potential to earn more badges based on the additional content (experiments) in this version, but both groups had equal opportunity to earn the requisite 6 badges needed to request a free trial of NRT, and a higher proportion of EC users met this bar based on their app usage (78.6% EC users vs 62.1% SC users). Additionally, more EC users who earned the NRT, requested to receive it (36.4% EC vs 11.1% SC). Similarly, at the 1-month follow-up, motivation for quitting smoking trended higher in the EC group (8.3 EC vs 7.4 SC on a 10-point scale), even though groups had similar self-efficacy for quitting. More EC users clicked the Call Now button in the app to access free quitline counseling (17.9% of EC vs 3.4% of SC), although it is not known if these individuals actually enrolled in the free quitline program.

Finally, a slightly higher proportion of EC users (39.3%) reported making a quit attempt compared to SC users (37.9%) and 28.6% of EC users reported a meaningful reduction in daily smoking at the 3-month follow-up.

It is also notable that participants in this trial were lower–socioeconomic status heavy smokers, with high levels of concomitant substance use or lifetime substance-related or mental health diagnoses. These groups have been shown to be less likely to engage in treatment and successfully quit smoking [41,42] and, therefore, represent important targets for intervention.

Taken together, these findings confirm the conclusions drawn from our previous formative work that smokers who are ambivalent about quitting, including those who are more socioeconomically disadvantaged, are interested in using an mHealth app to help them reduce or stop smoking [17-19] and that designing this intervention to be sensitive to participants’ ambivalence about quitting could increase their likelihood of changing their smoking behavior.

Role of the Experiments

A key question in understanding the feasibility of this app was whether ambivalent smokers would engage with the self-directed, smoking-focused, cognitive, and behavioral experiments if they were not yet ready to commit to quitting smoking. The experiments were designed to teach users specific skills and lessons to help people resist the urge to smoke and encourage a quit attempt. These skills are consistent with the common elements of effective behavioral interventions identified in the US Public Health Service’s Tobacco Treatment Guidelines (ie, problem-solving skills, such as identifying high-risk situations, coping skills for managing urges without smoking, basic educational information, and supportive encouragement to make a quit attempt) [9]. Inclusion of these elements has been shown to increase the effectiveness of low-intensity counseling. The results of this pilot suggest these elements may also be useful in self-directed mHealth interventions, though we also acknowledge the importance of the EC reminder prompts. As hypothesized based on Fogg’s behavioral model for persuasive design, these prompts appear to have aided continued program engagement [29].

Findings from this study also indicate that most EC participants were willing to try the exercises. Completion rates ranged from 93% of EC users completing the first experiment (clarifying one’s values) to 61% completing the last experiment (making a practice quit attempt). These rates are encouraging. Because the addition of the experiments was the key content difference between the 2 app versions, engagement with the exercises likely drove the favorable trends in the outcomes noted above. This is further supported by the fact that EC participants were less likely than SC participants to read the smoking cessation Quit Guide. This was likely an artifact of the differences in the positioning of this content in the app (it was on the home page in the SC app version and located in the Toolbox linked from the home page in the EC app version), but because EC participants were less likely to view this content, exposure to the Quit Guide cannot explain the more favorable outcomes observed in the EC arm.

The graphical user interface for accessing the Quit Guide does not appear to have been an impediment to app usage or behavior change in the EC arm, but it is worth considering if the Quit Guide should be featured more prominently in a future EC version and, if so, whether this would add additional value to users or not.

Limitations and Strengths

The findings from this work must be viewed in the context of the study limitations. Chief among these is the small sample size; the study was not powered to detect minimal clinically
meaningful differences with statistical significance, and the sample size limits our ability to draw any firm conclusions about the generalizability of the findings, particularly with regard to smoking behavior change. Additionally, cessation outcomes are based on self-reported data and are subject to social desirability bias. However, biochemical confirmation is not generally recommended in trials with no face-to-face contact and where the demand characteristics to misreport abstinence are low [43], such as this remote trial of smokers who are ambivalent about quitting smoking. Moreover, relying on remote biochemical confirmation of smoking abstinence has been shown to bias outcomes due to low rates of participation [44]. For these reasons, the use of self-reported cessation outcomes is reasonable for this preliminary work. However, self-reporting also has its limitations. In this study, we saw a higher rate of attrition at the 3-month follow-up in the EC arm, resulting in a higher number of imputed smokers in this arm. Despite this, cessation outcomes still favored the EC group.

To our knowledge, this is the first app to have been designed specifically for smokers who are ambivalent about quitting, thus addressing an important intervention gap. Other strengths include the recruitment of a high-risk and low–socioeconomic status sample, a rigorous methodological design that allows the unique effects of the experiments to be tested, reliance on both self-report and automated tracking data for outcomes, and overall strong follow-up participation at 3 months (47/57, 82.5%).

Conclusions
This study provides encouraging evidence that people who are ambivalent about quitting smoking will voluntarily use and remain engaged with an mHealth app that is designed to help them cut back or quit smoking, even if they are not actively planning to change their smoking behavior at program initiation. Further development of app-based interventions targeted at smokers who are ambivalent about quitting is warranted, as is further evaluation of the effectiveness of EC app version.

Acknowledgments
This work was supported by a grant from the National Cancer Institute (R21CA234003; JBM principal investigator). Additional in-kind support for the app development was provided by Kaiser Permanente. We are deeply grateful to Brooks Tiffany for creating the user interface design of the app; Dhaval Patel for developing the app and supporting database; Hiren Desai for his technical support and sponsorship of this work; Tushar Gokhale and Kaiser Permanente’s Telehealth and Mobility team for their support of the app development; Kaiser Permanente’s Mobility Center of Excellence (particularly, Colin Moore, Tonja Williams, and Jocelyn Dela Rosa) for their technical review of the app and ongoing support; Ella Thompson for her assistance managing this study; Yishi Xian for her assistance enrolling participants and collecting follow-up data; Ladia Albertson-Junkans for programming the REDCap surveys; Dr Andrea Cook for her statistical consulting; Sarah Randall for her help preparing this manuscript, and Umesh Singh for his analytic programming support.

Data Availability
This pilot work was not subject to the National Institutes of Health data sharing requirements and did not obtain consent or institutional review board approval for publicly sharing data. As such, the data sets analyzed for this study are not publicly available, but we will consider sharing data upon request and with institutional review board approval.

Conflicts of Interest
JLH has received research support from Pfizer unrelated to this study. None of the other authors have financial or other conflicts of interest to report.

Multimedia Appendix 1
CONSORT eHEALTH checklist (V 1.6.1).
[PDF File (Adobe PDF File), 15360 KB - mhealth_v11i1e46155_app1.pdf ]

References


Abbreviations

AUDIT-C: Alcohol Use Disorders Identification Test
CUDIT-R: Cannabis Use Disorder Identification Test-Revised
EC: enhanced care
FTND: Fagerström Test of Nicotine Dependence
KPWA: Kaiser Permanente Washington mHealth: mobile health
NRT: nicotine replacement therapy
PPA: point prevalent abstinence
RR: relative risk
SC: standard care
Abstract

Background: Conversational user interfaces, or chatbots, are becoming more popular in the realm of digital health and well-being. While studies mostly focus on measuring the cause or effect of a digital intervention on people’s health and well-being (outcomes), there is a need to understand how users really engage and use a digital intervention in the real world.

Objective: In this study, we examine the user logs of a mental well-being chatbot called ChatPal, which is based on the concept of positive psychology. The aim of this research is to analyze the log data from the chatbot to provide insight into usage patterns, the different types of users using clustering, and associations between the usage of the app’s features.

Methods: Log data from ChatPal was analyzed to explore usage. A number of user characteristics including user tenure, unique days, mood logs recorded, conversations accessed, and total number of interactions were used with k-means clustering to identify user archetypes. Association rule mining was used to explore links between conversations.

Results: ChatPal log data revealed 579 individuals older than 18 years used the app with most users being female (n=387, 67%). User interactions peaked around breakfast, lunchtime, and early evening. Clustering revealed 3 groups including “abandoning users” (n=473), “sporadic users” (n=93), and “frequent transient users” (n=13). Each cluster had distinct usage characteristics, and the features were significantly different (P<.001) across each group. While all conversations within the chatbot were accessed at least once by users, the “treat yourself like a friend” conversation was the most popular, which was accessed by 29% (n=168) of users. However, only 11.7% (n=68) of users repeated this exercise more than once. Analysis of transitions between conversations revealed strong links between “treat yourself like a friend,” “soothing touch,” and “thoughts diary” among others. Association rule mining confirmed these 3 conversations as having the strongest linkages and suggested other associations between the co-use of chatbot features.

Conclusions: This study has provided insight into the types of people using the ChatPal chatbot, patterns of use, and associations between the usage of the app’s features, which can be used to further develop the app by considering the features most accessed by users.

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Introduction

Chatbots, or conversational user interfaces, can take diverse roles in supporting mental health. In particular, chatbots are becoming increasingly popular as digital mental health and well-being interventions, with initial evaluations of efficacy showing promise [1-3]. Chatbots may be targeted toward a variety of outcomes such as medication adherence, treatment compliance, aftercare support, delivery of appointment reminders, psychoeducation, user empowerment, and improvement in the self-management of mental health and well-being through monitoring mood or symptom change [1]. They can also be used to promote help-seeking [1]. The potential benefits are recognized by both practitioners and clients [2-5]. In addition to supporting those with mental ill health, digital technologies are also considered to have the potential for preventing mental health problems and for improving the overall mental health of the population [6].

Event logging plays an important role in modern IT systems with many apps logging their events to a local or remote server. These event logs can be used to determine the use of an app and identify user patterns. The analysis of user patterns involves event correlation—a conceptual interpretation procedure where new meaning is assigned to events that occur within a set time frame [7]. Event logging can be easily incorporated into digital products, including apps and websites. The most basic event log data consists of an anonymous unique identifier assigned to each individual, a date-time stamp, and an activity or event, but may also include other contextual variables. These user interaction log data provide useful information on how digital technologies are actually being used, providing valuable insights into user behavior [8]. Event log analysis typically focuses on quantitative data, but it may provide even greater insights when combined with qualitative data such as ecological momentary assessment (EMA) [8-11]. EMA involves asking questions, for example, “how do you feel right now,” repeatedly over a period of time in an individual’s own environment (ecology). Users answer EMA questions “in the moment,” which helps to avoid recall bias [11]. Previous trials with mental health chatbots have used app interaction data [12,13]. For example, participants trialing the mental health chatbot “Wysa” were characterized based on their app usage into more engaged users, termed “high users,” and less engaged users, or “low users” [13]. A multilingual mental health and well-being chatbot named “ChatPal” was developed to promote good mental well-being of citizens living in sparsely populated areas across Europe. Once the chatbot was released into the wild, all interactions between the chatbot and users were logged.

The aim of this research is to analyze event log data from the ChatPal chatbot with the objectives of providing insight into the different types of users using k-means clustering, exploring usage patterns, and associations between the usage of the app’s features.

Methods

Ethics Approval

This study received ethical approval from the Ulster University Research Ethics Committee (reference numbers REC.21.0021 and FCPSY-21-038-A), the Munster Technological University Research Ethics Committee (reference number MTU21034A), the Ethics Review Authority in Sweden (reference Etikprövningsmyndigheten number 2020-00808), and the University of Eastern Finland Committee on Research Ethics gave a supporting statement (statement 14/2021).

Intervention

The ChatPal chatbot was co-designed with end users and developed as part of the ChatPal project [14], a collaboration between universities and mental health service providers. The remit of the project was to develop and evaluate a chatbot to promote the positive mental well-being of individuals living in rural areas across Europe. This was achieved using an iterative approach similar to a previous study on how users engage and are redirected through a chatbot for depression [15]. A prototype chatbot was released early to support individuals at the beginning of the COVID-19 pandemic, and feedback from this initial phase of the study was used to refine the chatbot [16]. This refined version was then trialed in Northern Ireland, the Republic of Ireland, Scotland, Sweden, and Finland. Individuals across these regions were recruited to take part in a pre-post intervention study, using the ChatPal app as they wished for a period of 12 weeks. The chatbot was also advertised on social media and was freely available on the Apple App Store and Google Play Store. The chatbot was developed based on the concept of positive psychology, with elements of psychological well-being and happiness. Known as the PERMAH model [17], it includes content to encourage positive emotions, engagement, relationships, meaning, accomplishment, and health. Based on mostly scripted conversations with predefined responses, ChatPal can maintain a basic dialogue with a user in order to advise them on how to maintain positive emotions and mental well-being. An overview of the content available in ChatPal can be found in Multimedia Appendix 1.

Chatbot Development

The ChatPal chatbot was developed using the Rasa and PhoneGap frameworks. Rasa (Alan Nichol and Alex Weidauer) is an artificial intelligence (AI)–assisted framework for building contextual chatbots and provides the infrastructure and tools necessary for high-performing, resilient, proprietary contextual assistants. PhoneGap is an open-source framework for developing cross-platform mobile apps, including iPhone and Android. The PhoneGap framework was used to develop the front end of the ChatPal app, resulting in a cross-platform mobile
app using HTML5, JavaScript, and CSS (Figure 1). Communication with the ChatPal backend is achieved using HTTP requests or responses. Upon receiving user inputs, the Rasa backend analyzes these inputs using its Natural Language Understanding unit, which extracts user intentions and relevant metadata from the input. Once the intentions and metadata are identified, corresponding actions and responses are decided by the AI Rasa core. ChatPal dialogues required additional functionality such as language selection, onboarding, log entries, and visualized responses (graphs), which were addressed by custom development in Rasa.

Figure 1. Screenshots of the ChatPal chatbot app.

User Log Data Provenance
The log data file initially contained all interactions between users and the app (including detailed app events) that occurred during a prepost study period (January 24-June 22, 2022). During data cleaning, it was necessary to identify only the events made by users and extract these user event log details for analysis. While users remained anonymous, each user was assigned a unique ID. Log entries were timestamped to facilitate the tracking of interactions over time. The app afforded users the opportunity to converse with the chatbot to help users manage their mental health, with their current mood being logged each time they used the chatbot. Users were also given the option to complete 5 questions relating to the World Health Organization-Five Well-being Index (WHO-5), a measure of current mental well-being [18].

Data Analysis and Machine Learning
Jupyter notebooks [19] with the programming language Python were used to analyze the log data, with the matplotlib [20] and seaborn [21] libraries used to visualize the results. The scipy [22] and sklearn [23] libraries were used to normalize and perform k-means clustering, and the mlxtend [24] library was used for association rule mining.

Figure 2 shows the methodology for analyzing the ChatPal chatbot event log data. Data on each user were collated, including age, gender, and interactions with the chatbot. As only data pertaining to users older than 18 years was permitted, only users who had completed the age question could be included in the analysis. Of these users, those who did not complete the gender question were assigned an “unknown” status for gender.
**User Interactions**

The total number of user interactions with the chatbot was examined across hours of the day to gain insight into daily patterns of use. The tenure (ie, the number of days from first to last use of the app) was calculated for each user along with the number of unique days of use. User retention was then calculated to discover the percentage of users still using the app over time.

**User Types**

K-means clustering was used to determine the different types of users who interacted with the chatbot, with 6 features relating to the behavioral usage of the chatbot being identified within the log data (Table 1). Before submitting these features to the clustering algorithm, these features were normalized, resulting in the standardization of all variables to ranges between 0 and 1. In order to determine the optimum number of clusters, the k-means algorithm was applied to the data for clusters $k=2$ to $k=15$, with the average distance to the centroid from all data points (within-cluster sum of square) being calculated for each iteration. These were then plotted to identify the “pivot” where the resulting graph creates an “elbow,” which corresponds to the optimum k value (ie, the number of user groups or clusters that exist). The k-means algorithm was then used for this “k,” and the resulting output was visualized using principal component analysis which reduced the multiple (high-dimensional) features to just 2 dimensions, enabling the clusters to be plotted for visual inspection and verification. The resulting cluster labels were then mapped back onto the original feature data set to allow each cluster to be analyzed. Independent $t$ tests were carried out to evaluate the significance of the difference in the means of the groups.

**Table 1. Features used for k-means clustering.**

<table>
<thead>
<tr>
<th>Feature</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unique days</td>
<td>This is the number of unique days the user accessed the chatbot.</td>
</tr>
<tr>
<td>Tenure</td>
<td>This is the number of days between the first use and last use of the chatbot.</td>
</tr>
<tr>
<td>Mood logs completed</td>
<td>This is the number of times the user recorded their mood over their period of use of the app. This gives an indication of how many times the app was used as the user’s mood was requested each time they used the chatbot, there may be multiple mood logs for each day.</td>
</tr>
<tr>
<td>Conversations accessed</td>
<td>This is the number of conversations accessed during their period of use of the chatbot.</td>
</tr>
<tr>
<td>Total interactions</td>
<td>This is the total number of interactions with the chatbot.</td>
</tr>
</tbody>
</table>

**Feature Usage Analysis**

The key feature of the chatbot, a series of scripted “conversations,” was chosen for further analysis. Users could access these conversations via the main menu and were asked to rate the conversation as “good,” “neutral,” or “bad” on completion. The log data was analyzed to examine the number of times each conversation was accessed during the prepost study period, the percentage of users that accessed each conversation, and the rating awarded by users on the completion of each conversation. The date and time when each user accessed any conversation were logged, making it possible to create a daily-ordered set of conversations for each user for analysis. From these sets, it was possible to examine associations between conversations; in other words, examine the pathway from one conversation (the antecedent) to the next (the consequent) using association rule mining.

**Results**

**User Interactions**

There were a total of 1403 individual users that accessed the app between January 24, 2022, and June 22, 2022. Only data from users older than 18 years were included in the analysis; thus, the results report on data from 579 adult users, of whom 348 (60.1%) were recruited specifically for a 12-week prepost
The majority of users identified as female (387/579, 66.8%), male (153/579, 26.4%), or other (6/579, 1%), while other users preferred not to say (12/579, 2.1%) or elected not to answer (21/579, 3.6%). Nonresponses were treated as unknown. The ages of participants were well distributed, with responses of 18-24 (190/579, 32.8%), 25-34 (150/579, 25.9%), 35-44 (95/579, 16.4%), 45-54 (77/579, 13.3%), 55-64 (56/579, 9.7%), and >65 (11/579, 1.9%).

Over the study period, from January 24, 2022, to June 24, 2022, there were a total of 29,298 user interactions with the app, averaging 246 interactions per day. While users interacted with the app throughout the day, peaks in interactions can be seen at key times of the day: breakfast (8 AM-10 AM), lunch (1 PM), and the end of the working day (5 PM) (Figure 3).

A large proportion of users interacted with the app for a short period of time, with 440 users (76%) interacting for less than 10 days. Analysis of the number of unique days of interaction with the app also showed that although there were users who interacted with the app over almost the whole study period, these interactions were sporadic, with the most ardent user interacting with the chatbot over 19 unique days (Figure 4). Overall user retention shows a steady drop-off in users over time (Figure 4). The average tenure of a user was 11.4 days.

A total of 6 features representing the behavioral usage of the app were selected for k-means clustering to identify the different types of users accessing the app. These features represent user characteristics, including the number of unique days the user accessed the app, the tenure of each user, the number of mood logs recorded, the number of conversations accessed, and the total number of interactions with the app.

The optimum number of types of users (clusters) was determined using the elbow method. This method runs k-means clustering on the data set for a range of k values (eg, k=1-15), calculating the average distances to the centroid from all data points, known as the within-cluster sum of squares. These distances are then plotted on a graph, which will show where the distances fall, creating an elbow in the graph. This elbow represents the optimum k value for the clustering solution. Figure 5 shows the results, indicating 2 possible solutions, k=2 and k=3 in this case.

**Figure 3.** User interactions over the course of the day.
User Types

Both a 2- and 3-cluster solution were explored. Using k=3 results in a similar principal component analysis plot as in the 2-cluster solution, with 3 well-defined clusters with distinct usage characteristics (Figure 6).

The 3-cluster solution (Figure 7) appeared to be a refinement of the 2-cluster solution, with the largest cluster equating to “abandoning users” and the remaining 2 clusters revealing a more granular look at more invested users. Analysis of the archetypal characteristics of these 3 clusters (Table 2) suggested that “abandoning users” (473/579, 81.7%), “frequent transient users” (13/579, 2.2%), and “sporadic users” (93/579, 16.1%) would be appropriate labels.

Abandoning users generally access the app on 1 or 2 unique days, with an average tenure of 3.6 days (Table 2). They recorded the highest number of mood logs (6-12) and conversations (7-12) and had the highest number of interactions with the app (193-258). While sporadic users only used the app for a small number of unique days (3-5), they did so over a longer period (22-61 days) (Table 2). In all other metrics, they exceeded those recorded by abandoning users but did not achieve the numbers attributed to frequent transient users: mood logs (2-5), conversations (2-5), and interactions (20-123). Independent t-tests on these results found that the 3 archetypes are significantly different statistically across all metrics (P < .001).

Daily patterns of usage of ChatPal differed for each archetype (Figure 8). Abandoning users recorded low numbers of interactions with the app over the course of the day, with a small peak of usage in the morning (9 AM). Interactions for sporadic users were higher than those seen for abandoning users, and in general, lower than those for frequent transient users, the exception being in the morning (8 AM), when interactions for sporadic and frequent transient users were the same. Sporadic users showed peak usage times around breakfast (8 AM) and lunch (1 PM). Frequent transient users generally recorded the highest number of interactions with the app over the course of
the day, with frequent peaks in usage. These users showed high levels of interactions over most of the morning (4-9 AM), with further peaks in usage at lunchtime (1 PM), afternoon (4 PM), and evening (8 PM).

**Figure 6.** Principal component analysis plot of output from the k-means algorithm (3-cluster solution).
Figure 7. Boxplots of feature values for the different clusters (3-cluster solution).

Table 2. Archetypal characteristics for each cluster (3-cluster solution).

<table>
<thead>
<tr>
<th>Feature</th>
<th>Cluster 1: abandoning users</th>
<th>Cluster 2: frequent transient users</th>
<th>Cluster 3: sporadic users</th>
</tr>
</thead>
<tbody>
<tr>
<td>Users, n (%)</td>
<td>473 (81.7)</td>
<td>13 (2.2)</td>
<td>93 (16.1)</td>
</tr>
<tr>
<td>Unique days, mean (SD)</td>
<td>1.3 (0.7)</td>
<td>11.2 (3.9)</td>
<td>4.0 (1.7)</td>
</tr>
<tr>
<td>Tenure, mean (SD)</td>
<td>3.6 (8.1)</td>
<td>68.9 (35.4)</td>
<td>43.0 (25.2)</td>
</tr>
<tr>
<td>Mood logs completed, mean (SD)</td>
<td>1.3 (0.8)</td>
<td>8.8 (3.8)</td>
<td>3.8 (1.9)</td>
</tr>
<tr>
<td>Conversations accessed, mean (SD)</td>
<td>0.8 (1.0)</td>
<td>10.8 (6.3)</td>
<td>4.0 (2.4)</td>
</tr>
<tr>
<td>Total interactions, mean (SD)</td>
<td>36.7 (16.8)</td>
<td>229.3 (83.0)</td>
<td>96.1 (36.6)</td>
</tr>
</tbody>
</table>
Feature Usage Analysis

A key element of the app was the provision of mental well-being conversations between the chatbot and the user. Analysis of users’ choice of conversations showed that of the 579 users, almost one-third chose to access the “Treat yourself as a friend” conversation (168/579, 29%), with over one-fifth of users accessing the “Relax (140/579, 24.2%),” “Thoughts Diary” (136/579, 23.5%), and “Soothing Touch” (118/579, 20.4%) conversations. Of these, only 68 (11.7%) returned to the “Treat yourself as a friend” conversation on 2 or more occasions, with this number falling to 40 (6.9%) returning on 3 or more occasions. The conversation with the highest return rate was “Thoughts Diary” (109/579, 18.8% for 2 or more occasions; 69/579, 11.9% for 3 or more occasions), while the conversation with the lowest return rate was “How to Help Someone” (2/579, 0.3% for both metrics) (Figure 9). The top conversations received good ratings, reflecting their popularity with users. “Treat yourself as a friend” received the highest percentage of good ratings of the 4 (62.5%), followed by “Relax” (56.3%), “Thoughts Diary” (52%), and “Soothing Touch” (53.7%). Interestingly, the conversations that were used the fewest number of times elicited more positive ratings. “How to help someone,” which was only accessed by 0.9% of the total users, resulted in a 100% good rating, with “Goal Setting” and “Goal Quality Check” receiving 80% good ratings (Figure 10).
Figure 9. Percentage of users accessing chatbot conversations. WHO: World Health Organization.
Analysis of the number of times each user accessed conversations showed that the majority of users used each conversation between 1 and 3 times. “Thoughts diary,” “tips to manage loneliness,” and “WHO well-being scale” had a median number of users of 3. A small number of users who accessed these conversations multiple times are represented as outliers on the graph (Multimedia Appendix 2).

The log data relating to “conversations” were examined for each user on a daily basis in order to provide insight into how users accessed conversations. Each time a user moved between 2 conversations, no matter the direction, the transition was counted. Statistical analysis of the resulting 307 transitions revealed the median to be 4, the lower quartile to be 2, and the upper quartile to be 11. Using these statistics, Figure 11 shows the results of the analysis, with low numbers of transitions represented in blue (<2), average represented in green (2-11), high in pink (12-50), and very high in red (>50). The transition between “treat yourself as a friend” and “soothing touch” was the most popular, being performed 168 times. Additionally, high on the scale were the transitions between “positive emotion” or “thoughts diary” (72) and “relax” or “thoughts diary” (62). Association rule mining supports these findings, with the linkage between “treat yourself as a friend,” and “soothing touch” receiving the highest support of 0.16 and the highest support of a rule with more than one antecedent being “soothing touch” or “thoughts diary” with “treat yourself like a friend” with support of 0.072 (Table 3).
Figure 11. Associations between conversations (blue=low <2, green=average 2-11, pink=high 12-50, red=very high >50). WHO: World Health Organization.
Table 3. Summary of results of association rule mining on conversations ordered by lift.

<table>
<thead>
<tr>
<th>Antecedents</th>
<th>Consequents</th>
<th>Support</th>
<th>Confidence</th>
<th>Lift</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soothing touch</td>
<td>Treat yourself like a friend</td>
<td>0.160</td>
<td>0.712</td>
<td>2.069</td>
</tr>
<tr>
<td>Treat yourself like a friend</td>
<td>Soothing touch</td>
<td>0.160</td>
<td>0.463</td>
<td>2.069</td>
</tr>
<tr>
<td>Thoughts diary</td>
<td>Treat yourself like a friend</td>
<td>0.121</td>
<td>0.391</td>
<td>1.135</td>
</tr>
<tr>
<td>Treat yourself like a friend</td>
<td>Thoughts diary</td>
<td>0.121</td>
<td>0.352</td>
<td>1.135</td>
</tr>
<tr>
<td>Relax</td>
<td>Treat yourself like a friend</td>
<td>0.104</td>
<td>0.396</td>
<td>1.150</td>
</tr>
<tr>
<td>Treat yourself like a friend</td>
<td>Relax</td>
<td>0.104</td>
<td>0.302</td>
<td>1.150</td>
</tr>
<tr>
<td>Soothing touch</td>
<td>Thoughts diary</td>
<td>0.094</td>
<td>0.420</td>
<td>1.352</td>
</tr>
<tr>
<td>Thoughts diary</td>
<td>Soothing touch</td>
<td>0.094</td>
<td>0.303</td>
<td>1.352</td>
</tr>
<tr>
<td>Positive emotion</td>
<td>Thoughts diary</td>
<td>0.093</td>
<td>0.475</td>
<td>1.530</td>
</tr>
<tr>
<td>Thoughts diary</td>
<td>Positive emotion</td>
<td>0.093</td>
<td>0.299</td>
<td>1.530</td>
</tr>
<tr>
<td>Soothing touch</td>
<td>Relax</td>
<td>0.092</td>
<td>0.410</td>
<td>1.562</td>
</tr>
<tr>
<td>Relax</td>
<td>Soothing touch</td>
<td>0.092</td>
<td>0.350</td>
<td>1.562</td>
</tr>
<tr>
<td>Relax</td>
<td>Thoughts diary</td>
<td>0.090</td>
<td>0.342</td>
<td>1.101</td>
</tr>
<tr>
<td>Thoughts diary</td>
<td>Relax</td>
<td>0.090</td>
<td>0.289</td>
<td>1.101</td>
</tr>
<tr>
<td>Positive emotion</td>
<td>Treat yourself like a friend</td>
<td>0.089</td>
<td>0.453</td>
<td>1.314</td>
</tr>
<tr>
<td>Treat yourself like a friend</td>
<td>Positive emotion</td>
<td>0.089</td>
<td>0.257</td>
<td>1.314</td>
</tr>
<tr>
<td>Health</td>
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<td>0.370</td>
<td>1.193</td>
</tr>
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<td>0.236</td>
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<td>Treat yourself like a friend</td>
<td>0.072</td>
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Discussion

Principal Results

The majority of users (348/579, 60%) of the ChatPal chatbot app were recruited as volunteers in a 12-week prepost study [25]. User interactions occurred at all hours of the day, with the majority being during working hours. It was notable that spikes in usage occurred at the start of the working day (9 AM), lunchtime (1 PM), and end of the working day (5 PM). This may simply reflect the fact that users felt they could devote some time to evaluating the app at these times, or it could reflect a need for support during times of the day when users are not pressured by other commitments. User interactions with the app late into the evening and through the night may indicate the need for support at these times. Recent studies found that the COVID-19 pandemic resulted in increased sleep disturbances and worsening mental health in the general population [26-28]. This is one advantage of offering digital solutions in mental health care, as these technologies can be accessed 24/7 when traditional face-to-face services are unavailable.

Analysis of user interaction with the chatbot conversations reflects a high proportion of “abandoning users.” The majority of conversations were accessed only once, and only a small percentage of total users accessed conversations more than once. Interestingly, the conversation with the highest return rate was the “thoughts diary,” where users could record their thoughts and feelings and review them in subsequent sessions. This indicates that these users felt comfortable enough with the app to share their feelings, and they presumably felt some benefit from doing so as they returned on multiple occasions. Journaling about stressful events has been shown to be beneficial for individuals to understand and make sense of what happened [29].

The majority of conversations received a “good” or “neutral” rating, with “how to help someone” receiving a 100% good rating. While this is encouraging, it is important to recognize that the “how to help someone” conversation received the lowest percentage of overall users. Given these low figures, they may be biased by a small number of returning users. It is interesting that “how to help someone” was the least accessed conversation,
as it suggests that people are not using the app to access information that would help others but more for resources to benefit their own well-being.

Analyzing users’ transition from one conversation to another revealed that the most frequent transition was the reciprocal journey from “treat yourself like a friend” to “Soothing Touch,” followed by transitions between the “positive emotion” or “thoughts diary” and “relax” or “thoughts diary” pairs of conversations. Association rule mining supported these findings as these 3 conversations, “soothing touch,” “thoughts diary,” and “treat yourself like a friend,” were linked, with “thoughts diary” having strong links between the other 2 in either direction. This seems understandable as “treat yourself like a friend” and “positive emotions” are both conversations in which the user is writing something and may want to see it in the “thoughts diary” (saving the written message to the “thoughts diary” is suggested at the end of the “treat yourself like a friend” script, which may prompt the user to go there next). Additionally, “treat yourself like a friend,” “soothing touch,” and “relax” are all short dialogues or exercises, so users may want to go on chatting and access further conversations. This also demonstrates the value of incorporating efficient scripts into the app, providing quick exercises for users needing support [30].

Further analysis of the chatbot menu structure would provide clarity on whether these conversations naturally complement each other or whether some bias has been introduced. In either case, the associations observed will provide valuable data for the further development of the app, not only in highlighting the conversations that fit naturally with each other and presumably provide the most support for users, but also in highlighting those that do not.

**Comparison With Prior Work**

The majority of users (76%) accessed the app for a period of less than 10 days with 62.7% accessing ChatPal for 1 day. While the remaining 24% accessed the app for more than a 10-day period, analysis of the number of unique days of usage shows that the app was used for a maximum of 19 unique days by an individual user with the average being 2 unique days. While the app was designed to be beneficial to all users’ mental well-being, the results indicate that only a small proportion of participants became invested in using the app. While this lack of user retention is disappointing, it is not unusual. Benchmarking the ChatPal app against a study of 93 mobile apps, 59 of which specialized in mental health [31] shows that ChatPal performed better than average with a drop-off rate in the first 10 days of 77% compared with the average of 80% and a drop off between day 15 and day 30 of 7.1% compared with an average of 20% for other mental health apps. While this indicates that ChatPal has a better than average retention of users over the first 10 days, it also suggests that the remaining users may find benefit in using the app leading to a low drop off of users between days 15 and 30. A recent study [32] found that digital interventions for depression with human guidance yielded better results compared to digital interventions without any external guidance. Perhaps if chatbots such as ChatPal were used in conjunction with health professionals this may encourage usage and result in improved benefits to users, however further work would be needed to confirm this.

Discovering the types of users accessing chatbots and their patterns of usage is essential for the further development and targeting of the services provided by the app. K-means clustering was used to discover 3 different groups of users (abandoning users, frequent transient users, and sporadic users) based on 6 key features extracted from the log data. Further analysis found significant differences between the features for each group of app users.

Abandoning users, making up 87.2% of total users, generally accessed the app on 1 or 2 unique days with an equally low average tenure of 5.7 days. They had significantly less interactions with the app resulting in less moods being logged than invested users and participated in significantly less conversations. In contrast, frequent transient users and sporadic users were more generally invested users, accessing across more unique days with an average tenure of 50.5 days and 68.9 days, respectively. During this time, these users logged their mood on more occasions and generally interacted with the chatbot a lot more, accessing between 5 to 10 different conversations. This gives rise to the possibility that a small number of users found value in the support offered by the chatbot. These results are comparable with previous analyses of the initial trial of the prototype chatbot [16]. Further analysis is needed to explore the demographics of the users in each of these archetypes in order to understand why users belong to the archetype they are associated with and provide insight into users who repeatedly use specific features in order to understand if certain subgroups of users tend to favor certain features over others. The AI could then be used to direct users toward these features within the bot. This may also have the added benefit of increasing adherence and retention.

**Policy and Practice Implications**

We have included policy and practice implications based on the findings from this study, which may benefit others who are designing digital mental health technologies (Textbox 1).
Textbox 1. Recommendations for policy and practice.

- As the app was used by some during the night, conversations or exercises specifically for treating insomnia could be added to the available conversations and offered when users access the app during the nighttime. However, promoting screen time during the evening or middle of the night may not be appropriate.
- Given the drop-off rate of users over time, strategies could be used to improve user retention. For example, further development of the chatbot, to make it more spontaneous, "remembering" the last conversation or mood, more personalization and added daily reminders.
- Three main groups of app users were identified: “abandoning users,” “sporadic users,” and “frequent transient users.” While there will always be abandoning users due to the free nature of the app, the chatbot could have other engaging features such as peer communication and support to encourage use.
- The most used conversations within the chatbot were not necessarily the best-liked. The app could adapt based on user feedback, possibly changing the order of conversations offered based on ratings or allowing users access to the ratings in order to make informed decisions.
- Users’ moods were only collected at the start of each session. In order to gauge the effectiveness of the app, user moods could be collected at the start and end of each session.
- The World Health Organization-Five Well-being Index (WHO-5) well-being scale within the chatbot gave no feedback to the user. It may be more beneficial to display the score as a time series graph and provide insights to the user on their well-being over time.

Limitations

Despite the detailed event log data captured, tracking the length of individual sessions was difficult due to the lack of “end of session” variable. Almost all users chose not to select the “need to go” option in the chatbot which would have been recorded as “end of session,” and instead must have exited or closed the app which was not recorded in the logs. For this reason, user sessions were tracked on a daily basis. An additional variable to track the end of the session would be useful to explore individual user sessions rather than sessions per day. This omission may also have contributed to the low retention rates as the app was unable to provide little feedback to the user. With the addition of session data, user moods could be logged giving the app the ability to personalize its interactions with the user. For example, returning users could be asked “are you still feeling…” or “Hello again”. In addition, if users’ moods were asked at the start and end of each session, it would be possible to gauge changes in well-being that resulted from using the app. A bias may also have been introduced into the way users interacted with the app due to the rigid structure of the menus presented to the user. These may have caused some users to follow the list of available conversations in the order they are presented in the first instance before deciding which conversations provided the most support for their circumstances. Mood logs were asked each time the app was launched and, while these were used in the discovery of user archetypes, no further analysis was possible due to the following reasons. As users were only asked about their mood at the start of the session, there is nothing to compare the responses to. The addition of session data and requesting a user’s mood at the end of a session would have allowed comparisons to be made and facilitated the analysis of the effect of the app on the users’ mental well-being.

The app recorded interactions based on server time, not local time. This means that log data will be incorrect by 1 hour for Swedish users and 2 hours for Finish users. Not all users reported their country, thus no adjustments were made to account for differing geographical locations. As the WHO-5 scale questions were optional, there was no substantial data collected during the trial period.

Conclusions

The ChatPal app was developed as part of a research project into the use of chatbots to promote positive mental health and well-being. From the log data gathered, 3 main types of users accessed the chatbot: abandoning users, sporadic users, and frequent transient users. Due to the high numbers of abandoning users, it is difficult to evaluate the effectiveness of the app though analysis of the other 2 groups of invested users allows a glimpse into the benefits the app could bring to a user’s mental well-being. It is clear that some users returned to the app on several occasions although there is no evidence that this was linked to improvement in well-being. Improvements incorporated in future versions of the app suggested in this paper would provide data on participants’ moods at the beginning and end of each session and would provide evidence as to what effect the app has on users. Analysis of user transitions from conversation to conversation indicated that some dialogues may complement each other and provide targeted support to users although further analysis may be necessary. Future versions of the chatbot should be enhanced to make each interaction with the user more personalized, learning and adapting from the previous interactions with each user.

Acknowledgments

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Conflicts of Interest
None declared.

Multimedia Appendix 1
Overview of available content in the ChatPal chatbot.
[PNG File - 307 KB - mhealth_v11i1e43052_app1.png]

Multimedia Appendix 2
Conversations by number of times accessed.
[PNG File - 121 KB - mhealth_v11i1e43052_app2.png]

References


Abbreviations

EMA: ecological momentary assessment

WHO-5: World Health Organization—Five Well-being Index

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Patterns and Predictors of Engagement With Digital Self-Monitoring During the Maintenance Phase of a Behavioral Weight Loss Program: Quantitative Study

Nicole Crane¹, MS; Charlotte Hagerman¹, PhD; Olivia Horgan¹, BS; Meghan Butryn¹, PhD
Center for Weight, Eating, and Lifestyle Science, Department of Psychological and Brain Sciences, Drexel University, Philadelphia, PA, United States

Corresponding Author:
Nicole Crane, MS
Center for Weight, Eating, and Lifestyle Science
Department of Psychological and Brain Sciences
Drexel University
3141 Chestnut Street
Stratton Hall
Philadelphia, PA, 19104
United States
Phone: 1 724 740 8648
Email: nvt24@drexel.edu

Abstract

**Background:** Long-term self-monitoring (SM) of weight, diet, and exercise is commonly recommended by behavioral weight loss (BWL) treatments. However, sustained SM engagement is notoriously challenging; therefore, more must be learned about patterns of engagement with digital SM tools during weight loss maintenance (WLM). In addition, insight into characteristics that may influence SM engagement could inform tailored approaches for participants at risk for poor adherence.

**Objective:** This study explored patterns of digital SM of weight, diet, and exercise during WLM (aim 1) and examined timing, patterns, and rates of disengagement and reengagement (aim 2). This study also assessed relationships between individual-level factors (weight-related information avoidance and weight bias internalization) and SM engagement (aim 3).

**Methods:** Participants were 72 adults enrolled in a BWL program consisting of a 3-month period of weekly treatment designed to induce weight loss (phase I), followed by a 9-month period of less frequent contact to promote WLM (phase II). Participants were prescribed daily digital SM of weight, diet, and exercise. At baseline, self-report measures assessed weight-related information avoidance and weight bias internalization. SM adherence was objectively measured with the days per month that participants tracked weight, diet, and exercise. Repeated-measures ANOVA examined differences in adherence across SM targets. Multilevel modeling examined changes in adherence across phase II. Relationships between individual-level variables and SM adherence were assessed with Pearson correlations, 2-tailed independent samples t tests, and multilevel modeling.

**Results:** During WLM, consistently high rates of SM (≥50% of the days in each month) were observed for 61% (44/72) of the participants for exercise, 40% (29/72) of the participants for weight, and 21% (15/72) of the participants for diet. Adherence for SM of exercise was higher than that for weight or diet (P<.001). Adherence decreased over time for all SM targets throughout phase II (P<.001), but SM of exercise dropped off later in WLM (mean 10.07, SD 2.83 months) than SM of weight (mean 7.92, SD 3.23 months) or diet (mean 7.58, SD 2.92 months; P<.001). Among participants with a period of low SM adherence (ie, <50% of the days in a month), only 33% (17/51 for weight, 19/57 for diet) to 46% (13/28 for exercise) subsequently had ≥1 months with high adherence. High weight-related information avoidance predicted a faster rate of decrease in dietary SM (P<.001). Participants with high weight bias internalization had the highest rates of weight SM (P=.03).

**Conclusions:** Participants in BWL programs have low adherence to the recommendation to sustain daily SM during WLM, particularly for SM of diet and weight. Weight-related information avoidance and weight bias internalization may be relevant indicators for SM engagement. Interventions may benefit from innovative strategies that target participants at key moments of risk for disengagement.

*(JMIR Mhealth Uhealth 2023;11:e45057) doi:10.2196/45057*
**Introduction**

**Background**

Self-monitoring (SM) of weight, diet, and exercise is a cornerstone of behavioral weight loss (BWL) treatment [1], and daily SM of these key weight control behaviors is associated with better weight loss and maintenance [2-4]. Nevertheless, despite its importance, rates of engagement with SM are modest and tend to decrease over time, particularly during weight loss maintenance (WLM) [5,6]. With the rise of digital devices for SM (eg, food tracking apps, digital scales, and Fitbit activity trackers), technology is routinely being incorporated into BWL programs [7,8]. Digital devices may facilitate SM adherence by decreasing burden via time-saving features (eg, nutrition databases and saving frequent foods), portability for real-time monitoring, and passive recording of behavior (ie, Fitbit wristwatch for active minutes) [7]. Research shows that adherence to SM via digital format is higher than that via traditional methods [9], likely for these reasons, and that digital SM facilitates calorie reduction and weight loss [10].

There is a growing body of literature examining rates of engagement with digital SM formats to understand how participants in BWL programs use these tools. A recent systematic review analyzed randomized controlled trials of BWL interventions that incorporated digital SM (at least 12 weeks of treatment and 6-month outcome assessments) and found that 48% (23/48) of studies prescribed daily SM of weight, 69% (37/54) prescribed daily SM of diet, and 71% (39/55) prescribed daily SM of exercise. Across the intervention periods (median 6, range 3-24 months), 58% of studies achieved rates of ≥50% for SM engagement, and only 9% reached ≥75% engagement [7]. SM rates decreased over time, with only 45% of the studies showing SM rates of ≥50% by 6 months (n=33), and 38% had rates of ≥50% by ≥12 months (n=8). Engagement was the highest for SM of weight, followed by SM of diet and exercise. Synthesis of these results suggests that, although higher than rates of engagement for traditional SM methods, rates of engagement with digital SM tools are modest, and difficulties with sustaining adherence over time remain prevalent. Within this body of work, however, few prior studies have included assessment beyond 6 months; therefore, the dynamics of digital SM during the WLM phase are still unclear. Further work is needed to conceptualize digital SM engagement during this critical period (eg, 6 months and beyond when SM rates decline).

To explore this question, this project is focused on SM behavior during the WLM phase of a previously published clinical trial that assessed whether providing weight loss coaches with access to participants’ digital SM data enhances outcomes during lifestyle modification (LM) [11]. A previous publication from this parent study found that participants enrolled in a WLM intervention were more likely to self-monitor weight and eating behavior when coaches remotely monitored their data and used the data to drive treatment contacts (SMS text messages and telephone calls) versus when coaches did not have access to their data. Data sharing was also associated with less weight regain over time (although total weight loss did not differ by condition), and the frequency of dietary SM mediated the effect of treatment condition on weight loss [11]. This prior report supports the central role of SM for weight loss and maintenance and suggests that providing coaches with access to data via digital SM tools may maximize the efficacy of these tools for long-term weight control. Nevertheless, no previous analyses have been conducted to understand the nuanced patterns of SM behavior during the WLM phase when participant adherence becomes more variable owing to the difficulty of sustaining behavior change over long periods.

Furthermore, the majority of prior work on digital SM tools attempts to understand their use through the lens of percentage of adherence based on prescribed frequency, with most studies reporting the mean percentage of days that participants successfully self-monitor or the percentage of participants who maintained a certain level of SM [7]. A more nuanced exploration of SM would be helpful, including the timing of disengagement and rates of complete disengagement (ie, 0 days tracked) as well as how patterns of engagement vary across participants; for example, Robertson et al [12] used profile analyses to assess different patterns of SM engagement. The results showed 4 distinct profiles of use for digital SM tools among participants enrolled in a 6-month workplace weight loss intervention: minimal users (29% of the sample), activity trackers (55%), dedicated all-around users (11%), and dedicated all-around users with exceptional food logging (5%) [12]. Weight outcomes were only substantially better among the dedicated all-around users with exceptional food logging, aligning with other work that highlights the importance of dietary SM for weight loss [9,13]. Another study focused on self-weighing behavior during a 12-month BWL treatment and found 3 profiles: high/consistent (75% of the sample; SM of weight ≥6 days per week regularly), moderate/declined (16.2%; SM of weight 4-5 days per week, then declined to 2 days gradually) and minimal/declined (8.8%; SM of weight 5-6 days per week, then declined to 0 days suddenly), with the high/consistent group losing more weight at 6 and 12 months [14]. These findings show intriguing preliminary evidence for between-persons variation in patterns of engagement with digital SM tools, which has implications for weight loss success and needs further research, particularly during the WLM period.

Another gap in the literature on digital SM tools for weight control surrounds predictors and moderators of engagement. Little is known about what individual-level variables relate to strong adherence to SM prescriptions in BWL programs. Some previous work has found that higher initial weight loss [15], enhanced social support [16,17], and heightened binge eating severity [18] were associated with higher rates of SM during BWL programs (uncontrolled eating and emotional eating were explored as predictors of SM engagement but were not substantially related) [18]. There is also theoretical support for the idea that previous SM behavior is likely a strong predictor...
of consistent long-term use of SM, given that past behavior is a strong indicator of future behavior [14,19]. To our knowledge, no studies have explored individual-level predictors of long-term use of digital SM tools during WLM.

Weight-related information avoidance, which is the tendency to prevent or delay acquisition of potentially unwanted weight-related information [20], has strong theoretical support for a relationship with digital SM use. Digital SM tools provide BWL program participants immediate detailed information on progress and goal attainment, which should increase awareness of current eating or exercise patterns [16,21]. This may be differentially helpful (vs distressing) for SM engagement based on an individual’s level of weight-related information avoidance. Those with low weight-related information avoidance may be eager to engage with digital SM data and find value in reflecting on patterns of behavior [22]. However, for those with high weight-related information avoidance, viewing SM data may be distressing and reduce willingness to engage in future SM [23]. Research on health information avoidance suggests that people avoid health information for three reasons as follows: (1) it may cause unpleasant emotions (ie, guilt and shame), (2) it may dictate undesired action (ie, seeing weight gain on the scale dictates a reduction in calories and change in eating habits), and (3) it may dictate a change in beliefs (ie, seeing the calories associated with one’s favorite menu item at a restaurant may dictate changing beliefs about the feasibility of incorporating it into a weight loss diet) [20]. For all these reasons, the data provided via digital SM tools have the potential to be highly upsetting for those with high health information avoidance. This can have long-term implications for SM engagement because avoidance is likely to continue owing to negative reinforcement (ie, avoidance decreases distress associated with confronting weight-related information). Previous work from the initial BWL phase of the parent study for this analysis shows a relationship between higher weight-related information avoidance and poorer SM of exercise and weight but not diet [24]. Other studies have found that confronting information that can be perceived as a failure (eg, high calorie intake and weight gain) is associated with a higher likelihood of avoiding subsequent SM (eg, self-weighing) [25,26], supporting a relationship between health information avoidance and SM engagement. Further work is needed to replicate these results and explore the relationships during WLM to see whether health information avoidance continues to predict decreased SM engagement as time progresses.

There is also a theoretical and empirical rationale for a relationship between weight bias internalization and digital SM engagement during WLM. Weight bias internalization happens when individuals are aware of negative stereotypes associated with weight, apply these stereotypes to themselves, and engage in self-critical dialogue because of their body size [27]. This negative self-concept (eg, being lazy and lacking willpower) can be associated with lower confidence and self-efficacy [28], which is a consistent predictor of poorer engagement in weight control behaviors during LM [29] and lower weight loss success [30,31]. As participants view data from their digital SM tools and reflect on progress, the lack of goal attainment may contribute to feelings of failure or frustration. For those with high internalized weight bias, these perceived failures may be associated with more intense experiences of shame, guilt, and self-blame than for those with low internalized weight bias, further worsening their confidence and self-efficacy and leading to decreased engagement in SM [28,32]. In addition, in some cases (including the parent study), digital SM information is addressed by BWL coaches who monitor participant progress and provide personalized feedback (eg, SMS text messages) based on data [11]. Although this is meant to enhance supportive accountability, allow coaches to provide more tailored feedback, and increase motivation, this type of surveillance may deter those with high weight bias internalization from engaging in digital SM because they may have heightened sensitivity to the shame surrounding potential negative evaluations that may occur while others are monitoring their data [33,34]. A small body of prior work shows a relationship between high internalized weight bias and lower rates of SM engagement among those attempting weight loss [27,35], but this has not been examined in WLM.

**Objectives**

In line with precision medicine initiatives [36], insight into individual characteristics (weight-related information avoidance and weight bias internalization) that influence SM engagement will help to drive more tailored intervention approaches for those who may be at risk for poor adherence to this key weight control behavior. This study aimed to address current gaps in the literature by exploring patterns of adherence to daily SM of weight, diet, and exercise via digital tools during the WLM phase of a BWL program (aim 1). Among BWL program participants with low SM adherence, this study also examined timing and patterns of disengagement and explored the extent to which participants reengaged with SM after low rates of earlier engagement (aim 2). Finally, this study also sought to determine how individual-level factors (weight-related information avoidance and weight bias internalization) were associated with SM of weight, exercise, and diet during WLM (aim 3).

**Methods**

**Overview**

This study is a secondary analysis of data from a completed randomized controlled trial (ClinicalTrials.gov NCT03337139) [11] assessing whether coach contact with access to digital SM data enhanced WLM outcomes compared with coach contact without access to digital SM data. Participants (N=77) were adults (aged 18-70 years) with overweight or obesity (BMI 25.45 kg/m<sup>2</sup>) who had access to a smartphone and internet and could safely engage in exercise. The exclusion criteria of the parent study included a medical or psychiatric condition that posed a risk for program adherence or safety; pregnancy or plan to become pregnant or move from study area; the use of a pacemaker; a history of bariatric surgery; recent start of, or change to, a medication that can affect weight; and weight loss of ≥10% in the past 3 months.
Ethics Approval and Informed Consent

The parent study was approved by the Drexel University Institutional Review Board (institutional review board protocol number: 1611004954), and all participants provided written informed consent before participation.

Study Flow and Description of BWL Treatment

For a summary of the flow of the study, refer to Figure 1. During months 0 to 3 (phase I), all participants received 12 weeks of standard weekly group BWL treatment, which included tailored calorie goals, traditional behavioral skills adapted from the Look AHEAD (Action for Health in Diabetes) and Diabetes Prevention programs [37,38] (eg, goal setting and problem-solving), and progressive exercise goals of up to 250 minutes per week. Coaches had training in BWL treatment and degrees in psychology or a related field. All participants were provided with digital tools to track weight, exercise, and diet: Yunmai smart scale (weight), Fitbit Flex (exercise; Fitbit Inc), and Fitbit app (diet). Participants were instructed to (1) weigh themselves weekly during weeks 1 to 10 and then weigh daily, (2) wear their Fitbit Flex daily to monitor active minutes, and (3) log all food and drink intake daily. Coaches did not have access to device data during phase I.

Figure 1. Summary of study flow, including data collection and treatment details. BWL: behavioral weight loss; LM: lifestyle modification; LM+SHARE: lifestyle modification plus device data sharing; SM: self-monitoring.

At the end of phase I, participants were randomly assigned (matched for phase I weight loss) to 1 of 2 remote WLM treatment conditions for months 4 to 11. Both conditions included weekly SMS text messages with a coach and monthly one-on-one coach telephone calls (15 minutes) that reviewed ≥1 core behavioral skills taught during group sessions. All participants were prescribed continued daily SM of weight, diet, and exercise throughout phase II. Monthly coach calls were focused on positive reinforcement and self-reflection when participants were succeeding with behavior changes and weight loss goals and focused on problem-solving barriers or fostering motivation when participants were struggling with goal attainment. The conditions differed in terms of coaches’ access to participants’ digital SM data. In the standard LM condition, coaches did not have access to SM device data. Instead, participants self-reported goal progress during monthly calls, and coaches used that self-report to drive discussion of behavioral skills. In the LM condition, weekly SMS text messages were standardized across participants and were not personalized by a coach. In the LM plus device data sharing (LM+SHARE) condition, coaches viewed participants’ SM outcomes on a web-based portal and used these data to personalize telephone calls and SMS text messages. Coaches were trained in how to use data to enhance a sense of supportive accountability and to use data to drive more tailored personalized feedback and goal setting. SM adherence was a key discussion point during monthly coach telephone calls, given the critical role of SM behavior for WLM. Whether coaches were viewing participants’ SM data themselves (LM+SHARE condition) or reacting to participants’ self-reported SM adherence (LM...
condition), they were trained to identify barriers to success, facilitate effective problem-solving and tailored goal setting, and engage in motivational enhancement when adherence was poor. Coaches handled the lack of goal achievement and lack of weight loss progress in similar ways. The results from the parent study indicated that participants in the LM+SHARE condition had higher rates of weight and dietary SM [11]; therefore, treatment condition will be controlled for in analyses.

**Measures**

**Data Collection**

Assessments were completed at baseline, month 3 (the end of phase I and beginning of phase II), month 6, and month 12 (the end of phase II). This study used self-report questionnaire data from baseline assessments as well as continuous SM data collected daily from participants’ devices throughout phase II (months 4-11). The participants’ SM devices (Fitbit Flex, wireless scale, and Fitbit dietary SM app) automatically uploaded data remotely to a research portal. Thus, once SM data were recorded by the participants’ SM devices, there was no additional burden on participants to transfer these data to the research team.

**Weight-Related Information Avoidance**

An adapted version of the Information Avoidance Scale (IAS) [39] was created for the parent study to assess the level of weight-related information avoidance surrounding key weight control behaviors. The 10 items on this self-report measure include statements about attitudes or tendencies to seek out versus avoid information about calorie intake, physical activity, and weight. At baseline, participants responded to each statement on a 7-point Likert scale (ranging from 1=strongly disagree to 7=strongly agree). Total scores were calculated as the average across the 10 items. The measure created showed strong internal consistency (Cronbach α=.85) [24].

**Weight Bias Internalization**

The Weight Bias Internalization Scale (WBIS) [40] is an 11-item self-report measure that assesses the extent to which the respondent believes that negative stereotypes or self-statements about weight apply to them. At baseline only, participants were presented with certain statements (eg, “As an overweight person, I feel that I am just as competent as anyone”) and asked to rate their agreement on a 7-point Likert scale (ranging from 1=strongly disagree to 7=strongly agree). Total scores are calculated as the average rating across the 11 items. The questionnaire has high internal consistency and construct validity [40].

**SM Adherence (Phase I and Phase II)**

For all months 1 to 11, the percentage of days per month that participants successfully self-monitored weight, diet, and exercise was calculated to create an average monthly adherence score for each month. For each participant, average overall phase I (months 1-3) and phase II (months 4-11) adherence scores were also calculated for each SM target (separate variables for phase I vs phase II). A valid day of exercise SM was defined as logging ≥5 foods, both of which have precedent in the literature [24,41,42].

**Patterns of SM Engagement and Adherence**

Several metrics were calculated to understand patterns of SM engagement throughout phase II (calculated separately for SM of exercise, weight, and diet). A cutoff of 50% of days was chosen as a threshold to define low versus high adherence to SM and was selected for several reasons. First, previous work has used 50% as a cutoff for defining SM adherence versus nonadherence [43], and moderate adherence has been defined as 12 to 16 days per month (approximately 50%) [14]. In addition, the systematic review of digital SM within BWL interventions showed that, by months 6 to 12 of the intervention period, engagement rates of ≥50% were achieved in only a minority of studies (38%-45%) [7], suggesting that adherence of >50% is relatively difficult to achieve. Finally, within this sample, exploratory analyses were conducted to ensure that a 50% cutoff indicated a meaningful shift in adherence rates rather than adherence hovering right around 50% (eg, changing from 52% to 48%), which would not necessarily be clinically relevant. For each participant, the first month in which average adherence dropped to <50% (separate for each SM target) was identified as their drop-off month. For SM of weight, diet, and exercise, 2-tailed paired sample t tests confirmed that average monthly adherence in the month before drop-off was significantly higher than adherence during the drop-off month, and average monthly adherence in the month after drop-off was significantly lower. This further supports the use of 50% as a clinically relevant metric for high versus low adherence because adherence meaningfully shifts before and after reaching this cutoff.

The percentage of participants who maintained high adherence (≥250%) throughout all of phase II was calculated, as well as the typical time during phase II where low adherence first occurs (ie, early in WLM during months 4-7 or late in WLM during months 8-11). For those participants whose adherence dropped to <50%, rates of reengagement were also calculated by establishing the number of participants who successfully rebounded to adherence rates of ≥50% at some point during the rest of phase II. The total number of months that participants exhibited complete disengagement (0% adherence) and the number of consecutive months that participants completely disengaged during phase II were also calculated for each SM target. Adherence to SM during phase II was also compared with participants’ phase I SM adherence. The month in which adherence for each SM target dropped by ≥10% compared with average adherence during phase I was identified, as well as the number of months that participants maintained adherence equal to the average of phase I. In addition, we investigated whether participants’ adherence successfully rebounded back to phase I levels once it dropped in phase II.

**Data Analysis**

All data analyses were conducted in SPSS (version 28; IBM Corp) and SAS (version 9.4; SAS Institute Inc) software, and α was set to .05. All data were screened before statistical testing to assess for outliers and normality. The distributions for weight-related information avoidance scores and for SM adherence during phase II were nonnormally distributed.
Although most parametric tests are robust to skewness [44], nonparametric tests and bootstrapping were conducted for analyses using these variables as sensitivity analyses. Given the results from the parent study showing differences in weight and dietary SM between the LM and LM+SHARE conditions [11], our results are reported separately by condition where appropriate to help illustrate any differences between the groups.

For aim 1, descriptive statistics for adherence to SM of weight, diet, and exercise throughout phase II were calculated, within each month and across all of phase II (months 4-11). The percentages of participants who maintained high adherence and those who maintained low adherence were also calculated. Repeated-measures ANOVA (robust to assumptions of nonnormality [45]) assessed for differences in average phase II adherence rates across SM of diet versus weight versus exercise. Multilevel modeling was used to examine changes in adherence rates for each type of SM time in phase II (ie, month in study; level 1) while accounting for between-person variance (level 2). Analyses also controlled for study condition (level 2), and the time x condition interaction was explored too. Chi-square likelihood tests examined whether the inclusion of random participant slope effects improved model fit. The results of the best-fitting model are presented.

For aim 2, all aforementioned SM engagement variables (eg, month adherence dropped to <50% and month adherence dropped to <phase I average adherence) were calculated for each SM target, and descriptive statistics were calculated. Repeated-measures ANOVA assessed for differences in average month where adherence dropped to <50% and <phase I average across SM of diet, weight, and exercise (separate models).

For aim 3, Pearson correlations were used to assess relationships between phase II SM adherence for weight, diet, and exercise and weight-related information avoidance and weight bias internalization (bootstrapping with 1000 samples was conducted as sensitivity analysis to confirm results in nonnormally distributed variables). Two-tailed independent samples t tests (Mann-Whitney U tests for nonnormally distributed variables) were used to assess group differences in weight-related information avoidance and weight bias internalization between participants with low phase II adherence and those with high phase II adherence on each SM target. Using iterative multilevel model building procedures, we also tested cross-level interactions between the hypothesized person-level predictors (ie, weight bias internalization and weight-related information avoidance; level 2) and time (ie, month in study; level 1) for each type of SM adherence. Between-person variables were grand-mean centered. Cross-level interactions were compared with random slope models for fit. For significant cross-level interactions, simple slopes were calculated and graphed to depict SM adherence across time at the mean of, as well as 1 SD above and 1 SD below, the between-person predictor, which allows for better visualization of interaction effects and in a way that is more interpretable and clinically meaningful [44].

Results

Descriptive Statistics

Of the 77 participants, 72 (94%) provided phase II data and were included in these analyses. Participants were on average aged 51.27 (SD 13.47) years, predominantly female (58/72, 81%), and non-Hispanic/Latino (69/72, 96%). Approximately half of the participants (37/72, 51%) identified as White, 38% (27/72) as Black/African American, 7% (5/72) as other or >1 race, 3% (2/72) as Asian, and 1% (1/72) as American Indian/Alaska Native. On average, participants lost 5.89% (SD 4.31%) of their body weight during phase I. Higher percentage of weight loss during phase I was correlated with higher engagement in SM of weight (r=−0.28; P=.02), diet (r=−0.41; P<.001), and exercise (r=−0.26; P=.03) in phase I. The relationships between previous SM behavior (during phase I) and SM engagement during phase II can be seen in Table 1.
### Table 1. The correlation matrix of individual-level variables and phase II adherence for each self-monitoring (SM) target.

<table>
<thead>
<tr>
<th>Variable, mean (SD)</th>
<th>Average adherence to SM of weight in phase II</th>
<th>Average adherence to SM of diet in phase II</th>
<th>Average adherence to SM of exercise in phase II</th>
<th>Baseline IAS&lt;sup&gt;a&lt;/sup&gt; Score</th>
<th>Baseline WBIS&lt;sup&gt;b&lt;/sup&gt; Score</th>
<th>Average adherence to SM of weight in phase I</th>
<th>Average adherence to SM of diet in phase I</th>
<th>Average adherence to SM of exercise in phase I</th>
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<tbody>
<tr>
<td>Average adherence to SM of weight in phase II, 53.2% (3%)</td>
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<td>Average adherence to SM of diet in phase II, 49.34% (2.9%)</td>
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<td>Average adherence to SM of exercise in phase II, 80.01% (2.3%)</td>
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<td>Baseline IAS Score, 2.13 (0.96)</td>
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<td>Baseline WBIS Score, 3.58 (1.09)</td>
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<td>P value .99</td>
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<td>Average adherence to SM of weight in phase I, 88.25% (1.5%)</td>
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<td>Average adherence to SM of diet in phase I, 86.63% (1.5%)</td>
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<tr>
<td>Average adherence to SM of exercise in phase I, 94.13% (1.4%)</td>
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<td>P value .006</td>
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</table>

<sup>a</sup>IAS: Information Avoidance Scale.  
<sup>b</sup>WBIS: Weight Bias Internalization Scale.  
<sup>c</sup>Not applicable.  
<sup>d</sup>Italics denotes significance (meeting threshold of \( P < 0.05 \)).

### Aim 1

At the end of phase I (month 3), 86% (62/72) of the participants had high adherence (≥50%) to SM of weight, 88% (63/72) had high adherence to SM of diet, and 97% (70/72) had high adherence to SM of exercise, indicating that most of the participants were still actively engaged with SM at the end of month 3 and presumably entered phase II with goals to maintain that behavior. During the WLM phase, consistently high rates (≥50% for every month) of SM were observed for 61% (44/72) of the participants for exercise, 40% (29/72) of the participants for weight, and 21% (15/72) of the participants for diet. Throughout phase II, the average percentage of adherence for SM of exercise (mean 80.01%, SD 2.3%) was significantly higher than the percentage of adherence to self-weighing (mean 53.2%, SD 3%) or food logging (mean 49.34%, SD 2.9%; \( F_{2,142}=64.95; P<.001; \eta_p^2=0.48 \)). Adherence to SM of weight and diet were not significantly different (\( P=.63 \)). Only 13% (9/72) of the participants consistently exhibited ≥50% adherence on all 3 SM targets. The best-fitting multilevel models examining the effect of time on all types of SM adherence retained a random slope. The average rates of SM adherence for weight (\( b=-0.05 \), SE 0.01; \( t_71=-8.75; P<.001 \)), diet (\( b=-0.06 \), SE 0.00; \( t_71=-12.30; P<.001 \)), and exercise (\( b=-0.20 \), SE 0.00; \( t_71=-6.53; P<.001 \)) significantly decreased over time throughout phase II (months 4-11) when controlling for study condition. Refer to Figure 2 for a depiction of monthly adherence for each type of SM across time for the LM versus LM+SHARE conditions. The models tested a significant time × condition interaction, but none of the interactions were significant (weight SM: \( P=.16 \); dietary SM: \( P=.13 \); and exercise SM: \( P=.71 \)).
Aim 2

Average Time to <50% Adherence by SM Type

Average adherence dropped to <50% at 10.07 (SD 2.83) months for SM of exercise, at 7.92 (SD 3.23) months for SM of weight, and at 7.58 (SD 2.92) months for SM of diet. The average month of drop-off for adherence to SM of exercise was significantly later in WLM than drop-off for adherence to SM of weight or diet ($F_{2,142}=33.22; P<.001; \eta^2_p=0.32$), but they did not differ from each other ($P=.97$). In the LM condition, average adherence dropped to <50% at 9.86 (SD 2.92) months for SM of exercise, at 7.03 (SD 2.95) months for SM of weight, and at 6.31 (SD 2.36) months for SM of diet. In the LM+SHARE condition, average adherence dropped to <50% at 10.27 (SD 2.76) months for SM of exercise, at 8.76 (SD 3.30) months for SM of weight, and at 8.78 (SD 2.92) months for SM of diet. Among those with low engagement at some point during phase II, the majority disengaged with SM early (months 4-7) rather than late (42/57, 74%, disengaged early for SM of diet; 35/51, 69%, disengaged early for SM of weight; and 16/28, 57%, disengaged early for SM of exercise).

Average Time to Drop of ≥10% From Original Adherence by SM Type

When comparing participants’ SM adherence during phase II to their phase I average adherence, adherence dropped by ≥10% compared with phase I adherence at 7.97 (SD 3.16) months for SM of exercise, at 5.88 (SD 2.63) months for SM of weight, and at 5.82 (SD 2.52) months for SM of diet. This occurred significantly later for SM of exercise than for SM of diet or weight ($F_{2,142}=19.53; P<.001; \eta^2_p=0.22$). Throughout WLM, participants achieved rates of adherence that were at, or above, their phase I average during more months for SM of exercise (mean 5.35, SD 2.49 months) than for SM of weight (mean 2.42, SD 2.69 months) and diet (mean 2.35, SD 2.56 months; $F_{2,142}=56.73; P<.001; \eta^2_p=0.44$).

Reengagement

Analyses examined the likelihood of participants returning to high adherence (ie, ≥50% of the days in any month) after a period of low adherence (ie, <50% of the days in a month). For SM of exercise, 46% (13/28) of the participants rebounded back to high adherence, whereas only one-third of the participants rebounded for SM of weight or diet (17/51, 33%, for weight and 19/57, 33%, for diet). Among those who successfully reengaged with SM of weight, the first month of rebounded
rates of ≥50% tended to be month 7.94 (SD 2.05) compared with month 8.16 (SD 1.80) for SM of diet and month 7.15 (SD 2.19) for SM of exercise. When rates of adherence fell by ≥10% below the phase I average, only 30% (19/64) of the participants went on to achieve weight SM adherence rates at or above phase I levels compared with 29% (19/65) of the participants for dietary SM and 69% (36/52) of the participants for exercise SM. When rates dropped below the phase I average, those who reengaged tended to do so at 7.53 (SD 1.84) months for weight SM, at 6.53 (SD 1.65) months for dietary SM, and at 7.56 (SD 1.86) months for exercise SM.

**Patterns of Complete Disengagement (0% Adherence)**

When looking at complete disengagement (0% monthly adherence), 43% (31/72) of the participants had at least 1 full month of complete disengagement from SM of diet, and 32% (23/72) had at least 1 full month with complete disengagement from SM of weight, whereas only 19% (14/72) totally disengaged from SM of exercise for a full month. Participants who completely disengaged from self-weighing did so for an average of 2.96 (SD 1.52) months. Those who completely disengaged from SM of diet did so for an average of 3.42 (SD 2.08) months, and those who disengaged from SM of exercise did so for an average of 3.00 (SD 1.66) months. For all 3 SM targets, the months of total disengagement tended to occur consecutively for most of the participants (15/31, 48% to 9/14, 64%), rather than as a pattern where adherence increased and then decreased back down to zero.

**Aim 3**

**Weight SM**

The patterns of the Pearson correlation analyses with bootstrapping and those without bootstrapping remained the same; therefore, for ease of interpretation, the results of Pearson correlations without bootstrapping are reported (Table 1). Phase II SM of weight was significantly correlated with past SM behavior during phase I (weight: r=0.44; P<.001; diet: r=0.34; P=.004; and exercise: r=0.32; P=.006) such that participants who had higher engagement on any of the SM targets throughout phase I engaged in more self-weighing in phase II. The average adherence to SM of weight throughout phase II was not correlated with baseline weight-related information avoidance or weight bias internalization.

When dichotomizing the sample into 2 groups based on self-weighing adherence (those who maintained high adherence to weight SM throughout all of months 4-11 and those who did not; Table 2), individuals who maintained consistently high self-weighing adherence in months 4 to 11 had higher baseline weight bias internalization scores than those who did not maintain high adherence to self-weighing (U=700.50; P=.03).

<table>
<thead>
<tr>
<th>Table 2. Results of group comparisons (high vs low self-monitoring [SM] adherence) on baseline levels of weight-related information avoidance and weight bias internalization.</th>
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<tbody>
<tr>
<td>High adherence</td>
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<tr>
<td>Weight SM</td>
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<tr>
<td>Baseline IAS score</td>
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<td>Baseline WBIS score</td>
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</table>

aThe high-adherence group maintained rates of ≥50% throughout all of months 4 to 11.
bMann-Whitney U tests were used for nonnormally distributed variables, and medians are reported (due to skewness).
cTwo-tailed independent samples t tests were used for normally distributed variables and mean (SD) values are reported.
dIAS: Information Avoidance Scale.
eN/A: not applicable.
fWBIS: Weight Bias Internalization Scale.
gP=.03 (significant difference from low-adherence group).

Cross-level interaction models examined whether baseline weight-related information avoidance and weight bias internalization moderated the influence of time on weight SM. Cross-level interaction models were not significant (P=.16 and P=.29, respectively) and did not improve model fit compared with the random slope models examining the influence of time on weight SM tested in aim 1.

**Dietary SM**

As seen in Table 1, average phase II adherence for SM of diet was unrelated to baseline weight-related information avoidance and weight bias internalization scores. Phase II dietary SM was significantly correlated with phase I SM of weight (r=0.26; P=.03) and diet (r=0.54; P<.001) but not exercise (r=0.21; P=.07). Participants who had higher engagement with dietary and weight SM previously tended to engage in more food logging during phase II. Group comparisons between those who maintained high adherence to dietary SM during months 4 to

https://mhealth.jmir.org/2023/1/e45057
and those who did not can be seen in Table 2. The groups did not differ on baseline weight-related information avoidance or weight bias internalization (none of the \(P\) values met the threshold for statistical significance).

Cross-level interaction models examined whether baseline weight-related information avoidance and weight bias internalization moderated the influence of time on dietary SM. There was a significant interaction between weight-related information avoidance and time on dietary SM (\(b=-0.01, SE=0.01; t_{73.7}=-2.13; P=.04\)). The cross-level interaction model fit was significantly improved from the random slope model of time on dietary SM tested in aim 1. Simple slope analyses found that participants with high (\(b=-0.07, SE=0.01; t_{74.4}=-8.61; P<.001\)) and moderate weight-related information avoidance (\(b=-0.06, SE=0.01; t_{69.8}=-10.38; P<.001\)) had a steeper decline in dietary SM over time than those with low weight-related information avoidance (\(b=-0.05, SE=0.01; t_{69.0}=-5.38; P<.001\)). Refer to Figure 3 for a depiction of this interaction. The cross-level interaction between weight bias internalization and time on dietary SM was not significant and did not improve model fit (\(P=.08\)).

**Figure 3.** Visualization of the cross-level interaction between weight-related information avoidance and time on dietary self-monitoring adherence (weight-related information avoidance was centered within person; more positive scores indicate more avoidance).

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**Exercise SM**

Average phase II adherence for exercise SM was not correlated with baseline weight-related information avoidance or baseline weight bias internalization scores (Table 1). Average phase II adherence for exercise SM was significantly correlated with phase I SM engagement for weight (\(r=0.38; P<.001\)), diet (\(r=0.59; P<.001\)), and exercise (\(r=0.42; P<.001\)) such that participants who had higher engagement on any of the SM targets throughout phase I engaged in more consistent exercise tracking during phase II. As seen in Table 2, participants who achieved consistently high adherence to exercise SM in phase II did not differ from those with low adherence on weight bias internalization or health information avoidance.

Cross-level interaction models examined whether between-person factors moderated the effect of time on exercise SM. The cross-level interaction between weight bias internalization and time (and health information avoidance and time) on exercise SM were not significant and did not improve model fit (\(P=.87\) and \(P=.56\), respectively).

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**Discussion**

**Overview of Study Objective**

Daily SM of weight, diet, and physical activity is a common prescription in BWL programs [1] because this practice is highly predictive of participant success [2-4]. However, adherence to SM tends to wane over time, especially during the WLM phase [5,6]. Very few studies have examined patterns of adherence to different SM tools over long periods of time, and almost none have examined how individual differences predict different types of SM adherence. This study explored changes in SM of different tools across time, the unique timing and patterns of disengagement and reengagement, and whether theory-based individual-level factors could predict SM adherence among participants in a year-long BWL program. The findings can inform attempts to prevent disengagement with SM tools and ultimately lead to greater weight control success.

**Rates of SM Adherence**

For all 3 SM targets, the rates of adherence declined across months 4 to 11. These data mirror results from previous analyses.
with these data during phase I (months 0-3), in which adherence to SM of weight and diet but not exercise decreased over 12 weeks [41]. SM adherence during phase II was strongly related to previous SM engagement during phase I, an expected association owing to the consistently strong association between past and current behavior [19]. Throughout phase II, the rates of SM of weight (53%, of the days) and diet (49%, of the days) were significantly lower than those of exercise (80%, of the days). These rates of SM of diet and weight are comparable with the median rates seen in past interventions, whereas the rates of SM of exercise were higher than usual [7]. Of the 72 participants, only 9 (13%) of the participants had strong (ie, ≥50%) adherence for all 3 SM targets throughout phase II, and total disengagement was common: almost half of the participants (31/72, 43%) had at least 1 month with no dietary SM, and almost one-third (23/72, 32%) had at least 1 month with no weight SM. SM engagement was modest in both conditions; however, the rates of participants achieving high SM adherence tended to be higher in the LM+SHARE condition, and more LM+SHARE participants achieved strong adherence across all 3 targets than those in the LM condition. These results parallel findings from the parent study on the potential benefit of coach surveillance of SM data [11]. The results suggest that nonadherence to SM, particularly of diet and weight, is a major problem in BWL treatment, although coach monitoring of SM data may provide 1 avenue for improvements.

The comparatively low rates of dietary SM are unsurprising because calorie tracking is a high-burden behavior that requires ample time and patience. Participants continually struggle with this behavior during BWL trials [46], and past research shows that this type of active SM (ie, calorie tracking) has lower engagement than passive SM (eg, wearing a Fitbit band) [7]. Efforts should be made to help participants track their food more easily, either by creating more user-friendly food tracking technology or by identifying tracking strategies that reduce participant burden without sacrificing effectiveness (eg, tracking only dietary lapses [47]). However, the low rates of self-weighing compared with the higher rates of exercise SM are notable, given that self-weighing, much like exercise tracking, is a low-burden behavior (ie, participants simply need to step on a scale). Therefore, the discrepancy between exercise SM and weight SM may be due to deliberate health information avoidance [48]. Weighing can be highly distressing for participants in BWL programs, and many people with overweight or obesity report avoiding the scale in fear of experiencing the negative feelings it may evoke [49]. Past studies show that people are less likely to weigh themselves when they have recently gained weight [50] or eaten more calories than usual [24], suggesting that the declining adherence for self-weighing may be a result of avoidance of the scale as eating and exercise behavior become less stringent than they were at the start of the program. The results of this study too suggest that efforts to enhance participant engagement with self-weighing may require addressing participant reactions to weight information (eg, with self-compassion training) rather than logistical efforts related to decreasing burden of the SM behavior.

Patterns of Disengagement and Reengagement

Average adherence for diet and weight SM fell to <50% around 7 months into the program, whereas average adherence for exercise SM fell off later, 10 months into the program. Among those who did have low engagement, most dropped off fairly early (ie, months 4-7) in phase II. Among participants who had a meaningful decrease in adherence (ie, >10%) compared with their phase I frequency of SM, the drop-off tended to occur just before month 6 (ie, 2 months into phase II) for diet and weight and around month 8 for SM of exercise. These results suggest that participants are at risk for SM disengagement, particularly with diet and weight, around the 6-month mark of BWL programs; thus, this may be an optimal time for a potential intervention.

Only approximately one-third of the participants whose weight and dietary SM adherence dropped to <50% ever reengaged (ie, restored levels of SM to ≥50% by the end of the program; 17/51, 33% for weight SM and 19/57, 33% for dietary SM). However, almost half of the participants (13/28, 46%) whose exercise SM adherence dropped to <50% were able to reinstate those levels later during WLM. Therefore, when participants disengage with SM of weight and diet in particular, they are highly unlikely to reengage. It seems to be more likely that participants will pick back up with SM of exercise even if they have had low levels of SM disengagement previously, suggesting that this behavior is more resilient against prior difficulties. Both rates of disengagement and reengagement were more promising when data were shared with coaches (LM+SHARE), suggesting that remote coach monitoring may be 1 way to help protect participants against dropping the key weight control behavior of SM.

Explaining SM Adherence and Adherence Trajectories

Although nonadherence to weight SM may be evidence of deliberate avoidance, self-reported weight-related information avoidance at baseline was not predictive of SM of weight or exercise. It is possible that the preference to deliberately avoid weight-related information predicts SM less strongly than expected because avoidance is a dynamic factor that changes owing to situational factors; for example, 1 study found that the preference to avoid weight-related information was associated with state variables (such as shame and negative mood) among adult women with overweight or obesity but not with trait variables (such as BMI, age, or past stigma regarding weight) [51]. Nevertheless, higher baseline weight-related information avoidance was associated with a steeper decline in dietary SM over time. Participants with a stronger tendency to avoid negative weight-related information may find it difficult to confront their calorie intake when they expect that the numbers will elicit shame [49]. As time progresses in WLM, and more participants drift from their calorie goals, recording that information seems to be more challenging for those who enter BWL treatment with higher weight-related information avoidance tendencies. Future work should confirm the dynamics of this relationship with more frequent assessment of weight-related information avoidance throughout WLM.

Contrary to expectations, in this study, baseline weight bias internalization was associated with higher adherence to weight SM. This finding is surprising because past research shows that
weight bias internalization is associated with body image avoidance [52] and the avoidance of healthcare interventions [27]. It is possible that weight bias internalization could lead to greater motivation for weight loss to reduce weight-related guilt and shame; however, research consistently shows that such internalization is ultimately maladaptive [27]. Further work is needed to clarify these conflicting results and elucidate the underlying mechanisms by which weight bias internalization predicts higher levels of weight SM. Research is also needed to determine whether the value of self-weighing is different between those with high weight bias internalization and those with low weight bias internalization.

**Implications for BWL Treatment**

Overall, the results emphasize the fact that SM of diet and weight is a challenge during BWL treatment (even when using digital tools) and should be prioritized as intervention targets. Long-term SM adherence was associated with higher engagement at earlier points of the BWL program (phase I), suggesting that individuals who can establish a consistent, regular SM routine early in treatment will find it easier to maintain it during WLM. Deliberate weight-related information avoidance may occur, as evidenced by the low rates of SM of weight despite its being a low-burden behavior in comparison with SM of diet. Thus, strategies to increase rates of self-weighing among participants in BWL programs may be best designed to target participants’ reaction to SM (eg, self-compassion training) versus logistical problem-solving to decrease burden. This study is the first to identify potential individual-level factors related to use of digital SM tools during WLM. The findings suggest that participants in BWL programs entering treatment with higher rates of weight-related information avoidance and lower rates of weight bias internalization may be at higher risk for low long-term engagement with dietary and weight SM, respectively. This has clinical utility because these individuals can then be identified at baseline and targeted throughout treatment with specific strategies to facilitate sustaining SM as a key weight control behavior. The findings point to the utility of just-in-time adaptive interventions (JITAIs) to promote reengagement with SM tools among participants whose SM starts to decline. JITAIs are dynamic, identifying critical moments for intervention and providing tailored support [53]. Such interventions may be especially effective 6 to 8 months into treatment because, in this study, this was a critical period with high rates of disengagement from SM. Without this intervention, participants may have a difficult time resuming adherence to these crucial behaviors because the current data suggest that few participants who disengage will ever reengage. Future research should identify what psychological or practical support participants need at these times to inspire them to reengage.

**Strengths and Limitations**

This study had several strengths. It included long-term assessment of the use of digital SM tools after the intensive phase of a BWL program, which was a noted gap in the literature. SM data were collected objectively from wireless scales and passive Fitbit sensors, which is a particularly valid method of data collection. Given the design of the parent study, these analyses also provided a chance to look at SM patterns with remote coach monitoring of participant SM data and those without. Data sharing with coaches is a new development within BWL treatment innovation that is not included in most interventions. Thus, it is helpful to clarify what long-term digital SM behavior looks like with coach data surveillance and without. A limitation of the study is its sample size of 77 participants, limiting power to detect small effects. Additional research in a larger, more diverse (specifically, sex diverse) sample would increase the generalizability of, and confidence in, the findings. There was also attrition throughout phase I, where 10 (11%) of the 87 participants dropped out before randomization into phase II and 5 (6%) of the 77 enrolled in phase II did not provide data for this analysis. It is possible that these individuals were more likely to have disengaged from SM and thus would have exhibited poor rates of adherence. Thus, phase II SM adherence rates may have been lower (and the results may have differed) if these analyses were conducted using a data set that included all participants. Furthermore, definitions of SM adherence (eg, high adherence: ≥50% and valid days of calorie tracking: logging ≥5 foods) were based on past literature but are still somewhat arbitrary; for example, it is unclear whether using a threshold of 800 calories per day or at least 2 eating episodes per day is a better determinant of valid calorie days [43].

**Conclusions**

This study found that weight, diet, and exercise SM declined over time during the maintenance phase of a BWL intervention. Adherence to dietary SM was the poorest, followed by adherence to weight SM, whereas adherence to exercise SM was comparatively higher. Few participants maintained high levels of SM across the full study, and total disengagement from SM was common, with low rates of reengagement. These rates of adherence are particularly troubling, given the trial’s strong emphasis on SM. Higher baseline health information avoidance and lower baseline weight bias internalization were associated with poorer SM. The findings suggest that future BWL interventions may benefit from JITAIs that identify when participants are at risk for disengagement and provide adaptive support to promote better SM adherence.

**Acknowledgments**

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Authors' Contributions
NC and MB conceptualized the study aims. NC completed data preparation. NC and CH completed data analyses. NC, OH, and CH wrote the initial draft of the manuscript. All authors contributed to revisions and approved the final manuscript.

Conflicts of Interest
None declared.

References


Abbreviations

AHEAD: Action for Health in Diabetes
BMJ: behavioral weight loss
IAS: Information Avoidance Scale
JITA1: just-in-time adaptive intervention
LM: lifestyle modification
LM+SHARE: lifestyle modification plus device data sharing
SM: self-monitoring
WBIS: Weight Bias Internalization Scale
WLM: weight loss maintenance
WeChat-Based HIV e-Report, a New Approach for HIV Serostatus Requests and Disclosures Among Men Who Have Sex With Men: Prospective Subgroup Analysis of a Randomized Controlled Trial

Hai-Tong Sun1,2*, BSc; Xiao-Ru Fan1,2*, BSc; Yu-Zhou Gu3, MSc; Yong-Heng Lu4, BSc; Jia-Ling Qiu1,2, MSc; Qing-Ling Yang1,2, MSc; Jing-Hua Li1,2, PhD; Jing Gu1,2, PhD; Chun Hao1,2, PhD

1Department of Medical Statistics, School of Public Health, Sun Yat-Sen University, Guangzhou, China
2Sun Yat-Sen Global Health Institute, Institute of State Governance, Sun Yat-Sen University, Guangzhou, China
3Guangzhou Center for Disease Control and Prevention, Guangzhou, China
4Lingnan Community Support Center, Guangzhou, China

*these authors contributed equally

Corresponding Author:
Chun Hao, PhD
Department of Medical Statistics, School of Public Health, Sun Yat-Sen University
74 Zhongshan 2nd Rd Yuexiu District
Guangzhou, 510080
China
Phone: 86 87332517
Email: haochun@mail.sysu.edu.cn

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This is a corrected version. See correction statement: https://mhealth.jmir.org/2023/1/e48961/

Abstract

Background: Requesting and disclosing HIV serostatus is associated with a reduction in HIV transmission among men who have sex with men (MSM). However, the reliability of common methods for HIV serostatus request and disclosure is inadequate. Validated approaches for requesting and disclosing HIV serostatus are necessary.

Objective: The objective of this study was to investigate the use of the HIV e-report as authentic evidence of HIV serostatus among the MSM community in Guangzhou, China. Additionally, the study aimed to explore its correlation with HIV serostatus requesting and disclosure receiving behavior.

Methods: This study is a subgroup analysis of a cluster randomized controlled trial (RCT) that enrolled 357 participants during the first year. Participants in this RCT were recruited from the WeChat-based HIV testing service miniprogram developed by Guangzhou Center for Disease Control and Prevention, China. Participants completed web-based questionnaires at baseline and at the month 3 follow-up, which covered sociodemographic characteristics, HIV-related, HIV serostatus requests, receiving HIV serostatus disclosures, and HIV e-report usage.

Results: The WeChat-based HIV e-report was available in Guangzhou when the RCT project started. At the month 3 follow-up, 32.2% (115/357) of participants had their own HIV e-reports, and 37.8% (135/357) of them had received others’ HIV e-reports. In all, 13.1% (27/205) and 10.5% (16/153) of participants started to use HIV e-reports to request the HIV serostatus from regular and casual male sex partners, respectively. Moreover, 27.3% (42/154) and 16.5% (18/109) of the regular and casual male sex partners, respectively, chose HIV e-reports to disclose their HIV serostatus. Compared to MSM who did not have HIV e-reports, those who had HIV e-reports and stated, “I had had my own HIV e-report(s) but hadn’t sent to others” (multivariate odds ratio 2.71, 95% CI 1.19-6.86; \( P = .02 \)) and “I had had my own HIV e-reports and had sent to others” (multivariate odds ratio 2.67, 95% CI 1.07-7.73; \( P = .048 \)) were more likely to request HIV serostatus from their partners. However, no factor was associated with receiving an HIV serostatus disclosure from partners.
Conclusions: The HIV e-report has been accepted by the MSM community in Guangzhou and could be applied as a new optional approach for HIV serostatus requests and disclosures. This innovative intervention could be effective in promoting infectious disease serostatus disclosure among the related high-risk population.

Trial Registration: ClinicalTrials.gov NCT03984136; https://clinicaltrials.gov/show/NCT03984136

International Registered Report Identifier (IRRID): RR2-10.1186/s12879-021-06484-y

(JMIR Mhealth Uhealth 2023;11:e44513) doi:10.2196/44513

KEYWORDS
behavioral intervention; HIV serostatus disclosure; HIV testing; men who have sex with men; mHealth

Introduction

Men who have sex with men (MSM) are a population bearing a disproportionate burden of HIV infection in China [1]. It accounted for 25.5% of new HIV infections [1], and the prevalence in China reached 6% in 2020 [2]. Having unprotected anal intercourse with partners of unknown HIV status accelerates the rising rates of HIV among this population. To prevent HIV acquisition and transmission in the context of condomless sex, it is crucial that MSM are aware of their own and their partner’s HIV status [3]. Such awareness necessitates frequent HIV testing and mutual HIV status disclosure before engaging in condomless sex with partners [4].

Studies indicated that over half of MSM used verbal communication and guessing for HIV serostatus request and disclosure among MSM [5,6]. While taking HIV tests together is a reliable approach to confirm partners’ HIV status, some individuals doubt the reliability of HIV self-testing, and self-test kits may not always be readily available. Deception of HIV serostatus in verbal information is prevalent [7] and difficult to confirm. Trusting partners without reliable evidence will lead to an increased risk of HIV infection [6]. It is crucial for MSM to engage in more verified HIV serostatus disclosure before sexual activity, as this can effectively reduce the risk of HIV infection. However, current methods of disclosure are insufficient in meeting this need, indicating a need for more effective strategies.

WeChat, a popular social media app with over 1.2 billion active users [8], similar to Twitter or the mix of WhatsApp and Facebook, is a ubiquitous daily-use app in China [9]. WeChat miniprograms are subapps within the WeChat ecosystem. It has great potential for health intervention research [10]. In Guangzhou city, a unique and well-established WeChat miniprogram of the HIV testing service system in China has been developed by Guangzhou Centers for Disease Control and Prevention (CDC) and the MSM community-based organization Lingnan Partners Community Support Center (hereinafter called “Lingnan Center”) [11]. This miniprogram served web-based HIV testing service appointments, web-based-to-offline referral, offline clinic testing, and HIV results e-report delivery after midyear 2019 coinciding with the start of this research project. The HIV result e-report is convenient and well-reserved on the internet. It is an MSM community demand-driven tool which is codeveloped by CDC and Lingnan Center. Due to the use of digital technology, an HIV e-report cannot be forged, ensuring the CDC authenticity of the serostatus results.

Regular or exchangeable HIV e-reports were applied as an intervention in our whole randomized controlled study [12]. In the context of social exchange theory [13], which posits that individuals engage in rational, reciprocal, and fair exchanges in order to achieve desired outcomes, MSM engage in HIV serostatus disclosure as a means of promoting safe sex. By disclosing their own HIV serostatus or requesting their partner’s status, these principles promote mutual disclosure. If a partner’s HIV serostatus is unknown, the desire for sexual activity may drive MSM to autonomously test for HIV, thus promoting HIV testing behavior.

The objective of this study is to describe the usage of the HIV e-report after it was available in Guangzhou and investigate whether it is associated with promoting HIV serostatus requests and disclosure-related behaviors among this high-risk population.

Methods

Study Design

This study is an early-stage subgroup analysis of a cluster randomized controlled trial that was conducted based on the WeChat miniprogram of HIV testing service system in Guangzhou, China (see Figure 1). Guangzhou, the capital city of Guangdong province, where some headquarters of high-tech companies sit, such as Tencent, Huawei, etc, is a megalcity with 18 million population in China [14]. On account of the booming economy and tolerant culture toward homosexuality, the earliest internet-based MSM dating platform in China was established in Guangzhou in 1998 [15]. The prevalence of HIV infection in Guangzhou reached 8.27% [16]. This randomized controlled trial aims to increase HIV testing behaviors by using an HIV e-report exchange mechanism among MSM. Further information on the project can be found elsewhere [12].

MSM who were enrolled in the study at the first year and completed the month 3 follow-up were included in the analysis of this study. The HIV e-report was available to MSM in Guangzhou at the beginning of this study.
Recruitment of Participants

The egocentric social network method [17] which involves participants nominating individuals from their social network to participate in a study, was used to recruit participants for this study. Egos were asked to nominate individuals from their social network (alters) to participate. These alters were then recruited to participate in the study. Figure 1 shows the progress of recruitment. People who went to Lingnan Center to take HIV antibody tests were recruited as “Egos.” Lingnan Center is an MSM-friendly clinic which is cooperated with Guangzhou CDC. In 2022, 10,292 HIV tests have been done in Guangzhou among MSM, and over 60% of HIV tests among MSM in Guangzhou are conducted by this clinic [11]. Every ego who tested for HIV at Lingnan Center got his own CDC-certified web-based HIV results report, hereinafter referred to as “HIV e-report.” Only MSM who went to Lingnan Center for offline HIV testing can get HIV e-reports. The HIV e-report includes the basic testing information and the test result, which is certified by Guangzhou CDC (see Figure 2). Egos nominated alters by sending HIV e-reports to their contacts via WeChat.

HIV e-report receivers were invited to complete the baseline questionnaire (the link to the questionnaire was attached at the bottom of the HIV e-report) and were recruited as “alters” participants. After 3 months, alters would receive WeChat messages which contain the link to the follow-up questionnaire. Once alters went to Lingnan Center to take HIV antibody tests within 3 months, they would get their own HIV e-reports.

Egos were included in the study if they met the following inclusion criteria: (1) were 18 years of age or older, (2) engaged in anal sex with men, and (3) had confirmed negative HIV status. Alters were included in the study if they met the following inclusion criteria: (1) were 18 years of age or older, (2) were engaged in anal sex with men, (3) planned to reside in Guangzhou for the next year, and (4) had unknown or confirmed negative HIV status. Individuals who were unable to complete the questionnaire for any reason were excluded from the study.
Figure 2. The WeChat-based HIV testing service system (smartphone-based HIV test results report module). The Chinese version image depicted in this figure is the screenshot of the smartphone-based HIV test result report in the WeChat miniprogram. Only Chinese version is available.

Measures

**Sociodemographic Characteristics**

All background characteristics of alters were collected in the baseline questionnaire. Sociodemographic characteristics collected include age, marital status, local residence, length of stay in Guangzhou, education, and income. Participants were asked about MSM-related characteristics, including sex orientation, sex role, and whether to recruit male sex partners on the internet. We dichotomized age by 25 years and income by 5000 RMB (US $700) according to the median.

**HIV-Related Information**

HIV-related information was collected at the month 3 follow-up questionnaire. Participants were asked whether they had intervened by any HIV-related programs and whether they had taken up HIV antibody testing and drug use during sex in the past 3 months.

The risk perception of HIV infection was evaluated with 2 questions. One is “How do you think the prevalence of HIV infection in MSM in Guangzhou.” Considering the prevalence of HIV infection in Guangzhou at 8.27% [16], responses options are “≥10%” and “<10%” as high perceived risk to HIV infection or not. The other is “Is someone close to you infected with HIV.”

HIV stigma was measured using a 7-item version of the HIV stigma scale [18], designed to measure the extent to which participants anticipated negative interpersonal and intrapersonal consequences were they to contract HIV in the future. All 7 items were rated on a Likert-type scale (1=Strongly Disagree and 4=Strongly Agree). Higher scores are indicative of greater perceived HIV-related stigma. The Cronbach α for HIV stigma was .728.
HIV testing social norms [19] were calculated using 3 survey items rated on a 4-point Likert scale in the web-based survey. All 3 items were rated on a Likert-type scale (1=Strongly Disagree and 4=Strongly Agree). Higher values indicate positive HIV testing social norms. The Cronbach α for HIV testing social norms was .737.

**HIV Serostatus Request and Disclosure Receiving From Different Kinds of Male Sex Partners**

Participants were asked for information about HIV serostatus in the past 3 months from regular male sex partners and casual male sex partners, respectively. Moreover, we used “or” to generate a variable called “any kinds of male sex partners.” First, we asked whether they had regular and casual male sex partners in the past 3 months and whether they had unprotected anal intercourse with their male sex partners. Once they had male sex partners, we asked them how they requested the HIV serostatus of their male sex partners, including “I didn’t request,” “I requested orally or by message,” “I requested by taking HIV test together,” “I requested by sending my own HIV e-report,” and “I requested by asking for partner’s HIV e-report” while HIV e-report was available at the month 3 follow-up. If participants request at the month 3 follow-up, then they were asked how they received the HIV serostatus of their male sex partners by checking the response options (1=I did not receive partner’s disclosure, 2=I received partner’s disclosure orally or by message [namely, without any evidence], 3=I received partner’s disclosure by HIV reports or HIV test kits, and 4=I received partner’s disclosure by HIV e-reports).

**HIV e-Reports**

Participants were asked whether they had HIV e-reports, whether they received others’ HIV e-reports, and whether they sent HIV e-reports to others in the past 3 months. HIV e-report has been operating in Guangzhou after the midyear of 2019 when the baseline of this study was initiated. HIV e-reports–related results were only available at the month 3 follow-up.

**Statistical Analysis**

Descriptive statistics were used to depict participants’ sociodemographic characteristics, MSM-related information, HIV-related information, HIV serostatus request, and disclosure receiving from different kinds of male sex partners.

A percentage stacked bar graph was used to describe the manner of HIV serostatus request at baseline and the month 3 follow-up. Another bar graph was used to depict the manner of receiving HIV serostatus disclosures at the month 3 follow-up.

Univariate associations were assessed using binary logistic regression to examine each of the independent variables listed above with the 2 outcomes of HIV serostatus request behavior, which were “Had request the HIV serostatus of any kinds of male sex partners at the month 3 follow-up?” and response behaviors to HIV serostatus request, “Had received HIV serostatus disclosure from any kinds of male sex partners at the month 3 follow-up?” Subsequently, significant variables (P<.05) from the univariate logistic regression analysis were included in the multivariate logistic regression analysis. Multivariate stepwise logistic regression was applied to select the final model.

Measures of association were presented as univariate odds ratio versus multivariate odds ratio (ORm), with 95% CI. All statistical analyses were performed using R (version 4.2.1) with 2-tailed test. A P<.05 was considered statistically significant. The packages used were dplyr, tableone, ggplot, and glm.

**Ethical Considerations**

The study protocol was approved by the Ethics Committee of Sun Yat-sen University (Institutional Review Board number 054/19; February 28, 2019). Informed consent was obtained from each ego at the clinic and from each alter on the internet through the WeChat-based system. The study data were collected and stored securely on the servers of the Guangzhou CDC HIV testing service system, WeChat-based database, and web-based questionnaire database, in accordance with relevant data protection laws and regulations. Access to these databases was restricted to the research team in order to ensure the confidentiality and privacy of the data.

**Results**

**Recruitment**

From September 2019 to August 2020, a total of 1607 MSM who took HIV testing at the Lingnan Center were invited to participate in this study. Of these, 1295 were recruited as Egos. Egos subsequently sent HIV e-reports to 1782 contacts via WeChat, and 702 of them (response rate, 22.3%, 702/1295) clicked the link to the questionnaire. At baseline, 397 participants were recruited as alters. Of these, 40 were lost at the month 3 follow-up whose HIV e-report information and HIV serostatus disclosure behavior information were missing. As a result, a total of 357 participants were included in the final analysis.

**Characteristics of Participants**

Out of 357 participants, around half of them were over 25 years of age (195/357, 54.6%), educated above high school (200/357, 56%), and earned more than 5000 RMB (US $700) per month (198/357, 55.5%). Most of them were not married to women (339/357, 95%).

Most participants were homosexual (295/357, 82.6%) and the proportion of self-identified sex role was approximately similar (122/357, 34.2% in insertive; 126/357, 35.3% in receptive; and 109/357, 30.5% in both).

A total of 79% (282/357) of participants took part in HIV-related programs in the past 3 months. HIV stigma scores ranged from 8 to 23 and were at a high level (median 19, IQR 17-22) overall. On average, participants’ social norm (median 3, IQR 2.67-3) inclined to a positive direction. Further details on participants characteristics participants’ characteristics were presented in Table 1.
Table 1. Background characteristics of alters who enrolled at the first project year from Sep 2019 to Aug 2020.

<table>
<thead>
<tr>
<th>Sociodemographic characteristics</th>
<th>Alters (N=357), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age (years)</strong></td>
<td></td>
</tr>
<tr>
<td>≤25 years</td>
<td>162 (45.4)</td>
</tr>
<tr>
<td>&gt;25 years</td>
<td>195 (54.6)</td>
</tr>
<tr>
<td><strong>Currently married to a woman</strong></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>339 (95)</td>
</tr>
<tr>
<td>Yes</td>
<td>18 (5)</td>
</tr>
<tr>
<td><strong>Guangzhou permanent resident (Hukou)</strong></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>106 (29.7)</td>
</tr>
<tr>
<td>Yes</td>
<td>251 (70.3)</td>
</tr>
<tr>
<td><strong>How long had been in Guangzhou</strong></td>
<td></td>
</tr>
<tr>
<td>≤3 years</td>
<td>151 (42.3)</td>
</tr>
<tr>
<td>&gt;3 years</td>
<td>206 (57.7)</td>
</tr>
<tr>
<td><strong>Highest education obtained</strong></td>
<td></td>
</tr>
<tr>
<td>High school or below</td>
<td>157 (44)</td>
</tr>
<tr>
<td>Above high school</td>
<td>200 (56)</td>
</tr>
<tr>
<td><strong>Personal monthly income (5000 RMB=US $700)</strong></td>
<td></td>
</tr>
<tr>
<td>≤5000</td>
<td>159 (44.5)</td>
</tr>
<tr>
<td>&gt;5000</td>
<td>198 (55.5)</td>
</tr>
<tr>
<td><em><em>MSM</em>-related characteristics</em>*</td>
<td></td>
</tr>
<tr>
<td><strong>Self-identified sex orientation</strong></td>
<td></td>
</tr>
<tr>
<td>Bisexual, heterosexual, or not sure</td>
<td>62 (17.4)</td>
</tr>
<tr>
<td>Homosexual</td>
<td>295 (82.6)</td>
</tr>
<tr>
<td><strong>Self-identified sex role</strong></td>
<td></td>
</tr>
<tr>
<td>Insertive only</td>
<td>122 (34.2)</td>
</tr>
<tr>
<td>Receptive only</td>
<td>126 (35.3)</td>
</tr>
<tr>
<td>Both</td>
<td>109 (30.5)</td>
</tr>
<tr>
<td><strong>Male sex partner mostly recruited from the internet</strong></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>13 (3.6)</td>
</tr>
<tr>
<td>Yes</td>
<td>344 (96.4)</td>
</tr>
<tr>
<td><strong>HIV-related information</strong></td>
<td></td>
</tr>
<tr>
<td>Had intervened in any HIV-related programs in the past 3 months</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>75 (21)</td>
</tr>
<tr>
<td>Yes</td>
<td>282 (79)</td>
</tr>
<tr>
<td>Had taken up HIV antibody testing in the past 3 months</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>182 (51)</td>
</tr>
<tr>
<td>Yes</td>
<td>175 (49)</td>
</tr>
<tr>
<td>Had drug use during sex in the past 3 months</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>279 (78.2)</td>
</tr>
<tr>
<td>Yes</td>
<td>78 (21.8)</td>
</tr>
</tbody>
</table>

How do you think the prevalence of HIV infection in MSM in Guangzhou
Alters (N=357), n (%)  
- <10%: 79 (22.1)
- ≥10%: 278 (77.9)

Is someone close to you infected with HIV  
- No: 226 (63.3)
- Yes: 131 (36.7)

aMSM: men who have sex with men.
bMedian HIV stigma score 19 (IQR 17-22) and median HIV testing social norm score 3 (IQR 2.67-3.00).

HIV e-Reports Emerging as the New Approach for HIV Serostatus Requests and Disclosure Receiving

At baseline, HIV serostatus request behaviors contained only 3 types of manners, including “I did not request,” “I requested orally or by message,” and “I requested by taking HIV test together.” The proportions for requesting manners were 15.1% (35/232), 50.0% (116/232), and 34.9% (81/232) in 232 participants with regular male sex partners and were 18.5% (34/184), 59.2% (109/184), and 22.3% (41/184) in 184 participants with casual male sex partners, respectively (Figure 3).

At month 3 follow-up, for all 357 participants, 57.4% (205/357) of them had regular male sex partners, 42.9% (153/357) of them had casual male sex partners, and 73.4% (262/357) of them had either kind of male sex partner in the past 3 months.

After HIV e-reports were available, out of all 357 participants, 32.2% (n=115) of them had their own e-reports, and 37.8% (n=135) of them had received others’ HIV e-reports at month 3 follow-up. For those who had their own HIV e-reports, 50.4% (58/115) of them had sent their own HIV e-reports to others. Therefore, 2 new request approaches for HIV serostatus using the HIV e-report emerged; namely “I requested by sending my own HIV e-report” and “I requested by asking for partner’s HIV e-report.” The proportions of these 2 approaches were 10.7% (22/205) and 2.4% (5/205) toward regular male sex partners, and 7.2% (11/153) and 3.3% (5/153) toward casual male sex partners, respectively. See Figure 3 and Table 2.

Participants’ casual sex partners were more likely to disclose HIV serostatus without any evidence (37/109, 33.9%) and with HIV regular reports or HIV test kits (35/109, 32.1%), compared with their regular sex partners (37/158, 24% and 44/158, 28.6%). Instead, participants were more likely to receive HIV serostatus disclosure via e-reports from regular male sex partners (42/158, 27.3%) than casual male sex partners (18/109, 16.5%; Figure 4).

Figure 3. The proportion of MSM’s HIV serostatus requesting manners in different types of male sex partners at baseline and the month 3 follow-up. MSM: men who have sex with men.

![Figure 3](https://mhealth.jmir.org/2023/1/e44513)
Table 2. HIV serostatus request and disclosure receiving behaviors toward different male sex partners among alters at month 3 follow-up.

<table>
<thead>
<tr>
<th>Information in the past 3 months</th>
<th>Participants (N=357), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Regular male sex partner</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Whether had regular male sex partners</strong></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>152 (42.6)</td>
</tr>
<tr>
<td>Yes</td>
<td>205 (57.4)</td>
</tr>
<tr>
<td><strong>Whether had had UAI&lt;sup&gt;a&lt;/sup&gt; with regular male sex partners</strong></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>60 (29.3)</td>
</tr>
<tr>
<td>Yes</td>
<td>145 (70.7)</td>
</tr>
<tr>
<td><strong>How did you request the HIV serostatus from regular male sex partners</strong></td>
<td></td>
</tr>
<tr>
<td>I did not request</td>
<td>51 (24.9)</td>
</tr>
<tr>
<td>I requested orally or by message</td>
<td>72 (35.1)</td>
</tr>
<tr>
<td>I requested by taking HIV test together</td>
<td>55 (26.8)</td>
</tr>
<tr>
<td>I requested by sending my own HIV e-report</td>
<td>22 (10.8)</td>
</tr>
<tr>
<td>I requested by asking for partner’s HIV e-report</td>
<td>5 (2.4)</td>
</tr>
<tr>
<td><strong>How did you receive disclosure of the HIV serostatus from regular male sex partners</strong></td>
<td></td>
</tr>
<tr>
<td>I did not receive partner’s disclosure</td>
<td>31 (20.1)</td>
</tr>
<tr>
<td>I received disclosure without any evidence</td>
<td>37 (24)</td>
</tr>
<tr>
<td>I received disclosure with HIV reports or HIV test kits</td>
<td>44 (28.6)</td>
</tr>
<tr>
<td>I received disclosure with HIV e-reports</td>
<td>42 (27.3)</td>
</tr>
<tr>
<td><strong>Casual male sex partner</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Whether had casual male sex partners</strong></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>204 (57.1)</td>
</tr>
<tr>
<td>Yes</td>
<td>153 (42.9)</td>
</tr>
<tr>
<td><strong>Whether had had UAI with casual male sex partners</strong></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>29 (19)</td>
</tr>
<tr>
<td>Yes</td>
<td>124 (81)</td>
</tr>
<tr>
<td><strong>How did you request the HIV serostatus of casual male sex partners</strong></td>
<td></td>
</tr>
<tr>
<td>I did not request</td>
<td>44 (28.8)</td>
</tr>
<tr>
<td>I requested orally or by message</td>
<td>66 (43.1)</td>
</tr>
<tr>
<td>I requested by taking HIV test together</td>
<td>27 (17.6)</td>
</tr>
<tr>
<td>I requested by sending my own HIV e-report</td>
<td>11 (7.2)</td>
</tr>
<tr>
<td>I requested by asking for partner’s HIV e-report</td>
<td>5 (3.3)</td>
</tr>
<tr>
<td><strong>How did you receive disclosure of the HIV serostatus from casual male sex partners</strong></td>
<td></td>
</tr>
<tr>
<td>I did not receive partner’s disclosure</td>
<td>44 (32.8)</td>
</tr>
<tr>
<td>I received disclosure without any evidence</td>
<td>37 (27.6)</td>
</tr>
<tr>
<td>I received disclosure with HIV reports or HIV test kits</td>
<td>35 (26.2)</td>
</tr>
<tr>
<td>I received disclosure with HIV e-reports</td>
<td>18 (13.4)</td>
</tr>
<tr>
<td><strong>Any kinds of male sex partner</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Whether had any kinds of male sex partners</strong></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>95 (26.6)</td>
</tr>
<tr>
<td>Yes</td>
<td>262 (73.4)</td>
</tr>
<tr>
<td><strong>Whether had UAI with any male sex partners</strong></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>66 (25.2)</td>
</tr>
</tbody>
</table>
### Participants (N=357), n (%)

#### How did you request the HIV serostatus of any kinds of male sex partners

<table>
<thead>
<tr>
<th>Request Method</th>
<th>n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I did not request</td>
<td>67 (25.6)</td>
</tr>
<tr>
<td>I requested orally, by message, or by taking HIV test together</td>
<td>160 (61)</td>
</tr>
<tr>
<td>I requested by HIV e-reports</td>
<td>35 (13.4)</td>
</tr>
</tbody>
</table>

#### How did you receive disclosure of the HIV serostatus from any kinds of male sex partners

<table>
<thead>
<tr>
<th>Disclosure Method</th>
<th>n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I did not receive partner’s disclosure</td>
<td>32 (16.4)</td>
</tr>
<tr>
<td>I received disclosure with no evidence, HIV reports, or HIV test kits</td>
<td>112 (57.4)</td>
</tr>
<tr>
<td>I received disclosure with HIV e-reports</td>
<td>51 (26.2)</td>
</tr>
</tbody>
</table>

#### HIV e-reports–related information in the past 3 months

- **Had sent your own HIV e-reports to others**
  - I didn’t have my own HIV e-reports: 242 (67.8)
  - I had my own HIV e-reports but didn’t send to others: 57 (16)
  - I had my own HIV e-reports and sent to others: 58 (16.2)

- **Had received others’ HIV e-reports**
  - No: 222 (62.2)
  - Yes: 135 (37.8)

---

**Factors Associated With HIV Serostatus Requests and Receiving Disclosures**

In univariate logistic analysis, 5 factors were significantly (P<.05) associated with HIV serostatus request behavior. Further details were described in **Table 3**.

The multivariate stepwise regression model showed that HIV e-report–related variables, namely, having had HIV e-reports but didn’t send to others (OR_m 2.71, 95% CI 1.19-6.86; P=.02; reference: participants who didn’t have their own HIV e-reports), having had HIV e-reports and sent to others (OR_m 2.67, 95% CI 1.07-7.73; P=.048; reference: participants who didn’t have their own HIV e-reports), and having had received others’ HIV e-reports (OR_m 2.03, 95% CI 1.04-4.11, P=.04) were significantly associated with HIV serostatus request behavior. For variables about HIV-related information in the past 3 months, namely higher HIV testing behavior social norm scores (OR_m 2.13, 95% CI 1.12-4.17; P=.02), having had intervened by any HIV-related programs (OR_m 2.28, 95% CI 1.12-4.65; P=.02), and having taken up HIV antibody testing (OR_m 1.85, 95% CI 1.00-3.44; P=.05) in the past 3 months, remained in the final model as well.

All variables listed in **Table 2** were not associated with receiving HIV serostatus disclosures (not tabulated).
Table 3. Univariate and multivariate regression analysis of associated factors with HIV serostatus request behavior. Univariate logistic regressions were conducted for “Had request the HIV serostatus of any kinds of male sex partners at the month 3 follow-up” and “Had any kinds of male sex partners inform you the HIV serostatus at the month 3 follow-up.” All variables in were contained in univariate logistic regressions, and those with \( P \) value of >.10 were excluded. No factor significantly associated with “Had any kinds of male sex partners inform you the HIV serostatus at the month 3 follow-up.”

<table>
<thead>
<tr>
<th>Had requested HIV serostatus(^a) from any kinds of male sex partners at the month 3 follow-up</th>
<th>All, N</th>
<th>Participants, n (%)</th>
<th>OR(^b) (95% CI)</th>
<th>OR(_m^c) (95% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I hadn’t had my own HIV e-reports</td>
<td>165</td>
<td>112 (67.9)</td>
<td>Reference</td>
<td>Reference</td>
</tr>
<tr>
<td>I had had my own HIV e-reports but hadn’t sent to others</td>
<td>47</td>
<td>39 (83)</td>
<td>2.31 (1.05-5.63)</td>
<td>2.71 (1.19-6.86)</td>
</tr>
<tr>
<td>I had had my own HIV e-reports and had sent to others</td>
<td>50</td>
<td>44 (88)</td>
<td>3.47 (1.49-9.53)</td>
<td>2.67 (1.07-7.73)</td>
</tr>
</tbody>
</table>

Had received other MSM’s HIV e-reports in the past 3 months

<table>
<thead>
<tr>
<th>Had taken up HIV antibody testing in the past 3 months</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
</tr>
<tr>
<td>Yes</td>
</tr>
</tbody>
</table>

Had intervened in any HIV-related programs in the past 3 months

<table>
<thead>
<tr>
<th>Had received other MSM’s HIV e-reports in the past 3 months</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
</tr>
<tr>
<td>Yes</td>
</tr>
</tbody>
</table>

\(^a\)Median HIV testing behavior social norm score was 3 (IQR 2.67-3.00) overall, while that for participants who had requested HIV serostatus from any kinds of male sex partners at month 3 follow-up was 1.5 (95% CI 1.03-1.28) (ie, OR group) and 2.13 (95% CI 1.12-4.17) (ie, OR\(_m^c\) group).

\(^b\)OR: univariate odds ratio.

\(^c\)OR\(_m^c\): multivariate odds ratio. Five variables were put in the multivariate model, and Akaike’s information criterion was used to select the variables in this model.

Discussion

Principal Results

e-Reports are a new approach for HIV serostatus request and disclosure for the HIV risk population. MSM chose HIV e-report as the web-based approach to disclose their own HIV serostatus or to request partner’s HIV serostatus with authenticity when it was available in Guangzhou. The most important is that HIV serostatus request behaviors were positively associated with having their own HIV e-report. To the best of our knowledge, this is the first study to discuss the use of HIV e-reports and explore its association. HIV e-report, codeveloped by the MSM community itself, could be considered a novel approach to promote mutual HIV status disclosure before engaging in sexual behaviors among HIV high-risk population, and being capable to be replicated in other countries and regions based on the ability of building information platforms.

The most interesting finding is that MSM who used HIV e-reports were more likely to actively request the HIV serostatus of their male sex partners. As e-report is a new modality in the HIV research area, studies to investigate the association between HIV e-reports and HIV serostatus request and disclosure behaviors have rarely been reported. The possible reason for this finding is the confidence in the e-report, which is the CDC-certified credible evidence of HIV serostatus that cannot be modified. Holding an HIV e-report may make MSM feel more confident and self-assured when requesting the HIV serostatus of their male sex partners. Therefore, HIV e-report has the potential to be applied as an intervention to control the risk of HIV infection by promoting HIV serostatus disclosure. However, it is important to emphasize that the HIV e-report is not a substitute for condom use. A meta-analysis conducted in 2017 showed that seroadaptive substitution for condoms can increase the risk of HIV infection [20]. This study demonstrates the favorable influence of HIV e-report on HIV-related behaviors in the MSM community in the short term, and the long-term impact of HIV e-report among HIV risk population is expected to be explored in the future.

After the HIV e-report was available, a new proportion of MSM had used the e-report to request their sex partner’s HIV serostatus (13.4%, 35/262) and had received their sex partner’s e-report as an HIV serostatus disclosure (26.2%, 51/195). In addition to e-report results certificated by CDC, the significance of HIV e-report is that it is driven by MSM community demand, which correspondingly engaged in the development of HIV e-report. MSM designed it because they feel sending out their own HIV e-report is the most natural and credible way to request male sex partners’ HIV serostatus as well as disclose their own HIV serostatus. According to the results, HIV e-report is becoming more acceptable within the MSM community.
We found that nearly one-third of MSM did not request the HIV serostatus of their usual male sex partners. A total of 74.9% (197/232) of alters requested their regular sex partner's HIV serostatus, while 71.5% (150/214) of alters requested their usual sex partner's HIV serostatus at baseline. Requesting a partner’s HIV serostatus before engaging in sexual activity is an active coping strategy to control the risk of HIV infection. However, most research on HIV serostatus focuses on self-disclosure rather than request behavior [21-25]. Only a few studies have investigated HIV serostatus request behavior, and our data contribute to the literature [5,6]. Some influence factors have been identified in studies, such as perceived high HIV risk, lower HIV-related stigma, and greater engagement with the MSM community [26,27]. HIV serostatus request, as a proactive behavior, which can elevate the importance of consciousness about HIV serostatus disclosure before sex, has ample room for improvement among MSM.

In our study, we found that 62.2% (163/262) of participants reported receiving disclosure from male sex partners. Other studies showed that the HIV serostatus self-disclosure rate among MSM in China was approximately 20% in 2016 and 2018 [22,28]. We hypothesize that this higher disclosure rate may be due to increased awareness of the importance of disclosure over the past 5 years. We did not identify any factors associated with receiving an HIV serostatus disclosure. The possible reason may be that receiving a disclosure is a passive behavior that is primarily influenced by the characteristics of the person who disclosed their status rather than the recipient. Furthermore, our study only collected information from the recipient’s perspective, which limits our ability to identify factors that may influence disclosure receiving behavior. Active coping strategies used by MSM, such as promoting the active behavior of requests by expanding the use of HIV e-reports, should be promoted.

Finally, previous studies indicated that HIV testing is positively associated with HIV serostatus request and disclosure [22,27], and our study found corroborating results. Furthermore, MSM who had higher HIV testing social norm scores and had intervened in any HIV-related programs were more likely to request HIV serostatus. This suggests that promoting both health education and HIV serostatus request and disclosure synchronously could be a promising route.

**Limitations**

This study is subject to several limitations. First, as the baseline and month 3 follow-up questionnaires collected alters’ information in the past 3 months, the information and recall bias might exist as other HIV-related publications [29,30]. Second, there might be selection bias since participants were recruited through HIV testers from a local MSM-friendly clinic in Guangzhou and questionnaires were conducted on the mobile app, which led to participants being younger and well educated. Third, this is an observational study. Though we found several factors associated with HIV serostatus request, the causation between them needs further study.

**Conclusions**

This study indicated that the HIV e-report, the health service tool coproduced by community members, has become acceptable and could be used as a new optional approach for HIV serostatus request and disclosure among populations at high risk of sexually transmitted infections. In particular, the use of HIV e-report has potential influence on promoting HIV serostatus request behaviors. It is anticipated that the e-report approach will have an extended spectrum of coverage to reach more target populations and ultimately accelerate the decline of infectious disease transmission.

**Acknowledgments**

Y-ZG and CH were both corresponding authors for this manuscript. H-TS and X-RF contributed equally to this manuscript. H-TS wrote the manuscript and conducted all statistical analyses; X-RF conducted baseline and follow-up data collection, quality control, project implementation, and manuscript revision; Y-HL is the coprincipal investigator being responsible for the web-based part of this project, including research design, WeChat-based miniprogram design, management, and supervision; J-LQ and Q-LY participated in the research design, data collection design, project launch, and beginning of baseline data collection, beginning of baseline quality control, and beginning of baseline project implementation; JG and J-HL participated in the research design, data collection design, and part of human and funding resources support during the project implementation; Y-ZG is the coprincipal investigator being responsible for site works, including research design, WeChat-based miniprogram design, clinic and telephone data collection, management, and supervision; and CH is the principal investigator of this project, in the management and leadership of the research project. This study was supported by the National Natural Science Foundation of China (grant #71974212, #71774178, #81803334, #72204059), Guangdong Basic and Applied Basic Research Foundation (grant #2020A1515010737) and The Scientific Research Plan Project of Guangzhou (grant #202201010078).

**Conflicts of Interest**

None declared.

**References**


Abbreviations

CDC: Center for Disease Control and Prevention
MSM: men who have sex with men
ORm: multivariate odds ratio
The Effectiveness of an eHealth Family-Based Intervention Program in Patients With Uncontrolled Type 2 Diabetes Mellitus (T2DM) in the Community Via WeChat: Randomized Controlled Trial

Yuheng Feng¹,²,³, BA; Yuxi Zhao¹,²,³, MD; Linqi Mao¹,²,³, MD; Minmin Gu⁴, BA; Hong Yuan⁵, BA; Jun Lu¹,²,³, PhD; Qi Zhang⁶, PhD; Qian Zhao¹,²,³, BA; Xiaohong Li¹,²,³, PhD

¹Department of Health Policy and Management, School of Public Health, Fudan University, Shanghai, China
²China Research Center on Disability Issues, Fudan University, Shanghai, China
³Key Laboratory of Health Technology Assessment, National Health Commission, Fudan University, Shanghai, China
⁴Juyuan New District Community Health Service Center, Jiading District, Shanghai, China
⁵Shanghai Jiading District Center for Disease Control and Prevention, Shanghai, China
⁶School of Community and Environmental Health, Old Dominion University, Norfolk, VA, United States

Corresponding Author:
Xiaohong Li, PhD
Department of Health Policy and Management
School of Public Health
Fudan University
220 Handan Rd
Yangpu District
Shanghai, 200433
China
Phone: 86 13918213586
Email: lixh@fudan.edu.cn

Abstract

Background: Intervention based on family support and risk perception can enhance type 2 diabetes mellitus (T2DM) patients’ self-care activities. In addition, eHealth education is considered to improve family members’ support for patients with T2DM. However, there is little evidence from rigorously designed studies on the effectiveness of an intervention combining these approaches.

Objective: This randomized controlled trial (RCT) aimed to assess the effectiveness of an eHealth family-based health education intervention for patients with T2DM to improve their glucose control, risk perception, and self-care behaviors.

Methods: This single-center, 2-parallel-group RCT was conducted between 2019 and 2020. Overall, 228 patients were recruited from Jiading District, Shanghai, and randomly divided into intervention and control groups. The intervention group received an eHealth family intervention based on community management via WeChat, whereas the control group received usual care. The primary outcome was the glycated hemoglobin (HbA₁c) level of the patients with T2DM, and the secondary outcomes were self-management behavior (general and specific diet, exercise, blood sugar testing, foot care, and smoking), risk perception (risk knowledge, personal control, worry, optimism bias, and personal risk), and family support (supportive and nonsupportive behaviors). A 2-tailed paired-sample t test was used to compare the participants at baseline and follow-up within the control and intervention groups. An analysis of covariance was used to measure the intervention effect.

Results: In total, 225 patients with T2DM were followed up for 1 year. After intervention, they had significantly lower HbA₁c values (β=–.69, 95% CI –0.99 to –0.39; P<.001). They also had improved general diet (β=–.60, 95% CI 0.20 to 1.00; P=.003), special diet (β=–.71, 95% CI 0.34 to 1.09; P<.001), blood sugar testing (β=–.50, 95% CI 0.02 to 0.98; P=.04), foot care (β=1.82, 95% CI 1.23 to 2.42; P<.001), risk knowledge (β=–.89, 95% CI 0.55 to 1.24; P<.001), personal control (β=–.22, 95% CI 0.12 to 0.32; P<.001), worry (β=–.24, 95% CI 0.10 to 0.39; P=.001), optimism bias (β=–.26, 95% CI 0.09 to 0.43; P=.003), and supportive behaviors (β=5.52, 95% CI 4.03 to 7.01; P<.001).
Conclusions: The eHealth family-based intervention improved glucose control and self-care activities among patients with T2DM by aiding the implementation of interventions to improve T2DM risk perceptions among family members. The intervention is generalizable for patients with T2DM using health management systems in community health centers.

Trial Registration: Chinese Clinical Trial Registry ChiCTR1900020736; https://www.chictr.org.cn/showprojen.aspx?proj=31214

(JMIR Mhealth Uhealth 2023;11:e40420) doi:10.2196/40420

KEYWORDS
public health; type 2 diabetes mellitus; intervention; randomized controlled trial; community health center

Introduction

Background

Worldwide, type 2 diabetes mellitus (T2DM) has become a serious public health problem; it leads to severe health outcomes and creates a heavy economic burden [1,2]. The prevalence of T2DM is rising across all regions [1]. For people aged over 60 years, the prevalence of T2DM exceeds 20%, and it is expected to increase with the aging of the world’s population [1].

China has the highest number of people with diabetes and mortality globally [1]. Among all types of diabetes, T2DM accounts for over 90% of diagnoses, and this type of the disease can cause various complications [3]. In 2021, health expenditures in China related to T2DM and complications reached about US $0.17 trillion, accounting for 1% of gross domestic product [1,4]. Therefore, it is urgent to explore practical measures to reduce the occurrence of T2DM and prevent complications from occurring in patients with T2DM.

Poor glucose control is associated with the occurrence of complications [5]. Glycated hemoglobin (HbA1c) can be used to determine glucose control level [6]. HbA1c ≥7% indicates that a patient has poor glucose control [7].

If HbA1c increases by 2%, the risk of T2DM all-cause mortality increases by 40% to 86% in the following 10 to 20 years [8]. However, most Chinese patients with T2DM have poor glucose control [9]. Studies show that many factors influence glucose control, such as psychosocial factors [10], self-care activities [11], risk perception [12], and social support [13].

China released the National Standard for Basic Public Health Services in 2009 [14], stating that the health management of T2DM is one of the main areas of focus and that community health service centers should regularly provide usual care to patients with T2DM, such as face-to-face follow-up, health education, physical examination, and glucose testing. Until 2016, although a large number of patients with T2DM received standardized management at community health service centers [15,16], the effectiveness of usual care was not good, leading to a failure to enhance perceptions among patients with T2DM of the importance of glucose control and improving self-care activities. The effectiveness of usual care is thus unsustainable due to poor understanding and compliance with such aspects of care as regular face-to-face follow-ups and glucose testing [17]. Therefore, it is essential to explore an effective way to implement health education interventions for patients with T2DM at the community level.

Prior Studies

Prior studies have explored various ways to improve self-care activities among patients with T2DM and improve interventions in many aspects.

First, the effectiveness of smartphone-based interventions has been confirmed for intervention platforms, and they can improve glucose control levels and self-care activities [18,19]. The development of technologies and apps that are self-developed or can be downloaded in app stores provides a valuable intervention tool for patients with diabetes [20-22]. Kho et al [23] developed an empirical diabetes app, but developing and popularizing such interventions is expensive, and they are difficult to generalize. Therefore, it is vital to explore cheap and generalizable intervention platforms. In China, WeChat, a free and popular social media platform with about 576 million users as of 2017, is used by people in daily life, [24,25] providing a potential platform to develop a generalized intervention program.

Second, the content of the intervention must focus on self-care activities, because these are important to achieve therapeutic targets and prevent the development of complications [26]; many prior interventions have therefore focused on self-care activities [27,28]. A majority of interventions implemented health education on behaviors such as diet, exercise, and foot care [27]. Self-care activities are directly influenced by T2DM risk knowledge and attitudes, such as risk perception [29]. However, few studies have conducted interventions via comprehensive programs [30]. Exploring a comprehensive intervention program that targets knowledge, health beliefs, and self-care behaviors is essential to improve glucose control among patients with T2DM [29,30], help them participate in community health management, and improve their communication with doctors via family members.

Third, for intervention subjects, prior studies focused on patients with T2DM [31], peers [32], and family members [33]. Family is an essential social support resource for self-care activities among patients with T2DM [34]. However, implementation of family-based intervention is difficult due to low participation rates of family members [35].

Aim

The study aimed to develop an eHealth family-based intervention program targeting knowledge, attitude, and behaviors and validate whether the intervention could improve glucose control among patients with T2DM registered in community health centers through a rigorously designed trial.
Methods

Study Design

According to the study protocol [36], the conceptual framework for this study was that the eHealth family-based intervention via WeChat would improve family members’ knowledge and risk perception of T2DM, which could help patients with T2DM to practice self-management, promote participation in community T2DM management, and improve communication with doctors, so that glucose control among patients with T2DM would ultimately be improved.

We conducted a single-center, 2-parallel-group randomized controlled trial that lasted 1 year to evaluate the effectiveness of this family-based intervention. Author LM was responsible for generating a random allocation sequence. The community health center enrolled the participants and assigned them to the intervention group or the control group. The intervention group received the eHealth intervention and usual care. The control group received usual care. The primary outcome was the HbA1c value. The secondary outcomes were self-care activities, risk perception, and family support. Notably, because the intervention was an eHealth intervention, participants knew they would receive the intervention when they provided informed consent; thus, the study participants could not be blinded. The study design strictly followed the Consolidated Standards of Reporting Trials (CONSORT) eHealth checklist (version 1.6.1).

Participants

According to the National Standard for Basic Public Health Services [14], community health service centers should maintain correspondence with patients and determine the prevalence of diabetes. This randomized control trial was conducted in the central area of Jiading District, which includes 2 community health service centers: Jiading Town Community Health Service Center and Juyuan New District Community Health Service Center. A total of 3874 individuals with diabetes were registered at these community health service centers. Of 1650 individuals with recorded HbA1c values, 879 had a value over 7%.

The inclusion criteria for the patients were as follows: (1) they were registered in 1 of the 2 community health service centers in the urban area in Jiading District, (2) they had been diagnosed with type 2 diabetes by a doctor at least 6 months before study enrollment, (3) they were aged 18 to 79 years, (4) their HbA1c level was ≥7%, (5) they had no plans to leave their place of residence in the following 12 months, and (6) they had a family member who could use WeChat and lived with the patient or visited them at least once a week.

The exclusion criteria for the patients were as follows: (1) they had other serious illnesses or illnesses not suitable for this study, (2) they were women who were pregnant or preparing for pregnancy, (3) they were unable to complete the 12-month follow-up for reasons such as moving and not transferring to another health care facility, (4) they were unwilling or unable to provide informed consent, and (5) they were currently participating in another intervention study.

Patients were required to choose 1 family member as a supporter to receive the corresponding intervention. The inclusion and exclusion criteria for the family members were as follows: (1) they were in regular contact with the patient, (2) they were nominated by the patient, (3) they were older than 18 years, and (4) they had never participated in other, similar research.

Patients and Public Involvement

Patients and the public were not involved in our research’s design, conduct, reporting, or dissemination plans.

Sample Size Calculation

We calculated the sample size based on a formula for comparing 2 means with a ratio of 1:1 between the intervention and control groups. This study used the HbA1c value as the most important indicator. The formula for comparing 2 sample means was as follows:

\[
\alpha = .05 \quad \beta = .20 \quad \delta = \text{effect size, which ranged from 0.25 to 0.70 [37-39]. In this study, we supposed that the effect size was 0.50, and } \sigma = 1.2 [36]. \quad \therefore \text{The ratio of participants was required in each group. Considering a dropout rate of 20%, we planned to recruit about 110 patients in each group. The ratio of family members to patients was 1:1.}
\]

Intervention Tool

The study established an official WeChat account called Jiading Sugar Steward, which included 3 modules: blood glucose data, complications, and notices. The intervention was implemented by using this account to deliver intervention articles. First, following the Guidelines for the Prevention and Treatment of T2DM, the study searched 4 domains of health intervention, including diabetes knowledge, complications, risk, and self-care activities (eg, diet, exercise, medication, lifestyle, glucose testing, and skills). All intervention articles were then developed based on the Knowledge-Attitude-Practice (KAP) model [40] and the Health Belief Model (HBM) [41]. The KAP model guided the relationship between basic knowledge and risk knowledge about T2DM, behaviors related to improving daily self-care activities among patients with T2DM, and family members’ attitudes on reminding patients with T2DM to improve their self-care activities. The HBM guided two aspects of family members’ attitudes: (1) knowledge that T2DM can induce significant health complications and (2) knowledge of the benefits of self-care activities and the risk of not performing these activities. We used the KAP model and the HBM to develop 38 comprehensive articles on topics including basic knowledge, skills, and risk knowledge, that is, behaviors and psychology (Figure 1 and Multimedia Appendix 1). All articles were divided into 3 categories: acquisition (A-level articles, scored 4 to 5), familiarity (B-level articles, scored 3), and understanding (C-level articles, scored 1 to 2).
**Intervention Process**

The intervention was composed of an online intervention and an in-person intervention.

**Online Intervention: Family Members**

The online intervention included 3 phases. During phase 1 (from January 1 to February 28, 2019), family members of patients with T2DM in the intervention group were asked to follow the official WeChat account and add it to their personal WeChat. During phase 2 (from March 1 to May 31, 2019), the study regularly delivered the 38 articles described above (about 3 articles were delivered per week, on Monday, Wednesday, and Friday). A-level articles were sent one-to-one via the official WeChat account and messages. B-level articles were sent by forwarding individual WeChat Moments. C-level articles were released through the official WeChat account (Multimedia Appendix 2). All online intervention articles were delivered at 6 AM or 5 PM on the push day so that subjects could receive the intervention outside of working hours. During phase 3 (June 1, 2019, to February 29, 2020), we measured the effectiveness of the online intervention.

**In-Person Intervention: Patients With T2DM**

The National Standard for Basic Public Health Services [14] calls for all patients with T2DM to receive on-site health education once every 3 months. For the in-person intervention in this study, which we compared with usual care (diet control, glucose testing, and auxiliary activities during exercise), we developed risk-perception–based health education courses focused on the practice of skills. Taking exercise as an example, we conducted health education on how patients with T2DM should properly exercise to manage their glucose levels. We also educated patients with T2DM on the risks and benefits of self-care activities. An example of a risk is that patients with T2DM cannot spend a long time out of the home because of the possibility of their glucose becoming low. An example of a benefit is that exercise can help control glucose.

The intervention measure was implemented by family practitioners and doctors in the prevention and health section. Family practitioners were mainly responsible for conducting follow-ups every 3 months. Doctors in the prevention and health section were mainly responsible for background operations, maintaining the official WeChat account, and cooperating with family practitioners.

**Outcome Measures**

**Primary Outcome**

HbA₁c has been clinically used as a gold standard for assessing long-term blood glucose control and reflects blood glucose concentration over approximately 3 months [42,43]. Therefore, we selected HbA₁c as the primary outcome. HbA₁c was measured at Jiading Central Hospital. A lower HbA₁c level means that a patient with T2DM has better glucose control.

**Secondary Outcomes**

Four secondary outcomes were measured by questionnaires that were confirmed to be suitable for use by Chinese people. The questionnaires covered topics including diabetes self-care activities [44], risk perception of diabetes [45], and family support [46].

**Self-care Activities**

Self-care activities were measured using the Summary of Diabetes Self-Care Activities scale [47], which measures normal diet, abnormal diet, exercise, blood glucose monitoring, foot care, and smoking. Besides the last item, which is scored from 1 to 2, the other items range from 0 to 7. The higher the final score, the better the patient’s self-care behavior. A higher score means that a patient with T2DM has better performance of self-care activities.
Risk Perception
Risk perception was examined using the Risk Perception Survey–Diabetes Mellitus scale [48], which is divided into 2 modules (risk perception and risk knowledge), with 31 entries in 6 dimensions. However, the dimension “comparative environmental risk” was removed because it is unsuitable for people with a Chinese cultural background. This decision was made after expert consultation and interviews with patients with T2DM and their family members. The meanings of the remaining 5 dimensions are shown in Multimedia Appendix 3. The total risk knowledge score is the sum of the 5 items.

Family Support
Family support was evaluated using the Diabetes Family Behavior Checklist [49], which contains 16 items scored from 1 to 5. A score of 1 means that the patient never receives support from their family. A score of 5 means that the family always supports the patient. This indicator includes positive support and negative support. A higher positive support score or lower negative support score mean patients with T2DM have a better family living environment with better family support behaviors.

Data Collection and Randomization
From January 1 to February 28, 2019, the study recruited participants according to the inclusion and exclusion criteria. Eventually, 228 pairs of participants were enrolled in each group. They were randomly allocated to the intervention and control groups at the individual level via a random-number table; 114 pairs of participants were assigned to the intervention and control groups. The intervention measure was then implemented for a period of 12 months.

To measure HbA1c, we collected blood samples at baseline and the 12th month. Laboratory tests were done at the Jiading Central Hospital. Secondary outcomes were collected via on-site questionnaire surveys at baseline and the 12th month. The baseline questionnaire survey was conducted by 4 authors (XL, LM, YZ, and YF), who collected data from patients with T2DM and their family members individually at the community health service centers. At the 12th month, the participants were contacted by telephone and the research team re-collected their data.

Statistical Analysis
Sociodemographic characteristics were summarized for the intervention and control groups. Frequencies and percentages were used for categorical variables and mean (SD) for continuous variables.

To assess the effectiveness of the intervention, a 2-tailed paired-sample *t* test was used to compare the baseline and follow-up data in the intervention and control groups. Changes between the baseline and follow-up period in the intervention and control groups were measured with the 95% CI at baseline and the 12th month. Finally, since HbA1c was the primary outcome, we further analyzed sex subgroups to explore whether the results differed between males and females. Furthermore, we used an analysis of covariance to clarify the intervention effect and included the sex, age, and education of patients with T2DM, the family members’ education, and the family members’ relationship as covariables.

All data management and analyses were performed using Stata (version 15.0; Stata Corp). We set α=.05 and β=.20; the power was 80%. Statistical significance was set at *P*<.05.

Ethics Approval
Informed consent was provided by all participants. In addition, the trial was ethically approved by the Medical Research Ethics Committee of the School of Public Health Fudan University (2018-01-0663). All participants provided written informed consent.

Results
Participant Characteristics
In total, 225 patients (113 patients in the intervention group and 112 patients in the control group) completed this 1-year intervention study. Three participants (1 in the intervention group and 2 in the control group) were lost to follow-up. Figure 2 shows the process of inclusion in each analysis, starting with the originally assigned groups.

Among the 225 patients, 48.4% (n=109) were men and 51.6% (n=116) were women, with a mean age of 65.6 (SD 7.1) years. Of the 225 family members nominated by the included patients, 48% (n=108) were men and 52% (n=117) were women, with a mean age of 48.5 years. Spouses were the family members who most commonly lived with the patients. The baseline sociodemographic and clinical characteristics of the patients and their family members are shown in Table 1.
Figure 2. Flow diagram of trial participation.
Table 1. Characteristics of the patients and their family members at baseline.

<table>
<thead>
<tr>
<th>Participants/characteristics</th>
<th>Intervention group (n=113)</th>
<th>Control group (n=112)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Patients with type 2 diabetes</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender, n (%)</td>
<td></td>
<td></td>
<td>.64</td>
</tr>
<tr>
<td>Male</td>
<td>53 (46.9)</td>
<td>56 (50)</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>60 (53.1)</td>
<td>56 (50)</td>
<td></td>
</tr>
<tr>
<td>Age (years), mean (SD)</td>
<td>65.7 (6.7)</td>
<td>65.4 (7.5)</td>
<td>.78</td>
</tr>
<tr>
<td>Marriage status, n (%)</td>
<td></td>
<td></td>
<td>.20</td>
</tr>
<tr>
<td>Married</td>
<td>106 (93.8)</td>
<td>98 (87.5)</td>
<td></td>
</tr>
<tr>
<td>Divorced</td>
<td>2 (1.8)</td>
<td>2 (1.8)</td>
<td></td>
</tr>
<tr>
<td>Widowed</td>
<td>5 (4.4)</td>
<td>12 (10.7)</td>
<td></td>
</tr>
<tr>
<td>Education, n (%)</td>
<td></td>
<td></td>
<td>.59</td>
</tr>
<tr>
<td>Illiterate</td>
<td>12 (10.6)</td>
<td>12 (10.7)</td>
<td></td>
</tr>
<tr>
<td>Primary school</td>
<td>26 (23)</td>
<td>21 (19.4)</td>
<td></td>
</tr>
<tr>
<td>Junior school</td>
<td>45 (39.8)</td>
<td>39 (34.8)</td>
<td></td>
</tr>
<tr>
<td>Senior school</td>
<td>21 (18.6)</td>
<td>31 (27.7)</td>
<td></td>
</tr>
<tr>
<td>Undergraduate or college</td>
<td>9 (8)</td>
<td>6 (5.4)</td>
<td></td>
</tr>
<tr>
<td>Postgraduate or above</td>
<td>0 (0)</td>
<td>0 (0)</td>
<td></td>
</tr>
<tr>
<td>Employment status, n (%)</td>
<td></td>
<td></td>
<td>.19</td>
</tr>
<tr>
<td>Employed</td>
<td>11 (9.7)</td>
<td>14 (12.5)</td>
<td></td>
</tr>
<tr>
<td>Retired</td>
<td>99 (87.6)</td>
<td>98 (87.5)</td>
<td></td>
</tr>
<tr>
<td>Unemployed</td>
<td>3 (2.7)</td>
<td>0 (0)</td>
<td></td>
</tr>
<tr>
<td>Average household monthly income (US $), n (%)</td>
<td></td>
<td></td>
<td>.38</td>
</tr>
<tr>
<td>&lt;416.10</td>
<td>14 (12.4)</td>
<td>15 (13.4)</td>
<td></td>
</tr>
<tr>
<td>416.10-832.19</td>
<td>52 (46)</td>
<td>41 (36.6)</td>
<td></td>
</tr>
<tr>
<td>832.20-1248.30</td>
<td>32 (28.3)</td>
<td>39 (34.8)</td>
<td></td>
</tr>
<tr>
<td>&gt;1248.30</td>
<td>15 (13.3)</td>
<td>17 (15.2)</td>
<td></td>
</tr>
<tr>
<td>Duration of diabetes (years), mean (SD)</td>
<td>12.8 (6.3)</td>
<td>13.6 (7.2)</td>
<td>.37</td>
</tr>
<tr>
<td><strong>Family members</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender, n (%)</td>
<td></td>
<td></td>
<td>.39</td>
</tr>
<tr>
<td>Male</td>
<td>51 (45.1)</td>
<td>57 (50.9)</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>62 (54.8)</td>
<td>55 (49.1)</td>
<td></td>
</tr>
<tr>
<td>Age (years), mean (SD)</td>
<td>47.9 (14.5)</td>
<td>49.1 (11.8)</td>
<td>.50</td>
</tr>
<tr>
<td>Relationship, n (%)</td>
<td></td>
<td></td>
<td>.61</td>
</tr>
<tr>
<td>Spouse</td>
<td>36 (31.9)</td>
<td>38 (33.9)</td>
<td></td>
</tr>
<tr>
<td>Son</td>
<td>26 (23)</td>
<td>28 (25)</td>
<td></td>
</tr>
<tr>
<td>Daughter</td>
<td>7 (6.2)</td>
<td>11 (9.8)</td>
<td></td>
</tr>
<tr>
<td>Daughter-in-law</td>
<td>35 (31)</td>
<td>31 (27.7)</td>
<td></td>
</tr>
<tr>
<td>Son-in-law</td>
<td>1 (0.9)</td>
<td>0 (0)</td>
<td></td>
</tr>
<tr>
<td>Grandson or granddaughter</td>
<td>8 (7.1)</td>
<td>4 (3.6)</td>
<td></td>
</tr>
<tr>
<td>Education, n (%)</td>
<td></td>
<td></td>
<td>.98</td>
</tr>
<tr>
<td>Illiterate</td>
<td>1 (0.9)</td>
<td>1 (0.9)</td>
<td></td>
</tr>
<tr>
<td>Primary school</td>
<td>12 (10.6)</td>
<td>5 (4.5)</td>
<td></td>
</tr>
<tr>
<td>Junior school</td>
<td>24 (21.2)</td>
<td>26 (23.2)</td>
<td></td>
</tr>
</tbody>
</table>
Effectiveness Outcomes

In the intervention group, HbA1c level ($P<.001$) and nonsupportive behavior ($P=.03$) decreased and the scores for general diet ($P<.001$), specific diet ($P<.001$), exercise ($P=.002$), blood sugar testing ($P=.02$), foot care ($P<.001$), risk knowledge ($P<.001$), personal control ($P<.001$), worry ($P=.02$), optimism bias ($P=.03$), and supportive behaviors ($P<.001$) improved. In the control group, besides general diet ($P=.002$), there were no statistically significant differences between baseline and follow-up (Table 2).

Table 2. Primary and secondary effectiveness outcomes. The change in score is the follow-up score minus the baseline score. The 95% CIs that do not contain 0 are statistically used to show the intervention effectiveness after an individual received the intervention. $P$ values are the result of a paired-sample $t$ test to demonstrate whether the difference was statistically significant.

<table>
<thead>
<tr>
<th>Participants/characteristics</th>
<th>Intervention group (n=113)</th>
<th>Control group (n=112)</th>
<th>$P$ value</th>
<th>$P$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chronic disease, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>70 (61.9)</td>
<td>82 (73.2)</td>
<td>0.07</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>43 (38.1)</td>
<td>30 (26.8)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Glycated hemoglobin A1c level (%)</td>
<td>7.90 (0.75)</td>
<td>7.30 (1.07)</td>
<td>-0.60 (-0.82 to -0.38)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Gender (score)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>7.99 (0.87)</td>
<td>7.46 (1.11)</td>
<td>-0.53 (-0.88 to -0.18)</td>
<td>.004</td>
</tr>
<tr>
<td>Female</td>
<td>7.83 (0.61)</td>
<td>7.16 (1.01)</td>
<td>-0.62 (-0.95 to -0.37)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Self-care activities (score)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>General diet</td>
<td>5.36 (2.37)</td>
<td>6.39 (1.09)</td>
<td>1.03 (0.58 to 1.48)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Specific diet</td>
<td>3.59 (1.73)</td>
<td>4.31 (1.36)</td>
<td>0.72 (0.34 to 1.09)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Exercise</td>
<td>3.55 (1.96)</td>
<td>4.22 (1.99)</td>
<td>0.67 (0.26, 1.07)</td>
<td>.002</td>
</tr>
<tr>
<td>Blood sugar testing</td>
<td>1.53 (1.81)</td>
<td>2.09 (2.07)</td>
<td>0.56 (0.11 to 1.00)</td>
<td>.02</td>
</tr>
<tr>
<td>Foot care</td>
<td>1.56 (2.46)</td>
<td>3.23 (2.76)</td>
<td>1.67 (1.12 to 2.22)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Smoking</td>
<td>0.79 (0.41)</td>
<td>0.85 (0.36)</td>
<td>0.06 (-0.01 to 0.13)</td>
<td>.07</td>
</tr>
<tr>
<td>Risk perception of diabetes (score)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Risk knowledge</td>
<td>3.32 (1.63)</td>
<td>4.45 (1.13)</td>
<td>1.13 (0.79 to 1.47)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Personal control</td>
<td>2.94 (0.40)</td>
<td>3.15 (0.44)</td>
<td>0.21 (0.12 to 0.32)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Worry</td>
<td>2.73 (0.69)</td>
<td>2.91 (0.55)</td>
<td>0.18 (0.03 to 0.33)</td>
<td>.02</td>
</tr>
<tr>
<td>Optimism bias</td>
<td>2.75 (0.63)</td>
<td>2.92 (0.58)</td>
<td>0.17 (0.01 to 0.32)</td>
<td>.03</td>
</tr>
<tr>
<td>Personal risk</td>
<td>2.22 (0.55)</td>
<td>2.11 (0.62)</td>
<td>-0.11 (-0.25, 0.02)</td>
<td>.10</td>
</tr>
<tr>
<td>Family support (score)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Supportive behaviors</td>
<td>20.25 (6.65)</td>
<td>25.69 (6.67)</td>
<td>5.44 (4.07 to 6.81)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Nonsupportive behaviors</td>
<td>29.82 (3.93)</td>
<td>28.71 (4.48)</td>
<td>-1.11 (-2.09 to -0.14)</td>
<td>.03</td>
</tr>
</tbody>
</table>
The Effect of the eHealth Family-Based Intervention

Patients with T2DM who participated in the eHealth family-based intervention had significantly lower HbA1c values (β = –.69, 95% CI –.99 to –.39; P < .001) and improved scores for general diet (β = .60, 95% CI .20-1.00; P = .003), special diet (β = .71, 95% CI .34-1.09; P < .001), blood sugar testing (β = .50, 95% CI .02-.98; P = .04), foot care (β = 1.82, 95% CI 1.23-2.42; P < .001), risk knowledge (β = .89, 95% CI .55-1.24; P < .001), personal control (β = .22, 95% CI .12-.32; P < .001), worry (β = .24, 95% CI .10-.39; P = .001), optimism bias (β = .26, 95% CI .09-.43; P = .003), and supportive behaviors (β = 5.52, 95% CI 4.03-7.01; P < .001), as shown in Table 3.
Table 3. Results of analysis of covariance for the effect of the eHealth family-based intervention. The covariables included patient gender, patient age, patient education, family member education, and family member relationship. We only show covariables with statistical implications.

<table>
<thead>
<tr>
<th>Effective outcomes</th>
<th>β</th>
<th>SE (95% CI)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Glycated hemoglobin A1c level</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intervention</td>
<td>-.69</td>
<td>.15 (−.99 to −.39)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Baseline hemoglobin A1c level</td>
<td>.26</td>
<td>.11 (.04 to .47)</td>
<td>.02</td>
</tr>
<tr>
<td>General diet</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intervention</td>
<td>.60</td>
<td>.30 (.20 to 1.00)</td>
<td>.003</td>
</tr>
<tr>
<td>Baseline general diet</td>
<td>.23</td>
<td>.04 (.14 to .31)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Special diet</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intervention</td>
<td>.71</td>
<td>.19 (.34 to 1.09)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Blood sugar testing</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Intervention</td>
<td>.50</td>
<td>.24 (.02 to .98)</td>
<td>.04</td>
</tr>
<tr>
<td>Baseline blood sugar testing</td>
<td>.33</td>
<td>.06 (.20 to .45)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Foot care</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intervention</td>
<td>1.82</td>
<td>.30 (1.23 to 2.42)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Baseline foot care</td>
<td>.22</td>
<td>.07 (.09 to .35)</td>
<td>.001</td>
</tr>
<tr>
<td>Patient age</td>
<td>.79</td>
<td>.31 (.17 to 1.41)</td>
<td>.01</td>
</tr>
<tr>
<td>Smoking</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Intervention</td>
<td>.02</td>
<td>.04 (−.05 to .09)</td>
<td>.56</td>
</tr>
<tr>
<td>Baseline smoking</td>
<td>.57</td>
<td>.05 (.47 to .67)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Patient gender</td>
<td>.09</td>
<td>.04 (.01 to .17)</td>
<td>.03</td>
</tr>
<tr>
<td>Risk knowledge</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intervention</td>
<td>.89</td>
<td>.18 (.55 to 1.24)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Baseline risk knowledge</td>
<td>.15</td>
<td>.06 (.03 to .26)</td>
<td>.02</td>
</tr>
<tr>
<td>Patient age</td>
<td>.49</td>
<td>.18 (.12 to .89)</td>
<td>.009</td>
</tr>
<tr>
<td>Personal control</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Intervention</td>
<td>.22</td>
<td>.05 (.12 to .32)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Worry</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intervention</td>
<td>.24</td>
<td>.08 (.10 to .39)</td>
<td>.001</td>
</tr>
<tr>
<td>Baseline worry</td>
<td>.15</td>
<td>.06 (.04 to .26)</td>
<td>.009</td>
</tr>
<tr>
<td>Optimism bias</td>
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<td></td>
</tr>
<tr>
<td>Intervention</td>
<td>.26</td>
<td>.09 (.09 to .43)</td>
<td>.003</td>
</tr>
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<td>.01</td>
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<td>.75 (4.03 to 7.01)</td>
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T2DM to achieve ideal control could be explained by the fact that only patients with uncontrolled T2DM (HbA1c >7%) were enrolled in our study. Glycemic control in patients with T2DM is complex and is influenced by various factors, such as medicine adjustment, regular visits to a doctor, and lifestyle; the presence of these factors was confirmed during interviews with doctors and community health service providers. While ideal control was not achieved, patients with T2DM in the intervention group still had significantly lower HbA1c levels than patients in the control group after 12 months, suggesting that the eHealth family-based intervention was an effective way to improve glucose control. In future studies, specific factors influencing glucose control should be considered in combination with an eHealth family-based intervention to educate patients with T2DM and their family members.

Sun et al [19] conducted a study that was similar to ours based on a diet intervention conducted by dietitians among outpatients; their intervention was more effective (HbA1c decreased from 7.84% to 6.84%) than ours (HbA1c decreased from 7.9% to 7.3%). A possible reason is that the health providers were from a tertiary hospital and could provide more professional suggestions, making the patients more willing to comply. However, dietitian-based interventions are difficult to generalize due to the shortage of these professionals. Our study was a community-based intervention, and the community was a national health-management platform for patients with T2DM. Therefore, our community-based intervention is more generalizable in real life.

Yang et al [56] also conducted a study of patients with T2DM and obtained good results; however, effectiveness in their study (a change in HbA1c of 0.3%) was lower than in our study. One possible reason is that their intervention content was based only on the medical guidelines of the Korean Diabetes Association, while our study developed intervention content based on the National Standard for Basic Public Health Services [14] and provided specific family support. Although the Guidelines for the Prevention and Treatment of Type 2 Diabetes Mellitus in China (2020 revision) [3] reported that family members also play an important role in health management for patients with T2DM, this guideline does not provide specific measures. Our study added a specific family member–based health intervention to the basic health intervention in accordance with the guideline. Another possible reason for the differences between this study and the previous one is that we added information on risk perception during the process of health intervention development, which could have improved our health intervention.

New eHealth interventions, with their improved accessibility, have the potential to replace in-person interventions [57]. Despite their potential benefits, we identified certain limitations.
of eHealth interventions in our study. First, social support can be classified into 4 types: emotional, instrumental, informational, and appraisal [53,58,59]. It is, however, difficult to evaluate how eHealth interventions may contribute to the social support of patients with T2DM [53]. Second, commonly used eHealth interventions, such as text messages, apps, and web-based programs, are known to have a positive impact on the self-management behaviors of patients with T2DM; however, due to limitations related to character count per message, content type, interactivity, cost, accessibility, and internet connection capacity, it is difficult to compare and generalize findings across studies [60].

Considering the aforementioned limitations of eHealth interventions in previous studies, we used WeChat, a common and free app used daily by Chinese people [24,25], to address limitations related to accessibility, cost, and internet connection capacity, although we did not consider instrument support in our study. Additionally, for the delivery of the articles, we classified them into 3 types and delivered them in different ways, which solved the limitation related to character count. For articles in the official WeChat account, different types of content, such as video content, could be linked at the bottom of each article, which solved the limitation related to content type. To evaluate the extent of social support in our study, we sufficiently considered the impact of family members on patients with T2DM when designing the intervention tools by referring to the KAP and HBM conceptual frameworks.

**Strengths and Limitations**

The major strength of this study is that the eHealth family-based intervention used content usually delivered as part of in-person health education, as set out in the National Standard for Basic Public Health Services. The dropout rate of participants was very low (only 3 pairs of participants).

However, this study also has some limitations. First, the sample was small and only included patients enrolled in 1 city. Future studies should include larger samples from multiple sources. Second, the intervention time was 1 year, and we did not perform continuous follow-up of the patients with T2DM and their family members. Consequently, we could only conclude whether the intervention was effective over a period of time; we could not confirm its long-term effects. Third, participant compliance was not comprehensively documented; for example, we did not determine how long or how often patients with T2DM or their family members read the intervention articles. Fourth, due to a reduced workforce and funding restrictions, we did not collect data at 6 months. Restrictions also prevented us from collecting some indicators that were included in the protocol, such as weight, height, waist circumference, hip circumference, blood pressure, and BMI.

Additionally, during the process of intervention implementation, we revised the inclusion and exclusion criteria that were published in the protocol to remove “no history of diabetes” for the family members and add “never participated in other, similar research.” We made this revision because the study aimed to find an intervention program that is suitable for the real world. After the protocol was developed, we came to understand that the family members of patients with T2DM could also develop T2DM. If we had recruited participants based on the inclusion and exclusion criteria in the protocol, a large number of suitable participants would have been lost, because T2DM is a common disease in older adults. The patients with T2DM were often older people whose family members were a spouse, their child, or a son- or daughter-in-law; the mean age of these family members was greater than 45 years. In addition, to avoid influence from other research, we required that the family members had not participated in other research that was similar to our study.

**Conclusions**

We conducted a structured eHealth family-based intervention program that included T2DM-related knowledge, risks, and skills to enhance the ability and risk perceptions of family members regarding T2DM. This intervention was able to effectively help patients with T2DM to improve their glucose control by promoting participation in community health management and strengthening their self-management behaviors. Overall, this eHealth family-based intervention for patients with uncontrolled T2DM is a promising way to empower family members to support these patients in their endeavors to improve self-management behaviors. Our study also provides information for community health providers to develop health intervention content and mobile health intervention platforms for patients with uncontrolled T2DM.

**Acknowledgments**

This project was supported by the National Natural Science Foundation of China (grants 72274036 and 71573049), the National Social Science Foundation of China (grant 17ZDA078), and the 111 Project (grant B16031). We would like to thank the Community Health Service Center of Juyuan New District, Jiading District, Shanghai, China, for the trial implementation. We are also very grateful to all the family members and doctors for their time and participation in the study. In addition, we would like to thank Editage for English language editing.

**Authors’ Contributions**

YF contributed to data acquisition, analysis, and interpretation and the conception, design, drafting, and revision of the manuscript. YZ contributed to data acquisition and study design. LM and MG recruited the study participants, designed the study, collected baseline and follow-up data, and suggested the intervention. HY contributed to the provision of important information on chronic noncommunicable disease intervention and guided the implementation of the intervention. JL contributed to the design and revision of the manuscript. Q Zhao contributed suggestions on the study design, questionnaires, and intervention. Q Zhang provided suggestions on the study design, questionnaires, and intervention.
to data interpretation and manuscript revision. XL contributed to data acquisition and interpretation and conception, design, and revision of the manuscript. All authors approved the final draft submitted. YF is the guarantor of this work and, as such, has full access to all the study data and takes responsibility for the integrity of the data and the accuracy of data analyses.

Conflicts of Interest
None declared.

Multimedia Appendix 1
The list of intervention articles’ themes.
[DOCX File, 13 KB - mhealth_v11i1e40420_app1.docx ]

Multimedia Appendix 2
Online intervention flowchart.
[DOCX File, 122 KB - mhealth_v11i1e40420_app2.docx ]

Multimedia Appendix 3
The meanings of each indicator in Risk Perception Survey-Diabetes Mellitus.
[DOCX File, 12 KB - mhealth_v11i1e40420_app3.docx ]

Multimedia Appendix 4
CONSORT-eHEALTH checklist (V 1.6.1).
[PDF File (Adobe PDF File), 3261 KB - mhealth_v11i1e40420_app4.pdf ]

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JMIR Mhealth Uhealth 2023 | vol. 11 | e40420 | p.883
(page number not for citation purposes)


47. Toobert DJ, Hampson SE, Glasgow RE. The summary of diabetes self-care activities measure: results from 7 studies and a revised scale. Diabetes Care 2000 Jul;23(7):943-950 [FREE Full text] [doi: 10.2337/diacare.23.7.943] [Medline: 10895844]


Abbreviations

**CONSORT**: Consolidated Standards of Reporting Trials

**HbA1c**: glycated hemoglobin A1c

**HBM**: Health Belief Model

**KAP**: Knowledge-Attitude-Practice

**T2DM**: type 2 diabetes mellitus

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Testing Mechanisms of Change for Text Message–Delivered Cognitive Behavioral Therapy: Randomized Clinical Trial for Young Adult Depression

Michael J Mason1, PhD; J Douglas Coatsworth1, PhD; Nikola Zaharakis1, PhD; Michael Russell2, PhD; Aaron Brown3, PhD; Sydney McKinstry1, BA

1Center for Behavioral Health Research, College of Social Work, University of Tennessee, Knoxville, TN, United States
2Department of Biobehavioral Health, Pennsylvania State University, University Park, PA, United States
3College of Social Work, University of Kentucky, Lexington, KY, United States

Corresponding Author:
Michael J Mason, PhD
Center for Behavioral Health Research
College of Social Work
University of Tennessee
Center for Behavioral Health Research
202 Henson Hall
Knoxville, TN, 37996
United States
Phone: 1 18659749148
Email: mmason29@utk.edu

Abstract

Background: Current psychiatric epidemiological evidence estimates that 17% of young adults (aged 18-25 years) experienced a major depressive episode in 2020, relative to 8.4% of all adults aged ≥26 years. Young adults with a major depressive episode in the past year are the least likely to receive treatment for depression compared with other age groups.

Objective: We conducted a randomized clinical trial following our initial 4-week SMS text message–delivered cognitive behavioral therapy (CBT-txt) for depression in young adults. We sought to test mechanisms of change for CBT-txt.

Methods: Based on participant feedback, outcome data, and the empirical literature, we increased the treatment dosage from 4-8 weeks and tested 3 mechanisms of change with 103 young adults in the United States. Participants were from 34 states, recruited from Facebook and Instagram and presenting with at least moderate depressive symptomatology. Web-based assessments occurred at baseline prior to randomization and at 1, 2, and 3 months after enrollment. The primary outcome, the severity of depressive symptoms, was assessed using the Beck Depression Inventory II. Behavioral activation, perseverative thinking, and cognitive distortions were measured as mechanisms of change. Participants were randomized to CBT-txt or a waitlist control condition. Those assigned to the CBT-txt intervention condition received 474 fully automated SMS text messages, delivered every other day over a 64-day period and averaging 14.8 (SD 2.4) SMS text messages per treatment day. Intervention texts are delivered via TextIt, a web-based automated SMS text messaging platform.

Results: Across all 3 months of the study, participants in the CBT-txt group showed significantly larger decreases in depressive symptoms than those in the control group (P<.001 at each follow-up), producing a medium-to-large effect size (Cohen d=0.76). Over half (25/47, 53%) of the treatment group moved into the “high-end functioning” category, representing no or minimal clinically significant depressive symptoms, compared with 15% (8/53) of the control condition. Mediation analysis showed that CBT-txt appeared to lead to greater increases in behavioral activation and greater decreases in cognitive distortions and perseverative thinking across the 3-month follow-up period, which were then associated with larger baseline to 3-month decreases in depression. The size of the indirect effects was substantial: 57%, 41%, and 50% of the CBT-txt effect on changes in depression were mediated by changes in behavioral activation, cognitive distortions, and perseverative thinking, respectively. Models including all 3 mediators simultaneously showed that 63% of the CBT-txt effect was mediated by the combined indirect effects.

Conclusions: Results provide evidence for the efficacy of CBT-txt to reduce young adult depressive symptoms through hypothesized mechanisms. To the best of our knowledge, CBT-txt is unique in its SMS text message–delivered modality, the strong clinical evidence supporting efficacy and mechanisms of change.
Introduction

Background

In 2020, young adults (ages 18–25 years) in the United States experienced more major depressive episodes than other age groups and were the least likely to receive treatment for depression (eg, talking with a health provider or taking prescription medication) [1].

Even when the rates for the treatment of depression rose nationwide, the rates for the treatment of depression for young adults rose at a significantly lower rate [2]. Paradoxically, more young adults with depression report greater perceived unmet need for mental health services than other age groups [1]. From 2011 to 2019, the most common reason that young adults report for not receiving treatment is cost, followed by “not knowing where to go to receive treatment” [3]. This unmet treatment need has been consistent over the last decade and places this group at an increased risk for substance use disorders, possibly indicating self-medication with substances to reduce depressive symptoms [4].

Mobile Health Treatments

Creative mental health treatment strategies are needed to reach young adults to address this unmet need. Digitally delivered mobile health (mHealth) treatments (or mHealth interventions) show promise for reaching young adults and serving as a clinical tool to address depression in young adults. Because mHealth interventions can increase large-scale access to evidence-based treatments, some countries such as New Zealand are integrating these approaches into their national health service infrastructure [5]. The rapid development and use of these treatments is a promising step for addressing psychiatric disorders. However, there is reason to be cautious regarding the science behind these efforts. In particular, rigorous studies on 2 important features of mHealth interventions are lacking in the research literature: testing treatment dosage and clinical mechanisms of change. First, understanding the appropriate dosage for mHealth interventions is critical to advance an empirical database that has maximum clinical utility. Knowing the correct dosage (how much treatment is needed to be delivered to meet the treatment goals of particular patients) is a primary goal of clinical research. In a recent meta-analysis that assessed the relationship between mHealth intervention length and intervention effect, Lu et al [6] found that interventions of at least 7 weeks’ duration had larger effect sizes on anxiety symptom reduction. However, for depression treatment, the optimal dosage remains unclear. Second, understanding the mechanisms of behavior change has not been adequately studied in mHealth interventions. Digital interventions have tremendous potential for identifying mechanisms of behavior change because these can be cost-effectively delivered to large enough samples to sufficiently power studies to detect mechanisms of change, the content is delivered reliably and precisely, and the manipulation of the hypothesized mediators can be strategically sequenced within a study design [7]. Unfortunately, many mHealth studies lack scientific rigor (eg, the lack of a priori hypothesized causal mechanisms of change coupled with an appropriate design), which is necessary to conduct mediational analyses [7]. In addition, although the delivery of mHealth interventions for mental disorders continues to expand, accompanying rigorous randomized clinical trials, including those that test dosage and mechanisms, have not kept pace with this growth [8].

Clinical Foundation

This study was conducted to better understand the mechanisms of SMS text message–delivered cognitive behavioral therapy (CBT-txt) as well as the acceptability of the treatment length. Our recent randomized clinical trial treating 102 young adults in the United States with at least moderate depressive symptomatology found that CBT-txt was acceptable, feasible, and efficacious compared with a waitlist control condition [9]. This 2-month trial had 4 weeks of treatment and tested a single mediator, behavioral activation, with assessments at baseline and at 1- and 2-month follow-ups. The treatment length mirrored the duration of our successful text-delivered cannabis use disorder treatment [10]. The initial CBT-txt trial found that the strongest treatment effect appeared at the 1-month follow-up (immediately after the treatment ended), particularly for participants who began with severe depressive symptoms. Mediation analysis revealed significant indirect treatment effects of increases in behavioral activation on reducing depressive symptoms, suggesting a mechanism of change [9,11]. Based upon these promising findings, we examined the treatment satisfaction data from this study, which revealed participants’ interest in receiving more treatment content and an increase in the duration of the intervention. Accordingly, we expanded CBT-txt from 4 to 8 weeks, which is consistent with the average mHealth dosage of 7 to 8 weeks [6,12]. We also expanded the treatment’s clinical content to include cognitive distortions and perseverative thinking, 2 additional candidate mediators common to cognitive behavioral therapy (CBT) treatment of depression [13-15].

This Study

Four hypotheses were tested for this follow-up study. The first hypothesis was that participants allocated to the treatment condition would show greater reductions in their depressive symptoms immediately following treatment (2 months after enrollment) and at the 3-month follow-up than participants in the waitlist control condition. Because treatment response has been linked to baseline symptom severity [9,16], we also tested
whether treatment effects were moderated by the participants’ baseline severity level. The second hypothesis was that treatment effects would be mediated by behavioral activation, such that increases in behavioral activation would reduce depressive symptoms in the treatment condition relative to the controls. The third hypothesis was that treatment effects would be mediated by cognitive distortions, such that decreases in cognitive distortions would reduce depressive symptoms in the treatment condition relative to controls. The fourth hypothesis was that treatment effects would be mediated by perseverative thinking, such that decreases in perseverative thinking would reduce depressive symptoms in the treatment condition relative to the controls. In addition to testing these 4 hypotheses, we were interested in comparing the results (effect sizes and treatment response over time) from this 8-week intervention with those from our prior trial of the 4-week intervention.

Methods

Procedures

In total, 103 young adults (ages 18-25 years) were recruited and enrolled in a 3-month randomized clinical trial. Participants were recruited using age-targeted advertising on Facebook and Instagram for young adults residing in the United States. Recruitment occurred over a 7-week period from July 6 to August 28, 2022. The study was advertised to all those within the study age range (18-25 years) across the United States who used Facebook and Instagram. With the aim of recruiting a geographic, racial and ethnic, and socioeconomically diverse sample, we placed no restrictions on advertisements other than age, used advertisements with a variety of images featuring people of different racial groups, and used a variety of placements (eg, feeds, stories, and reels) to reach the widest swath of potential participants. Interested individuals were directed to a study website where they would read more about the study and answer eligibility screening questions on their phones.

The study was registered at ClinicalTrials.gov (identifier NCT05551702).

Design

The study design was a 2-arm randomized clinical trial with participants allocated to either the experimental condition or the waitlist control condition. Eligibility requirements were (1) age between 18 and 25 years; (2) a score of at least 10 on the Patient Health Questionnaire–9 (PHQ-9) [17], indicating at least moderate depressive symptom severity; (3) access to a smartphone; (4) fluent in English; (5) have not received treatment for depression in the past 3 months; and (6) did not endorse suicidal ideation (SI) on the PHQ-9 measure. All interested participants completed a screening questionnaire assessing eligibility. Those who screened positive for suicide and those who did not meet the study criteria were immediately referred to local and national mental health resources. To ensure that participants who did not qualify for the study still had access to care, participants who were not eligible based on the endorsement of SI had the option of speaking with a project staff member who is a licensed mental health professional for assistance with referral to care. Individuals who wanted to talk with a licensed mental health staff member were contacted within 1 business day and provided contact information to at least 3 mental health providers in their area, including at least 1 provider who offered sliding scale or safety net (ie, no cost) services. In addition, individuals were given the contact information to the National Alliance on Mental Illness location in their area. The National Alliance on Mental Illness provides additional mental health resources, including no-cost support groups for individuals living with mental illness [18].

Remote Data Collection Quality Control

Data were reviewed carefully on a daily basis for quality control. Beginning July 26, 2022, we noticed increased screening activity with similar name patterns. After carefully reviewing the screening data, including the name, mailing address, IP address, phone number with area code and service carrier, and survey responses, we determined that 17 enrolled cases may have been fraudulent. We reached out via text, phone, and email to these 17 cases to confirm their identity but none of the participants responded. All 17 cases were administratively removed from the study on July 28, 2022. We enacted other procedures, such as using Qualtrics (Qualtrics), the web-based survey program that flags responses likely to be from bots, attempts to prevent multiple submissions from a single respondent, and assigns a fraud score indicating the likelihood of a response being fraudulent [19]. Furthermore, at screening, participants must enter a unique phone number, which is then verified using a Twilio mobile phone app.

Eligible individuals were instructed to complete the baseline survey on their phones, where upon completion, they were randomized to either the treatment or waitlist control condition. Randomization was automated by Qualtrics as part of the baseline survey. Randomization was stratified by sex using block randomization with a fixed block size of 10 to reduce bias during randomization and to ensure equal representation of sex across both conditions. The participants completed follow-up assessments at the 1-, 2-, and 3-month follow-ups. Waitlist condition participants were eligible to receive the treatment texts upon the completion of the 3-month follow-up survey. Participants who completed the screening, baseline, and all follow-up assessments received US $150 in Amazon eGift cards.

Text-Delivered Treatment: CBT-txt

Overview

CBT-txt was adapted from an evidenced-based, in-person CBT treatment manual [20] shown to be effective in reducing depressive symptoms [21-23] and adaptable to digital formats [24]. CBT-txt focuses on empowering participants to understand how thoughts, activities, and other people affect their moods. CBT-txt is a fully automated SMS text message–delivered program that initiates a conversation at predetermined times and requires a participant response to activate the subsequent text message. Tailored messages are sent based on the participant’s responses or ratings of their depression. For example, a participant may be asked about their engagement with CBT skills and are given 3 response choices: a, b, or c. Each response option activates a different CBT-txt message providing tailored responses. The treatment provides
individualized text-based conversations every other day over the course of the intervention.

**Theoretical Underpinnings of CBT-txt**

The theory underlying CBT-txt is the Generic Cognitive Model, which specifies common cognitive and behavioral processes associated with disorders such as depression [25]. These processes manifest along a continuum from normal adaptive functioning to psychopathology. As individuals experience environmental, psychological, and social stimuli, their attentional response system is activated to determine an adaptive response. The attentional response activates schemas, defined as internally stored representations of stimuli that form underlying structures for organizing perceptions of the world [26]. When the schema is maladaptive or disproportionate relative to the stimuli, the individual experiences psychological problems that can escalate into a psychiatric disorder.

**Clinical Structure of CBT-txt**

We expanded our initial 4-week CBT-txt treatment [9] into an 8-week intervention. CBT-txt intervention content is guided by CBT core mechanisms [13] and is sequenced using the in-person treatment manual of Muñoz et al [20]. CBT-txt is organized around eight topical areas delivered across 8 weeks as indicated in Table 1:

1. introduction to CBT, moods, thoughts, feelings
2. how thoughts affect moods (Automatic thoughts; ABCD method)
3. how activities affect moods (Behavioral activation)
4. how repetitive negative thinking affects moods (Perseverative thinking)
5. how cognitive distortions affect moods (Cognitive distortion)
6. how activities, goals, and values affect moods (Behavioral activation)
7. how other people affect moods (Social support and moods); Summary
8. how we think about depression (Intro to CBT, moods, thoughts, feelings)

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<th>Week</th>
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<tr>
<td>2</td>
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<td>72</td>
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<td>3</td>
<td>4</td>
<td>62</td>
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</tr>
<tr>
<td>4</td>
<td>4</td>
<td>57</td>
<td>How thoughts affect our habits and health (ABCD method &amp; health)</td>
</tr>
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<td>5</td>
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<td>55</td>
<td>How repetitive negative thinking affects moods (Perseverative thinking)</td>
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<td>4</td>
<td>53</td>
<td>How cognitive distortions affect our moods (Cognitive distortion)</td>
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<td>59</td>
<td>How activities, goals, and values affect our moods (Behavioral activation)</td>
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<td>8</td>
<td>4</td>
<td>54</td>
<td>How other people affect moods (Social support and moods); Summary</td>
</tr>
</tbody>
</table>

Participants assigned to the CBT-txt intervention condition received 474 texts delivered every other day over a 64-day period, averaging 14.8 texts per treatment day. Participants indicated the time of day they would like to receive the intervention texts. Intervention texts were delivered via a web-based automated SMS text messaging platform called TextIt. Project staff programmed TextIt to deliver intervention texts and extract data from the web-based survey platform Qualtrics to automatically personalize intervention texts. Texts were individualized based on data provided by participants in the baseline survey as well as throughout the treatment period.

In addition to the scheduled intervention messages, participants could access automated booster messaging to provide on-demand supportive messages by texting “4MOOD” at any time, as needed. The “4MOOD” messages are organized around topics (eg, cognitive techniques and positive activities) such that participants select a category of message to receive each time they text “4MOOD” for additional support. All text messages end with the response, “If this is a crisis call 911.” If participants want to find out about receiving professional help, they choose option 4 and the program texts them a link to a list of national mental health services, suicide prevention hotlines, and a child and adult abuse hotline. This list includes a link to access Substance Abuse and Mental Health Services Administration’s treatment locator, which offers a database of treatment providers that can be filtered by location. Textbox 1 provides example SMS text messages of CBT-txt as well as an example booster message.
Fidelity of CBT-txt

We followed previous successful research in developing text-delivered interventions derived from in-person treatments [9,27-29]. The following four steps were used to ensure that the core mechanisms of CBT were incorporated into CBT-txt: (1) selected an evidence-based treatment manual as an adaptation source [20] as well as primary CBT source materials [26], (2) developed texts to match the treatment manual content and structure [20], (3) cross-checked the texts against the core mechanisms of CBT for depression [13], and (4) applied a CBT fidelity scale [30] to rate the texts with an outside expert, Dr John Curry, who provided independent quality assurance scoring. Dr John Curry is a professor of Psychiatry and Behavioral Sciences at Duke University and is a nationally recognized expert in CBT who wrote the protocol for the Treatment of Adolescents with Depression Study [31]. Finally, we applied the results of the fidelity review (average rating of 4 out of 5, with 5 being excellent) and made revisions as needed (provided more overview and summary content).

Participant Safety Protocol

We instituted a participant safety protocol that reviewed all incoming texts for crisis-related words both automatically (ie, autotext review) and with staff reading every text from all participants at least once per day. If participants indicated SI (provided more overview and summary content).
“4MOOD” booster messages were a helpful option. In addition, 5 items measured perceptions of the helpfulness of the intervention content (Cronbach α=.88), and 6 items assessed participants’ practice of the intervention skills taught (Cronbach α=.78). All of these items were rated on a 5-point Likert scale (1=strongly disagree to 5=strongly agree). Engagement with the intervention was measured using data passively collected that were programmed to be automatically gathered during the administration of the intervention, including the number of intervention texts a participant responded to each day and the number of booster SMS text messages requested. Intervention completion was defined as responding to ≥95% of all intervention texts (at least 192 responses out of a total of 198 responses across all intervention days).

**Screen of Depression Symptoms**

The PHQ-9 was used to determine eligibility [17]. The PHQ-9 is a questionnaire consisting of 9 criteria for major depressive disorder (MDD). Responses range from “not at all” (score=0) to “nearly every day” (score=3). Item scores are summed for a total score ranging from 0 to 27. The PHQ-9 has good validity, test-retest reliability, and internal consistency. Cronbach α in this study’s sample was .90.

**Depression Symptoms and Severity**

Baseline and follow-up assessment of depression severity was assessed with BDI-II [33]. There are 21 items, each corresponding with a symptom of depression, and possible scores on each item range from 0 to 3. The scores are summed to obtain a single severity score. A score of 0 to 13 indicates none or minimal depressive symptoms, a score of 14 to 19 indicates mild depressive symptoms, a score of 20 to 28 indicates moderate depressive symptoms, and a score of ≥29 indicate severe depressive symptoms. Cronbach α in this study’s sample at each assessment were .83, .89, .92, and .92, respectively.

**Behavioral Activation**

Behavioral activation was measured using the Behavioral Activation for Depression Scale, Short Form [34]. The Behavioral Activation for Depression Scale, Short Form is a 9-item scale used to assess activation toward goals during the treatment for depression. Items are scored from 0 to 6, and higher scores indicate greater activation toward goals and less avoidance of tasks. Cronbach α in this study’s sample at each assessment were .70, .70, .82, and .81, respectively.

**Perseverative Thinking**

Repetitive negative thinking was measured using the Perseverative Thinking Questionnaire (PTQ) [35]. The PTQ is a 15-item questionnaire used to characterize respondents thinking about negative experiences or problems. Items are scored on a 5-point scale from 0=never to 4=almost always and are summed with higher scores indicating more repetitive negative thinking. Cronbach α in this study’s sample at each assessment was .94, .95, .93, and .97, respectively.

**Cognitive Distortion**

Cognitive distortion was measured using the Cognitive Distortions Scale (CDS) [36]. The CDS assesses 10 types of thinking biases (eg, catastrophizing or all-or-nothing thinking). Participants rate the frequency of their use of each type of thinking. Items are scored on a 7-point scale from 0=never to 7=all the time and are summed with higher scores indicating more cognitive distortion. Cronbach α in this study’s sample at each assessment was .92, .94, .93, and .95, respectively.

**Statistical Analyses**

**Latent Change Score Modeling**

Latent change score (LCS) analyses were conducted in a structural equation modeling framework using the lavaan package in R (R Foundation for Statistical Computing). LCS was used instead of more commonly used modeling methods, such as latent growth modeling and repeated measures ANOVA, because it offers 2 unique capabilities. First, it allows for the estimation of wave-to-wave change in mediators and outcomes adjusted for previous levels, which controls for regression to the mean. Second, it does not force the pattern of change to follow a prespecified shape; wave-to-wave changes are allowed to freely vary across time [37,38]. LCSs are created by (1) specifying an autoregression of each score on its immediately previous time point while fixing the coefficient to 1 and (2) specifying a latent factor with a loading of 1 on the current time point to capture the difference. These LCSs are then used as dependent variables in regressions testing for CBT-txt intervention effects. BDI-II depression scores were centered on their pretreatment mean; CBT-txt was also centered (CBT-txt=0.51; control=−0.49). This centering strategy facilitates the interpretation of model intercepts as a change from the previous month for a person with average pretreatment levels of depression, averaged across conditions. All LCS regressions controlled for both pretreatment levels of depression and prior-month levels of depression to account for the likely association between pretreatment severity and posttreatment change.

**Mediation Analysis**

Mediation was also tested in LCS models. LCSs were created for (1) the baseline to 3-month change in the mediator (Behavioral Activation for Depression Scale, CDS, and PTQ in separate models) and (2) the baseline to 3-month change in the outcome (BDI-II). Pretreatment mediator and BDI-II scores at baseline were included as covariates in the model. The change in mediators was regressed on CBT-txt (and baseline covariates) to create the a path; the change in BDI-II was regressed on the change in the mediator (the b path) and CBT-txt (the direct effect or c’ path). The significance of the indirect effect (a*b) was tested using bias-corrected bootstrapped CIs with 10,000 bootstrap draws. The indirect effect tests the hypothesis that CBT-txt influences BDI-II through the mediator.

**Ethics Approval**

All procedures were approved by the institutional review board of The University of Tennessee (approval UTK IRB-20-06164-FB).
**Results**

**Demographic Results**
Our sample size was 103. The participants’ mean age was 22 (SD 2.2) years and 84.5% (87/103) were female, and they resided in 34 different states in the United States and the District of Columbia. The sample comprised 15.5% (16/103) Asian, 3.9% (4/103) Black or African American, 7.8% (8/103) Hispanic or Latino, 8.7% (9/103) more than 1 race, and 63.1% (65/103) White participants. While not used analytically, college student status, childhood socioeconomic status (“Has your family ever received food assistance, such as free or reduced lunch, or SNAP benefits?”), and past and current use of antidepressant medication were described to characterize the sample. Slightly more than half (55/103, 54.5%) were not enrolled in college part time or full time. Approximately one-third (35/103, 34%) of the participants endorsed a family history of government food assistance, and 42.7% (44/103) of participants had been prescribed antidepressant medication at some time in their life but only 20.4% (21/103) were currently prescribed antidepressant medication. Figure 1 provides details of the enrollment and allocation process via the CONSORT (Consolidated Standards of Reporting Trials) diagram.

**Acceptability and Engagement**
Participants endorsed levels of acceptability and engagement similar to our previous pilot of CBT-txt for young adult depression. Two-thirds (69/103, 67%) of the participants completed the intervention (responding to ≥95% of intervention texts), although somewhat lower than in our previous pilot (85%) [9] but still substantially higher than the average response rates for unguided internet-delivered CBT (40%) [39]. On average, participants completed 163.6 (SD 60.2) texts of the total potential 198 responses. Slightly more participants (37/50, 74%) completed the first month of texts (111 total potential responses; mean 95.3, SD 30.6) than the second month of texts (33/50, 66%; mean 68.3, SD 30.9). The participants endorsed high levels of satisfaction with the treatment content and features. More participants agreed or strongly agreed (35/44, 80%) that the intervention texts were more helpful than in our first pilot study (77%), that the number of days of texts received per day was “just right” (32/42, 79%) than previously (76%), and that the number of texts per day was “just right” (36/42, 86%) than in the previous study (72%) [9]. The overall mean of the helpfulness subscale (mean 4.0, SD 0.7) was very similar to that of the prior trial (mean 3.9, SD 0.8) [9]. However, fewer participants (36/44, 82%) reported that the texts were easy to understand and complete than those in the previous trial (93%) [9]. The participants endorsed moderate levels of implementing the skills learned (mean 3.2, SD 0.7), very similarly to our previous study [9]. Slightly more (32/44, 73%) number of participants agreed that the booster messages were a useful option compared with our prior study (68%) [9]. However, fewer participants (20/50, 40%) used booster messages than the previous trial (42%) [9].

**LCS Results**

**Main Effect of CBT-txt on Depression**
Figure 2 shows the Beck Depression Inventory means over time for the CBT-txt and control groups. Significant treatment–control group differences were observed at each of the 3 postenrollment follow-ups (P<.001 at each follow-up).
No treatment–control group difference was seen in pretreatment depression, supporting balance across groups in baseline levels. Table 2 shows the results of the LCS model testing whether the monthly changes differed between the CBT-txt and control groups. At each of the 3 follow-ups, young adults in the CBT-txt group showed significantly larger decreases in depression than those in the control group, producing a medium to large effect size (Cohen $d=0.76$).

**Figure 2.** Mean scores of the Beck Depression Inventory-II scores over time by condition. CBT-txt: SMS text message–delivered cognitive behavioral therapy.

**Table 2.** Latent change score model results testing SMS text message–delivered cognitive behavioral therapy (CBT-txt) efficacy for depression treatment.

<table>
<thead>
<tr>
<th>Baseline depression level</th>
<th>Estimate</th>
<th>SE</th>
<th>Z value</th>
<th>$P$ value</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.00</td>
<td>0.89</td>
<td>0.00</td>
<td>&gt;.99</td>
<td>-1.75 to 1.75</td>
</tr>
<tr>
<td>CBT-txt</td>
<td>-0.22</td>
<td>1.78</td>
<td>-0.12</td>
<td>.90</td>
<td>-3.71 to 3.27</td>
</tr>
</tbody>
</table>

**Change**

<table>
<thead>
<tr>
<th>Baseline–1 month</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-9.17*a</td>
<td>0.86</td>
<td>-10.63</td>
<td>&lt;.001</td>
<td>-10.86 to -7.48</td>
</tr>
<tr>
<td>CBT-txt</td>
<td>-9.02</td>
<td>1.73</td>
<td>-5.22</td>
<td>&lt;.001</td>
<td>-12.40 to -5.63</td>
</tr>
<tr>
<td>Baseline depression level</td>
<td>-0.51</td>
<td>0.10</td>
<td>-5.33</td>
<td>&lt;.001</td>
<td>-0.70 to -0.32</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>1 month–2 month</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-4.65</td>
<td>1.20</td>
<td>-3.88</td>
<td>&lt;.001</td>
<td>-7.00 to -2.30</td>
</tr>
<tr>
<td>CBT-txt</td>
<td>-3.79</td>
<td>1.82</td>
<td>-2.08</td>
<td>.04</td>
<td>-7.36 to -0.21</td>
</tr>
<tr>
<td>1-month depression Level</td>
<td>-0.27</td>
<td>0.10</td>
<td>-2.87</td>
<td>.004</td>
<td>-0.46 to -0.09</td>
</tr>
<tr>
<td>Baseline depression level</td>
<td>0.20</td>
<td>0.10</td>
<td>1.97</td>
<td>.049</td>
<td>0.00 to 0.40</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>2 month–3 month</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-6.68</td>
<td>1.27</td>
<td>-5.25</td>
<td>&lt;.001</td>
<td>-9.18 to -4.19</td>
</tr>
<tr>
<td>CBT-txt</td>
<td>-4.64</td>
<td>1.90</td>
<td>-2.44</td>
<td>.02</td>
<td>-8.37 to -0.91</td>
</tr>
<tr>
<td>2-month depression level</td>
<td>-0.50</td>
<td>0.09</td>
<td>-5.93</td>
<td>&lt;.001</td>
<td>-0.67 to -0.34</td>
</tr>
<tr>
<td>Baseline depression level</td>
<td>0.07</td>
<td>0.11</td>
<td>0.69</td>
<td>.49</td>
<td>-0.13 to 0.28</td>
</tr>
</tbody>
</table>

*aItalicized text indicates $P<.05$.

**Clinical Significance**

We used 2 measures of clinical significance. First, the number of participants at the end of the trial with high-end state functioning as defined by Jacobson and Truax [40] was measured. High-end state functioning is defined as a participant having a BDI-II score between 0 and 13. By examining the BDI-II severity levels based on total scores (none to minimal...
depressive symptoms = 0-13, mild depressive symptoms = 14-19, moderate depressive symptoms = 20-28, and severe depressive symptoms = 29-63), treatment responses can be understood clinically. Thus, scores between 0 and 13 represent high-end state functioning owing to the elimination of symptoms used to classify participants with MDD. Over half (25/47, 53%) of the treatment group moved to the “none to minimal” category, compared with 15% (8/53) of the control group. Second, we used a reliable change index (RCI), which is a measure of how much change has occurred during the course of treatment [40]. Our study produced an RCI of 4.46 with 95% confidence, which is twice the minimum required RCI of 1.96. This RCI represents 2 SDs of clinical change for the treatment group based on the baseline to 3-month follow-up BDI-II scores. Table 3 displays the depression severity level percentages at the 3-month assessment for comparison by experimental conditions.

**Table 3.** Depression severity level (BDI-II categories) percentages at 3 months by condition.

<table>
<thead>
<tr>
<th>Depression severity levels</th>
<th>CBT-txt</th>
<th>Control</th>
</tr>
</thead>
<tbody>
<tr>
<td>None to minimal</td>
<td>53%</td>
<td>15%</td>
</tr>
<tr>
<td>Mild</td>
<td>17%</td>
<td>5%</td>
</tr>
<tr>
<td>Moderate</td>
<td>13%</td>
<td>45%</td>
</tr>
<tr>
<td>Severe</td>
<td>17%</td>
<td>34%</td>
</tr>
</tbody>
</table>

**Main Effect of CBT-txt on Mechanisms**

Figure 3 shows the means of the hypothesized treatment mechanisms (behavioral activation, cognitive distortion, and perseverative thinking in panels A, B, and C, respectively) over time for the CBT-txt and control groups. None of the pretreatment means were significantly different between the CBT-txt and control groups. Significant treatment–control group differences were observed at each of the follow-up waves for each of the 3 mechanisms, with higher behavioral activation and lower cognitive distortions and perseverative thinking observed among CBT-txt versus control participants. Tables S1-S3 in Multimedia Appendix 1 show the LCS results for the 3 mechanisms. The largest and most consistently significant treatment effects were observed at the 1-month follow-up. Significantly larger 1- to 2-month decreases in cognitive distortions and perseverative thinking were seen for CBT-txt versus control participants; no significant treatment–control group differences in 1- to 2-month change in behavioral activation were seen. No significant treatment–control differences in the 2- to 3-month change were observed for any of the mechanisms.
**LCS Mediation Results**

Table 4 shows $a$, $b$, $c'$, indirect, and total effects for mediation models testing indirect effects of CBT-txt on change in depression through change in the 3 hypothesized mechanisms (Tables S4-S6 in Multimedia Appendix 1 show full model results for LCS mediations). Significant direct and indirect effects of CBT-txt on depression were observed in all 3 models.

CBT-txt appeared to lead to greater increases in behavioral activation and greater decreases in cognitive distortions and perseverative thinking across the 3-month follow-up period, which were then associated with larger baseline to 3-month decreases in depression. The size of the indirect effects was substantial: 57%, 41%, and 50% of the CBT-txt effect on changes in depression were mediated by changes in behavioral...
activation, cognitive distortions, and perseverative thinking, respectively.

Models testing all mediators simultaneously were also conducted and both combined and independent indirect effects were estimated (Table 5). The combined indirect effect, representing the combined action of all 3 mediators, was significant (estimate=−6.07, 95% CI −8.95 to −3.26) and explained 63% of the treatment effect on depression. Independent indirect effects were nonsignificant for behavioral activation (estimate=−2.09, 95% CI −4.92 to 0.24) and cognitive distortions (estimate=−1.14, 95% CI −3.40 to 1.20) but were significant for perseverative thinking (estimate=−2.83, 95% CI −5.80 to −0.57). Behavioral activation, cognitive distortions, and perseverative thinking independently explained 22%, 12%, and 30% of the CBT-txt effect on depression, respectively.

Table 4. Latent change score mediation model results testing SMS text message–delivered cognitive behavioral therapy (CBT-txt) efficacy for depression through mediators.

<table>
<thead>
<tr>
<th>CBT-txt &gt; behavioral activation &gt; depression</th>
<th>Estimate</th>
<th>SE</th>
<th>Z value</th>
<th>P value</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Paths</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CBT-txt &gt; BADS(^a) change (patha)</td>
<td>7.03 (b)</td>
<td>1.68</td>
<td>4.20</td>
<td>&lt;.001</td>
<td>3.75 to 10.30</td>
</tr>
<tr>
<td>BADS change &gt; depression change (path b)</td>
<td>−0.75</td>
<td>0.11</td>
<td>−6.78</td>
<td>&lt;.001</td>
<td>−0.96 to −0.53</td>
</tr>
<tr>
<td>CBT-txt &gt; depression change (path c′)</td>
<td>−4.01</td>
<td>1.83</td>
<td>−2.19</td>
<td>.03</td>
<td>−7.69 to −0.49</td>
</tr>
<tr>
<td>Indirect effect ((a*b))</td>
<td>−5.27</td>
<td></td>
<td></td>
<td></td>
<td>−8.69 to −2.54</td>
</tr>
<tr>
<td>Total effect ((a*b + c′))</td>
<td>−9.28</td>
<td></td>
<td></td>
<td></td>
<td>−13.19 to −5.09</td>
</tr>
<tr>
<td>Percent mediated ([indirect/total] (\times) 100%)</td>
<td>56.8</td>
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</table>

<table>
<thead>
<tr>
<th>CBT-txt &gt; cognitive distortion &gt; depression</th>
<th>Estimate</th>
<th>SE</th>
<th>Z value</th>
<th>P value</th>
<th>95% CI</th>
</tr>
</thead>
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<tr>
<td>Paths</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>CBT-txt &gt; CDS(^d) change (patha)</td>
<td>−15.98</td>
<td>4.06</td>
<td>−3.94</td>
<td>&lt;.001</td>
<td>−23.99 to −7.92</td>
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<tr>
<td>CDS change &gt; depression change (path b)</td>
<td>0.25</td>
<td>0.04</td>
<td>6.30</td>
<td>&lt;.001</td>
<td>0.17 to 0.32</td>
</tr>
<tr>
<td>CBT-txt &gt; depression change (path c′)</td>
<td>−5.67</td>
<td>2.11</td>
<td>−2.69</td>
<td>.007</td>
<td>−9.85 to −1.58</td>
</tr>
<tr>
<td>Indirect effect ((a*b))</td>
<td>−4.01</td>
<td></td>
<td></td>
<td></td>
<td>−6.51 to −2.04</td>
</tr>
<tr>
<td>Total effect ((a*b + c′))</td>
<td>−9.68</td>
<td></td>
<td></td>
<td></td>
<td>−13.67 to −5.35</td>
</tr>
<tr>
<td>Percent mediated ([indirect/total] (\times) 100%)</td>
<td>41.4</td>
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<table>
<thead>
<tr>
<th>CBT-txt &gt; perseverative thinking &gt; depression</th>
<th>Estimate</th>
<th>SE</th>
<th>Z value</th>
<th>P value</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Paths</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CBT-txt &gt; PTQ(^e) change (patha)</td>
<td>−10.33</td>
<td>2.40</td>
<td>−4.30</td>
<td>&lt;.001</td>
<td>−14.95 to −5.63</td>
</tr>
<tr>
<td>PTQ change &gt; depression change (path b)</td>
<td>0.50</td>
<td>0.06</td>
<td>8.43</td>
<td>&lt;.001</td>
<td>0.38 to 0.61</td>
</tr>
<tr>
<td>CBT-txt &gt; depression change (path c′)</td>
<td>−5.18</td>
<td>1.79</td>
<td>−2.89</td>
<td>.004</td>
<td>−8.64 to −1.57</td>
</tr>
<tr>
<td>Indirect effect ((a*b))</td>
<td>−5.12</td>
<td></td>
<td></td>
<td></td>
<td>−8.05 to −2.66</td>
</tr>
<tr>
<td>Total effect ((a*b + c′))</td>
<td>−10.30</td>
<td></td>
<td></td>
<td></td>
<td>−14.02 to −6.19</td>
</tr>
<tr>
<td>Percent mediated ([indirect/total] (\times) 100%)</td>
<td>49.7</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(^a\)BADS: Behavioral Activation for Depression Scale.
\(^b\)Italicized text indicate \(P<.05\).
\(^c\)Not available.
\(^d\)CDS: Cognitive Distortions Scale.
\(^e\)PTQ: Perseverative Thinking Questionnaire.
the direct treatment effect improved related to the treatment effect and acceptability of an 8-week
on CBT. Thus, an important general research question was
where participants indicated wanting more texts and more detail
Although we did not experimentally test dosage effects in this
the strongest independent indirect effect.
combined, these mechanisms explained 63% of the CBT-txt
mechanisms of change within the CBT-txt treatment structure.
analyses also supported our hypotheses regarding the
study, revealing a strong treatment effect. The mediation
Principal Findings
The findings from this investigation contribute to the mHealth
literature by providing convincing evidence that text-delivered
CBT treatment can significantly and consistently reduce depressive symptoms in young adults. These findings also
specify 3 treatment mechanisms that each explain a significant portion of the treatment effect when separately introduced into the mediation analysis models and even larger effects when combined. These results support the specification of 3 candidate therapeutic mechanisms of change within CBT-txt.
All 4 of our hypotheses were supported in this trial’s findings.
Our primary hypothesis tested the efficacy of CBT-txt to reduce depressive symptoms, relative to the control condition. The results supported this hypothesis across all 3 months of the study, revealing a strong treatment effect. The mediation analyses also supported our hypotheses regarding the mechanisms of change within the CBT-txt treatment structure. Separate models showed that each mediator accounted for a substantial proportion of the CBT-txt treatment effect on depression. Models with all mediators included showed that, combined, these mechanisms explained 63% of the CBT-txt treatment effect, with changes in perseverative thinking showing the strongest independent indirect effect.
Although we did not experimentally test dosage effects in this
trial, this study was a follow-up to our initial CBT-txt trial [9],
where participants indicated wanting more texts and more detail on CBT. Thus, an important general research question was related to the treatment effect and acceptability of an 8-week versus a 4-week treatment. The direct treatment effect improved over the first trial (Cohen $d=-0.63$ to Cohen $d=-0.76$), and significant treatment effects were found at 3 months after enrollment compared with 1 month after enrollment in the initial 4-week trial. The largest changes in mechanism scores occurred during the first month of treatment. This may be an indication that these mechanisms are new or novel to participants and, as such, they may be more likely to engage with the treatment to quickly reduce their MDD symptoms. As noted, acceptability and satisfaction improved compared with the first trial. Specifically, the content was deemed helpful and the number of days of treatment and the number of texts per day appeared acceptable, supporting the increase in treatment dosage and thus aligning CBT-txt with the average length of mHealth treatment for depression.
Finally, these findings provide further support for recruiting young adults with depression via Facebook and Instagram, providing an efficient pathway toward engaging this hard-to-reach and underserved population. We recruited a sample of 103 participants in 7 weeks with excellent rates of retention, satisfaction, and engagement. These findings also support the use of CBT-txt as part of a continuum of care. For example, CBT-txt could serve as a form of pretreatment while individuals are placed on waitlists to be seen by clinicians. This approach could quickly reduce the severity of symptoms, particularly for individuals who are experiencing moderate to severe depressive symptoms. Targeting those with the most severe depression with CBT-txt may provide rapid symptom relief, which could then be followed up by a clinician. For some, CBT-txt may be enough; for others, it may serve as a jump start to their treatment and others may find it useful to combine CBT-txt while seeing a clinician for therapy. Supporting this latter idea, it is noteworthy that 278 participants were excluded

<table>
<thead>
<tr>
<th>Paths</th>
<th>Estimate</th>
<th>SE</th>
<th>Z value</th>
<th>P value</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBT-txt &gt; BADS&lt;sup&gt;a&lt;/sup&gt; 2-month change (path a1)</td>
<td>7.29&lt;sup&gt;b&lt;/sup&gt;</td>
<td>1.68</td>
<td>4.34</td>
<td>&lt;.001</td>
<td>3.99 to 10.63</td>
</tr>
<tr>
<td>CBT-txt &gt; CDS&lt;sup&gt;c&lt;/sup&gt; 2-month change (path a2)</td>
<td>−18.72</td>
<td>3.75</td>
<td>−4.99</td>
<td>&lt;.001</td>
<td>−26.40 to −11.63</td>
</tr>
<tr>
<td>CBT-txt &gt; PTQ&lt;sup&gt;d&lt;/sup&gt; 2-month change (path a3)</td>
<td>−11.28</td>
<td>2.33</td>
<td>−4.85</td>
<td>&lt;.001</td>
<td>−16.05 to −6.83</td>
</tr>
<tr>
<td>BADS 2-month change &gt; depression 3-month change (path b1)</td>
<td>−0.29</td>
<td>0.16</td>
<td>−1.80</td>
<td>.07</td>
<td>−0.57 to 0.06</td>
</tr>
<tr>
<td>CDS 2-month change &gt; depression 3-month change (path b2)</td>
<td>0.06</td>
<td>0.06</td>
<td>1.02</td>
<td>.31</td>
<td>−0.07 to 0.17</td>
</tr>
<tr>
<td>PTQ 2-month change &gt; depression 3-month change (path b3)</td>
<td>0.25</td>
<td>0.11</td>
<td>2.34</td>
<td>.02</td>
<td>0.04 to 0.46</td>
</tr>
<tr>
<td>CBT-txt &gt; depression 3-month change (path c')</td>
<td>−3.52</td>
<td>2.12</td>
<td>−1.66</td>
<td>.10</td>
<td>−7.66 to 0.66</td>
</tr>
<tr>
<td>Indirect effect, BADS ($a1*b1$)</td>
<td>−2.09</td>
<td>_&lt;sup&gt;e&lt;/sup&gt;</td>
<td>—</td>
<td>—</td>
<td>−4.92 to 0.24</td>
</tr>
<tr>
<td>Indirect effect, CDS ($a2*b2$)</td>
<td>−1.14</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>−3.40 to 1.20</td>
</tr>
<tr>
<td>Indirect effect, PTQ ($a3*b3$)</td>
<td>−2.83</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>−5.80 to −0.57</td>
</tr>
<tr>
<td>Indirect effect, combined ($a1<em>b1 + a2</em>b2 + a3*b3$)</td>
<td>−6.07</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>−8.95 to −3.26</td>
</tr>
<tr>
<td>Total effect ($a1<em>b1 + a2</em>b2 + a3*b3 + c'$)</td>
<td>−9.59</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>−13.43 to −5.31</td>
</tr>
</tbody>
</table>

<sup>a</sup>BADS: Behavioral Activation for Depression Scale.
<sup>b</sup>Italicized text indicate $P<.05$.
<sup>c</sup>CDS: Cognitive Distortions Scale.
<sup>d</sup>PTQ: Perseverative Thinking Questionnaire.
<sup>e</sup>Not available.

Table 5. Latent change score mediation model results testing SMS text message–delivered cognitive behavioral therapy (CBT-txt) efficacy for depression through multiple mediators.

Discussion

Principal Findings
from the study for reporting current or recent treatment for depression, suggesting that some young adults may recognize a need for supplemental options to traditional depression treatment. Social media recruitment may also reach young adults seeking preventive or early intervention services. Of note, 110 participants were not eligible for the study, as they reported only minimal (25/110, 22.7%) or mild (85/110, 77.3%) depression symptoms on the PHQ-9.

Limitations
The study results should be considered in light of the following limitations. First, although this study was structured as a follow-up pilot study, having a larger sample size and longer follow-up periods may strengthen confidence in the findings. Second, the sample was 84% female, limiting the generalization across biological sexes. Although the rates of major depressive episodes are double for female young adults compared with male young adults (22.9% vs 11.1%) [1], the sample imbalance raises a methodological question as to how best to engage male young adults in treatment. More research is needed that tests varying recruitment methods, branding, and advertising content, including images and language, to engage more male young adults. Third, the control condition was a nonactive comparator and a waitlist control. The study findings could be strengthened by comparing CBT-txt against an active comparator. Fourth, experimental dosage testing could be conducted in future studies to determine the most clinically useful, acceptable, and efficient dosage. A larger multiarm study to test varying dosage levels and associated outcomes could be clinically and scientifically useful. Fifth, participants were not confirmed to have an MDD diagnoses, as we used the PHQ-9 as a screening and inclusion criterion. Finally, the sample was limited to individuals without SI. Given that this is very common among patients with MDD, this exclusion criterion altered the composition of the sample. Future studies with a more robust clinical infrastructure are needed to safely enroll patients with MDD and SI. Mobile interventions are not a replacement for standard depression treatment but may be used to quickly reduce symptoms while patients are on the waiting list, as an adjunct treatment component, or as part of a stepped-care model.

The results of this trial provide further support for CBT-txt as an efficacious, efficient, and reliable form of treatment to address depressive symptomatology among young adults. To the best of our knowledge, CBT-txt is unique in its SMS text message–delivered modality and in its strong clinical evidence supporting efficacy. While acknowledging the study limitations and the potential treatment effect fluctuations due to the sample size, these results build upon our first trial’s promising findings and provide more empirical evidence for the treatment format, delivery modality, and clinical possibilities of using CBT-txt at scale.

Acknowledgments
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Conflicts of Interest
None declared.

Multimedia Appendix 1
Full model results for latent change score mediations.
[DOCX File (.43 KB) - mhealth_v11i1e45186_app1.docx ]

Multimedia Appendix 2
CONSORT eHEALTH checklist (V 1.6.2).
[PDF File (Adobe PDF File). 99 KB - mhealth_v11i1e45186_app2.pdf ]

References


Abbreviations

BDI-II: Beck Depression Inventory-II
CBT: cognitive behavioral therapy
CBT-txt: SMS text message–delivered cognitive behavioral therapy
CDS: Cognitive Distortions Scale
CONSORT: Consolidated Standards of Reporting Trials
LCS: latent change score
MDD: major depressive disorder
mHealth: mobile health
PHQ-9: Patient Health Questionnaire–9
PTQ: Perseverative Thinking Questionnaire
RCI: reliable change index
SI: suicidal ideation
Virtual Digital Psychotherapist App–Based Treatment in Patients With Methamphetamine Use Disorder (Echo-APP): Single-Arm Pilot Feasibility and Efficacy Study

Tianzhen Chen1*, MD, PhD; Liyu Chen1*, MPsy; Shuo Li1, MPsy; Jiang Du1, MD, PhD; Hang Su1, MD, PhD; Haifeng Jiang1, MD, PhD; Qianying Wu1, MPsy; Lei Zhang1, MPsy; Jiayi Bao1, MPsy; Min Zhao1,2,3, MD, PhD

1Shanghai Mental Health Center, Shanghai Jiao Tong University School of Medicine, Shanghai, China
2Shanghai Key Laboratory of Psychotic Disorders, Shanghai, China
3Center for Excellence in Brain Science and Intelligence Technology (CEBSIT), Chinese Academy of Sciences, Shanghai, China
*these authors contributed equally

Abstract

Background: Substance use disorder is one of the severe public health problems worldwide. Inequitable resources, discrimination, and physical distances limit patients’ access to medical help. Automated conversational agents have the potential to provide in-home and remote therapy. However, automatic dialogue agents mostly use text and other methods to interact, which affects the interaction experience, treatment immersion, and clinical efficacy.

Objective: The aim of this paper is to describe the design and development of Echo-APP, a tablet-based app with the function of a virtual digital psychotherapist, and to conduct a pilot study to explore the feasibility and preliminary efficacy results of Echo-APP for patients with methamphetamine use disorder.

Methods: Echo-APP is an assessment and rehabilitation program developed for substance use disorder (SUD) by a team of clinicians, psychotherapists, and computer experts. The program is available for Android tablets. In terms of assessment, the focus is on the core characteristics of SUD, such as mood, impulsivity, treatment motivation, and craving level. In terms of treatment, Echo-APP provides 10 treatment units, involving awareness of addiction, motivation enhancement, emotion regulation, meditation, etc. A total of 47 patients with methamphetamine dependence were eventually enrolled in the pilot study to receive a single session of the Echo-APP–based motivational enhancement treatment. The outcomes were assessed before and after the patients’ treatment, including treatment motivation, craving levels, self-perception on the importance of drug abstinence, and their confidence in stopping the drug use.

Results: In the pilot study, scores on the Stages of Change Readiness and Treatment Eagerness Scale and the questionnaire on motivation for abstaining from drugs significantly increased after the Echo-APP–based treatment (P<.001, Cohen d=−0.60), while craving was reduced (P=.01, Cohen d=0.38). Patients’ baseline Generalized Anxiety Disorder-7 assessment score (β=3.57; P<.001; 95% CI 0.80, 2.89) and Barratt Impulsiveness Scale (BIS)–motor impulsiveness score (β=−2.10; P=.04; 95% CI −0.94, −0.02) were predictive of changes in the patients’ treatment motivation during treatment. Moreover, patients’ baseline Generalized Anxiety Disorder-7 assessment score (β=−1.60; P=.03; 95% CI −3.08, −0.14), BIS—attentional impulsivity score (β=−2.43; P=.004; 95% CI −4.03, −0.83), and BIS—nonplanning impulsivity score (β=2.54; P=.002; 95% CI 0.98, 4.10) were predictive of changes in craving scores during treatment.

Conclusions: Echo-APP is a practical, accepted, and promising virtual digital psychotherapist program for patients with methamphetamine dependence. The preliminary findings lay a good foundation for further optimization of the program and the promotion of large-scale randomized controlled clinical studies for SUD.
Introduction

Substance abuse and dependence seriously endanger public health worldwide. Globally, 3.5 million people die from alcohol and illicit drug abuse each year [1]. China is also facing huge challenges brought on by illegal drugs, tobacco, and alcohol. According to the latest report, there are more than 300 million tobacco users, 123 million people drink alcohol excessively, and 1.8 million people use illegal drugs in China [2-4]. Substance dependence brings a series of physical and psychological damage, resulting in a large economic burden of disease. Psychotherapy is one of the most important treatment methods for drug dependence currently, including cognitive behavioral therapy (CBT), meditation, motivational enhancement therapy (MET) [5,6]. It can help improve treatment motivation, ameliorate emotional disorders, and decrease cravings that patients face. However, many people with substance dependence do not receive proper treatment, and less than 20% of patients have received standard treatment [7]. The main reasons include shortage of professionals, fear of discrimination, and economic and transportation constraints.

Artificial intelligence (AI) and robotics can help solve the substance dependence treatment dilemma. These technologies have been gradually applied to various mental health scenarios such as emotion regulation, evaluation and treatment of mental diseases, treatment efficacy prediction, and rehabilitation management. By simulating the “intelligent brain,” an intelligent machine or program that responds in a manner similar to human intelligence can simulate psychotherapists in the field of psychological assessment, diagnosis, and treatment, which can save labor costs, realize remote intervention, and improve professional use. In the past period, automatic conversational agents have received attention [8]. Automated conversational agents can provide services similar to a therapist or physician, but without the need for human assistance. Studies have shown that text-based dialogue agents have good user engagement and are effective in the treatment of mental symptoms [9-11]. By playing the role of “psychotherapists,” AI devices reduce the patient’s sense of shame and fear of being discriminated against and increase the possibility of patients revealing their true feelings [12]. On the other hand, the widespread use of the internet and intelligent terminals makes electronic medical care based on apps and AI technology have good application prospects. In 2021, the number of smartphone-owning users in China reached 950 million [13]. The development of a mental health program suitable for mobile smart terminals will further enhance the interest of users.

AI has been applied in related fields such as insomnia, anxiety, depression, schizophrenia, substance dependence, and other diseases [14-18]. Among them, some programs are self-administered, that is, after self-assessment, the program provides mental health-related education [19]. Some programs are conversational agents. Research evidence for conversational agent interventions for addressing psychological problems is growing rapidly and has the potential in terms of acceptability and effectiveness [12]. In substance dependence studies, digital interventions have also been found to reduce substance use behaviors [20] and have the potential to reduce the economic burden of disease from substance use disorder (SUD). These apps mainly use text, animation, or dialogue to provide services to patients [8]. Although these programs are reported to be effective, there are still challenges such as poor interaction experience and high dropout rate due to the lack of a more realistic image. Recent studies suggested a potential improvement in treatment effects when incorporated with the virtual image. For instance, Yokotani and colleagues [21] found that virtual agent (with digital image) has advantages in participants’ disclosure of sex-related symptoms. The study by Philip [22] suggested that the smartphone-based virtual agent is feasible in screening patients with sleep complaints and provides acceptable behavior advice [22]. Virtual agents that show better look and feel achieve better user experience [23]. However, most of the virtual agent psychotherapists (with digital image) currently constructed are not vivid enough, with rigid expressions and movements. Besides, few studies have used computer techniques to construct a virtual digital psychotherapist image to provide psychological support services in the field of substance use disorder.

Based on these considerations, we propose, design, and develop a mobile- or tablet-based app (Echo-APP) for the assessment and treatment of substance dependence. Echo-APP, which features a virtual digital human image of a psychotherapist, is a key-based interactive conversational agent program that provides general mental health education, addiction-related symptom tracking and recording, and customized comprehensive psychotherapy. In this study, we describe the development and design of Echo-APP and aim to evaluate the feasibility and preliminary efficacy of Echo-APP through a single-arm pre-post–treatment design.

Methods

Development of a Virtual Digital Psychotherapist App (Echo-APP)

The design and development of Echo-APP started in 2019. The app development was proposed by the Addiction Research Group of the Shanghai Mental Health Center and was optimized through discussions with clinicians, patients with drug dependence, technician, and computer scientists from Mofa Technology Corporation. The multidisciplinary team of this project team meets regularly to form collaborations based on the necessary development techniques and patient-centered design-centric tenet. The core development period is from June 2019 to August 2020, and the first version of the app is finalized. The Echo-APP currently developed is in Chinese.
Echo-APP has been developed for the HUAWEI Android tablet above the application programming interface level 14 (version 4.0). Java (Oracle Corporation) and Python (Python Software Foundation) were used as the programming language, and Visual Studio (Microsoft Corporation) was used as the main development tool. In addition, the image of the virtual digital psychotherapist is developed based on digital human technology. Operationally, the main menu allows psychotherapists or social workers to add new subjects and refer to patients’ assessment and treatment records. A unique code is added to each patient. Three modules of “Psychological Assessment,” “Treatment Options,” and “Homework” are accessed via the buttons on the menu, “Start Assessment,” “Start Therapy,” and “Homework.” The process of assessment and treatment is completed by the virtual digital psychotherapist interacting with the patient. The image of the virtual digital psychotherapist (named “Xiaoying”) is shown in Figure 1.

Figure 1. Image of the virtual digital psychotherapist in Echo-APP.

Assessment Module

The current version of Echo-APP could investigate patients’ baseline demographic information, drug use history, emotional state, impulsivity trait, and treatment motivation. The interface of the assessment module is shown in Multimedia Appendix 1.

Demographic information is collected by self-designed scales, including the patient’s age, gender, education level, employment status, and drug use characteristics.

The patient's emotional status is assessed by Generalized Anxiety Disorder-7 (GAD-7) and Patient Health Questionnaire-9 (PHQ-9).

Impulsivity characteristics are assessed by the Barratt Impulsiveness Scale (BIS)-11. BIS-11 has 30 items and can be divided into 3 dimensions (attention impulsivity, motor impulsivity, and nonplanning impulsivity).

Treatment motivation is assessed by the Stages of Change Readiness and Treatment Eagerness Scale (Socrates), which is self-assessed. This scale evaluates the treatment motivation from the following 3 aspects: patients’ awareness of drug use, attitudes toward behavior change, and ambivalent attitudes toward drug dependence. There are 19 items, and the items on the scale are rated on a 5-point Likert scale (each item ranging from “strongly disagree” to “strongly agree”). The questionnaire on motivation for abstaining from drugs is also used to evaluate treatment motivation. The scale has a total of 36 items, which are divided into the following 5 subdimensions: “tending to rehabilitation-internal motivation,” “tending to rehabilitation-external motivation,” “avoiding abuse-internal motivation,” “avoiding abuse-external motivation,” and “confidence in abstaining from drugs.” The total score of treatment motivation is summed up by the scores of each dimension. The higher the scores, the stronger the treatment motivation.

Visual analogue scale (VAS) is used to assess the self-perception of the importance of drug abstinence (simply called “IMPORTANCE”), their confidence in stopping drug use (simply called “CONFIDENCE”), and their psychological craving for drug use (simply called “CRAVING”). The VAS scale ranges from 0 mm to 100 mm.

For the items of “IMPORTANCE” and “CONFIDENCE,” “0” means “doesn’t matter at all,” and “100” means very important.
For “CRAVING,” “0” corresponds to “no craving,” and “100” represents “highest craving intensity ever experienced for drug.”

The validity and reliability of the Chinese version of the following scale have been confirmed previously: GAD-7, PHQ-9, SOCRATES, BIS-11, and questionnaire of motivation for abstaining from drugs [24-28].

During the assessment, the virtual digital psychotherapist reads the questions, and the patients select options on the tablet screen.

**Treatment Module**

The treatment module of Echo-APP can provide patients with a variety of treatment options, aiming to help patients enhance their motivation to stop drug use, reduce drug cravings, strengthen self-control to avoid relapse, strengthen emotional management skills, and enhance individual and social functions (Multimedia Appendix 2).

The whole module includes the following 10 treatment units: (1) strengthening the motivation of drug withdrawal, (2) recognition of drug cravings and incentives, (3) high-risk situations identification and coping skill, (4) dealing with negative cognition, (5) understanding of emotions, (6) stress management, (7) understanding of family conflicts, (8) preventing relapse, (9) mindfulness, and (10) awareness of positive attitude and well-being (Multimedia Appendix 3). Based on the patient’s assessment results, the treatment unit that meets the needs of the patient’s condition will be selected to provide to the patient.

Each treatment unit follows a structured setting for CBT. At the beginning of each treatment unit, there will be a brief introduction to the treatment goals and themes of the unit. After that, it will enter the formal treatment session, in which various common tools of CBT [29,30] (eg, thinking record sheet, analysis sheet of drug use pros and cons, risk level evaluation sheet for external factor, alternative behavior selection sheet), mindfulness-based relapse prevention technique [31] (integrated into treatment unit 6, 8, and 9), motivational enhancement therapy [32] (integrated into treatment unit 1), and related knowledge popularization (eg, the damage of different drugs and the antecedent, behavior, and consequence theory of emotion) will be applied.

**Homework Module**

The homework module corresponds to the treatment module. There are 10 themed homework modules. After each treatment unit is completed, patients will be assigned their homework and asked to complete it offline (Multimedia Appendix 4).

**Feedback**

After completing each assessment, Echo-APP will provide patients with assessment reports and treatment recommendations. For each treatment unit, Echo-APP will first ask the patient about their treatment experience and their change (eg, treatment motivation and confidence to deal with negative emotions), and then provide the summary report of this treatment unit. The report form is shown in Multimedia Appendix 5.

**Instruction Booklet**

Although the clinical assessment and treatment implemented in Echo-APP can be useful for patients with substance dependence, good guidance is still required for initial use. To this end, in order to make the use of Echo-APP more practical, safer, and more extensive, we provide the Echo-APP instruction manual (Chinese version) and will provide an English version in the future. With a user-friendly and tailored interface, Echo-APP is easy to learn, and this manual will be an effective tool for patient self-learning. This manual shows the interfaces you may encounter in Echo-APP and what you need to do to complete the interface for each assessment or treatment.

**Study Design**

This study consists of 3 parts, the first of which describes the development and technical details of Echo-APP. Then, to assess the efficacy and feasibility of the Echo-APP–based assessment and treatment, we conducted a preliminary study in patients with methamphetamine dependence. Specifically, we conducted a single-arm self-control pilot study with the treatment unit “strengthening the motivation of drug withdrawal.”

**Ethical Considerations**

This study was carried out in accordance with the principles of the Declaration of Helsinki and approved by the institutional review board and the ethics committee of the Shanghai Mental Health Center (approval number: 2020-92). The participants provided their informed consent before the study. The study flow diagram is shown in Multimedia Appendix 6.

**Participants**

A total of 49 patients were recruited from the Shanghai Drug Rehabilitation Center. Eligible patients were diagnosed with methamphetamine use disorder by psychiatrists based on the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) criteria. The inclusion criteria were as follows: (1) met the DSM-5 criteria for methamphetamine use disorder, (2) aged 18-55 years, and (3) normal or corrected-to-normal vision and audition. The exclusion criteria were as follows: (1) with severe cognitive deficits or impairments; (2) with serious physical or neurological illness or a diagnosis of any other psychiatric disorder under DSM-5 criteria (except for nicotine use disorder); and (3) inability to understand and operate the app instructions. Two patients stopped from participating in the study after the screening. Therefore, 47 patients were finally included in the analysis.

**Treatment Settings**

All participants received one session of treatment unit, “strengthening the motivation of drug withdrawal” (Echo-APP–based MET), which was provided by a virtual digital therapist. The contents of the Echo-APP–based MET include an introduction to the damage of drugs, analysis and comparison of the pros and cons of drug abuse, sharing of stories and experiences of people who have successfully abstained from drugs, and improvement of motivation for change. The session duration is about 30 to 45 minutes. During the treatment, there will be a real psychotherapist familiar with the operation of Echo-APP to provide the necessary operation guidance for the
patients. Other than that, the real psychotherapist does not provide any therapy during treatment.

**Outcome Measures**

The primary treatment outcome was the change in SOCRATES score. The secondary outcomes include the following: (1) score change on the questionnaire of motivation for abstaining from drugs; (2) score change of the VAS items “IMPORTANCE,” “CONFIDENCE,” and “CRAVING.”

**Adverse Effect**

During assessment and treatment, no participant reported significant discomfort or adverse effects.

**Statistical Analysis**

To identify the treatment efficacy of Echo-APP, paired 2-tailed t test was used to analyze the changes in scale scores before and after treatment. For those clinical outcomes that have changed significantly before and after treatment (ie, SOCRATES, questionnaire of motivation for abstaining from drugs, IMPORTANCE, CONFIDENCE, and CRAVING), the general linear regression model was used to analyze potential factors affecting treatment efficacy. For each of the general linear regression models, the change in the scale scores (ie, SOCRATES, questionnaire of motivation for abstaining from drugs, IMPORTANCE, CONFIDENCE, and CRAVING) was used as the dependent variable, and baseline demographic information (ie, age, education, current marital status), drug use history, emotional state (ie, GAD-7 and PHQ-9), and impulsivity characteristics (ie, BIS-11) were included as independent variables in the model. The backward method was used to screen the independent variables. All the above statistical analyses were finished using SPSS 20.0 (IBM Corp).

**Results**

**Baseline Information**

Baseline demographic characteristics and clinical data are presented in Table 1. The average age of the patients is 38.85 (SD 8.08) years. The patients’ accumulated months of methamphetamine use is 99.89 (SD 56.71) months. Of the 47 participants, 12 (26%) use methamphetamine due to psychological craving.
Table 1. Demographic information and drug use history for all participants (N=47) in a study of Echo-APP–based Motivational Enhancement Therapy for methamphetamine use disorder.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Demographics</strong></td>
<td></td>
</tr>
<tr>
<td>Age (years), mean (SD)</td>
<td>38.85 (8.08)</td>
</tr>
<tr>
<td>Education, n (%)</td>
<td></td>
</tr>
<tr>
<td>Less than 7 years</td>
<td>1 (2)</td>
</tr>
<tr>
<td>7-9 years</td>
<td>18 (38)</td>
</tr>
<tr>
<td>10-12 years</td>
<td>17 (36)</td>
</tr>
<tr>
<td>More than 12 years</td>
<td>11 (23)</td>
</tr>
<tr>
<td>Currently married, n (%)</td>
<td>16 (34)</td>
</tr>
<tr>
<td><strong>Drug use history</strong></td>
<td></td>
</tr>
<tr>
<td>Accumulated months of methamphetamine use, mean (SD)</td>
<td>99.89 (56.71)</td>
</tr>
<tr>
<td>Methamphetamine use dosage (grams) per day, mean (SD)</td>
<td>0.71 (0.42)</td>
</tr>
<tr>
<td><strong>Methamphetamine use frequency, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Use every day</td>
<td>20 (43)</td>
</tr>
<tr>
<td>3-5 days per week</td>
<td>7 (15)</td>
</tr>
<tr>
<td>1 day per week</td>
<td>9 (19)</td>
</tr>
<tr>
<td>1-3 days per month</td>
<td>11 (23)</td>
</tr>
<tr>
<td><strong>Methamphetamine use reason, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Craving</td>
<td>12 (26)</td>
</tr>
<tr>
<td>Others</td>
<td>35 (74)</td>
</tr>
<tr>
<td><strong>Baseline clinical measures, mean (SD; range)</strong></td>
<td></td>
</tr>
<tr>
<td>Craving</td>
<td>18.09 (26.41; 0-100)</td>
</tr>
<tr>
<td>Awareness of the importance of drug abstinence</td>
<td>77.13 (32.47; 0-100)</td>
</tr>
<tr>
<td>Confidence in drug abstinence</td>
<td>83.09 (23.26; 0-100)</td>
</tr>
<tr>
<td>SOCRATES&lt;sup&gt;a&lt;/sup&gt;</td>
<td>65.13 (15.23; 26-91)</td>
</tr>
<tr>
<td>Questionnaire of motivation for abstaining from drugs</td>
<td>160.79 (19.48; 109-180)</td>
</tr>
<tr>
<td>PHQ-9&lt;sup&gt;b&lt;/sup&gt;</td>
<td>5.53 (4.84; 0-19)</td>
</tr>
<tr>
<td>GAD-7&lt;sup&gt;c&lt;/sup&gt;</td>
<td>3.79 (4.26; 0-16)</td>
</tr>
<tr>
<td>BIS-MI&lt;sup&gt;d&lt;/sup&gt;</td>
<td>73.13 (17.73; 34-100)</td>
</tr>
</tbody>
</table>

<sup>a</sup> SOCRATES: Stages of Change Readiness and Treatment Eagerness Scale.
<sup>b</sup> PHQ-9: Patient Health Questionnaire-9.
<sup>c</sup> GAD-7: Generalized Anxiety Disorder-7.
<sup>d</sup> BIS-MI: Barratt Impulsiveness Scale—motor impulsivity.

The Efficacy of Echo-APP–Based Motivational Enhancement Therapy

The Echo-app–based MET treatment has brought significant improvement in patients’ treatment motivation as assessed on the SOCRATES scales ($P<.001$, Cohen $d=-0.60$) and the questionnaire of motivation for abstaining from drugs ($P=.045$, Cohen $d=-0.30$). Besides, it had a significant effect on the reduction of self-reported craving ($P=.01$, Cohen $d=0.38$; Figure 2 and Multimedia Appendix 7).
Factors Affecting Echo-APP–Based Treatment Efficacy

To explore if the patients’ baseline characteristics may influence the treatment efficacy of Echo-APP–based MET, we investigated their associations. For the treatment motivation, the baseline GAD-7 score (β=3.57; P<.001; 95% CI 0.80, 2.89) and BIS—motor impulsivity scores (β=−2.10; P=.04; 95% CI −0.94, −0.02) were predictive of SOCRATES change after MET, and the baseline GAD-7 score (β=1.87; P<.001; 95% CI 0.93, 2.82) and abstinence duration (β=0.02; P=.01; 95% CI 0.01, 0.04) were predictive of questionnaire of motivation for abstaining from drugs change after MET.

None of the baseline characteristics were relative to the changes in the visual analogue scale score of “CONFIDENCE” and “IMPORTANCE.”

For psychological craving, the baseline GAD-7 score (β=−1.607; P=.03; 95% CI −3.08, −0.14), BIS—attentional impulsivity scores (β=−2.43; P=.004; 95% CI −4.03, −0.83), and BIS—nonplanning impulsivity (β=2.54; P=.002; 95% CI 0.98, 4.10) were predictive of self-reported craving reductions after MET.

None of the baseline characteristics were relative to the changes in the visual analogue scale score of “CONFIDENCE” and “IMPORTANCE.”
Discussion

Overview

The purpose of this study was to describe the design of Echo-APP, which is the virtual digital psychotherapist app, and conduct a preliminary evaluation of the efficacy of the Echo-APP–based intervention. The study found that 1 session of Echo-APP treatment can enhance patients’ treatment motivation and reduce psychological cravings.

The Design of Echo-APP

The core work of this study was to build standardized self-assessment and high-quality psychotherapy tools that are in line with the needs of patients with SUD. Therefore, medical staff and patients can use this professional digital tool for SUD treatment more conveniently and with more interest. Based on this consideration, we refer to the opinions of patients with SUD, discuss existing digital health programs with doctors, psychotherapists, and computer experts, and design new digital health program for patients with SUD. Our group mainly focuses on several points, including the following: (1) accessibility and convenience of the digital program, (2) standardization and effectiveness of assessment and treatment, and (3) optimizing the user-program interaction experience and enhancing immersion. Previous studies have found that both web-based and app-based text conversational agents are effective for patients [12], and app-based programs have advantages in improving accessibility [33]. However, dialogue agent tools that use text or animation to interact have their disadvantages, such as poor interaction and immersion. Besides, most digital programs also offer fewer treatment options, and patients are passively accepted [34]. In this context, we developed the first virtual digital psychotherapist program, Echo-APP, for patients with SUD, which is a more economical and interactive app that runs on the tablet platform.

This study describes the design and development process of Echo-APP and evaluates the utility of the Echo-APP in a single-arm design study. From a technical point of view, Echo-APP provides a more friendly operation interface. Patients are able to complete the assessment and treatment process through interaction with a virtual digital psychotherapist. According to the needs of patients with SUD, Echo-APP has 10 units, which can provide patients with comprehensive treatment. Throughout the assessment and treatment process, Echo-APP provides readable feedback reports for patients, doctors, and psychotherapists to clearly know the patient's condition changes and treatment efficacy.

Treatment Efficacy of Echo-APP

This study suggested that a single session of Echo-APP treatment can enhance patients’ treatment motivation and reduce psychological cravings. The design of this Echo-APP–based MET program is referred to the MET protocol of our group, which was found to significantly improve the treatment outcome of patients who are dependent on heroin [35]. Echo-APP also had an effect on reducing psychological cravings, which may be related to the improvement of treatment motivation [36]. To explore the factors that may affect the treatment effect, we analyzed the patient's baseline characteristics, and the results suggested that the patient's emotional state and impulsive personality characteristics may affect the effectiveness of the Echo-APP–based MET treatment. Therefore, the multi-unit comprehensive intervention system provided by Echo-APP may have better applicability. It is possible to improve the overall treatment effect through targeted intervention for different symptoms, which has been verified in other studies [37,38]. Although the results are promising, this work is a preliminary study, and further standardized evaluation of Echo-APP is still needed, and a multicenter randomized controlled clinical study is required to explore the efficacy and adverse reactions of Echo-APP.

Limitations

This study inevitably has some limitations. Firstly, the current assessment of Echo-APP is mainly based on scales, which may have similar shortcomings as paper scales. We plan to develop an effective addiction symptom assessment paradigm to reduce the subjective assessment content. Secondly, this study is a single-arm design, which can only provide a preliminary result of the therapeutic value of Echo-APP, whereas the most rigorous way to ensure the effectiveness of the developed APP would be to conduct a randomized controlled clinical study in comparison with a traditional psychotherapy. This randomized study is in progress and in its early stages. Thirdly, this study is only conducted on patients with methamphetamine use disorder, and the popularity of the study results needs to be improved, including further research on people who use legal drugs such as tobacco and alcohol.

Conclusion

In this study, we introduced the design and development of Echo-APP and preliminarily validated the efficacy of the Echo-APP–based treatment for patients with methamphetamine use disorder. This work fills the current lack of addiction treatment programs with the virtual digital psychotherapist on the market. In the future, we will continue to optimize the function of Echo-APP and carry out large-sample multicenter clinical controlled studies to verify the effect of Echo-APP and benefit more patients with SUD.

Acknowledgments

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Authors’ Contributions
LYC, JD, HS, QYW, LZ, and JYB conducted the research; TZC and LYC analyzed data; HFJ and JD provided the clinical support; MZ, TZC, and LYC designed the research. TZC drafted the manuscript. All authors have contributed to the interpretation of data, critically revised the manuscript, and approved the final version of the manuscript.

Conflicts of Interest
None declared.

Multimedia Appendix 1
The interface of the assessment module.
[ PNG File, 140 KB - mhealth_v11i1e40373_app1.png ]

Multimedia Appendix 2
The interface of the treatment module.
[ PNG File, 800 KB - mhealth_v11i1e40373_app2.png ]

Multimedia Appendix 3
Ten treatment units in the treatment module.
[ DOCX File, 16 KB - mhealth_v11i1e40373_app3.docx ]

Multimedia Appendix 4
The interface of the homework module.
[ PNG File, 431 KB - mhealth_v11i1e40373_app4.png ]

Multimedia Appendix 5
The feedback report form provided by Echo-APP.
[ PNG File, 673 KB - mhealth_v11i1e40373_app5.png ]

Multimedia Appendix 6
Flow diagram of the study.
[ PNG File, 19 KB - mhealth_v11i1e40373_app6.png ]

Multimedia Appendix 7
The changes of the clinical measures during the Echo-app–based motivation enhancement treatment.
[ DOCX File, 15 KB - mhealth_v11i1e40373_app7.docx ]

References


**Abbreviations**

AI: artificial intelligence  
BIS: Barratt Impulsiveness Scale  
CBT: cognitive behavioral therapy  
DSM-5: Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition  
GAD-7: Generalized Anxiety Disorder-7  
MET: motivational enhancement therapy  
PHQ-9: Patient Health Questionnaire-9  
SOCRATES: Stages of Change Readiness and Treatment Eagerness Scale  
SUD: substance use disorder  
VAS: visual analogue scale

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Improving Children’s Sleep Habits Using an Interactive Smartphone App: Community-Based Intervention Study

Arika Yoshizaki1, MA; Emi Murata1, PhD; Tomoka Yamamoto1, MA; Takashi X Fujisawa2,3, PhD; Ryuzo Hanaie1, OTR, PhD; Ikuko Hirata4, MD; Sayuri Matsumoto5, MD, PhD; Ikuko Mohri1,3, MD, PhD; Masako Taniike1,3, MD, PhD

1Molecular Research Center for Children’s Mental Development, United Graduate School of Child Development, Osaka University, Suita, Osaka, Japan
2Research Center for Child Mental Development, University of Fukui, Yoshida-gun, Fukui, Japan
3United Graduate School of Child Development, Osaka University, Suita, Osaka, Japan
4Department of Pediatrics, Osaka University Hospital, Suita, Osaka, Japan
5Higashiosaka City Health Center, Higashiosaka, Osaka, Japan

Corresponding Author:
Arika Yoshizaki, MA
Molecular Research Center for Children’s Mental Development
United Graduate School of Child Development
Osaka University
2-2-D5 Yamadaoka
Suita, Osaka, 5650871
Japan
Phone: 81 6 6879 3863
Email: arika@kokoro.med.osaka-u.ac.jp

Abstract

Background: Sleep problems are quite common among young children and are often a challenge for parents and a hinderance to children’s development. Although behavioral therapy has proven effective in reducing sleep problems in children, a lack of access to professionals who can provide effective support is a major barrier for many caregivers. Therefore, pediatric sleep experts have begun developing apps and web-based services for caregivers. Despite the substantial influence of cultural and familial factors on children’s sleep, little effort has gone into developing cultural or family-tailored interventions.

Objective: This study aimed to examine the effectiveness of the interactive smartphone app “Nenne Navi,” which provides culturally and family-tailored suggestions for improving sleep habits in young Japanese children through community-based long-term trials. The study also aimed to investigate the association between app-driven improvements in sleep and mental development in children.

Methods: This study adopted a community-based approach to recruit individuals from the Higashi-Osaka city (Japan) who met ≥1 of the following eligibility criteria for sleep problems: sleeping after 10 PM, getting <9 hours of nighttime sleep, and experiencing frequent nighttime awakenings. A total of 87 Japanese caregivers with young children (mean 19.50, SD 0.70 months) were recruited and assigned to the app use group (intervention group) or the video-only group (control group). Both groups received educational video content regarding sleep health literacy. The caregivers in the intervention group used the app, which provides family-tailored suggestions, once per month for 1 year.

Results: A total of 92% (33/36) of the caregivers in the app use group completed 1 year of the intervention. The participants’ overall evaluation of the app was positive. The wake-up time was advanced (base mean 8:06 AM; post mean 7:48 AM; F1,65=6.769; P=.01) and sleep onset latency was decreased (base mean 34.45 minutes; post mean 20.05 minutes; F1,65=23.219; P<.001) significantly in the app use group at the 13th month compared with the video-only group. Moreover, multiple regression analysis showed that decreased social jetlag (β=−0.302; P=.03) and increased sleep onset latency SD (β=.426; P=.02) in children predicted a significant enhancement in the development of social relationships with adults. At 6 months after the completion of the app use, all the caregivers reported continuation of the new lifestyle.

Conclusions: The present findings suggest that the app “Nenne Navi” has high continuity in community use and can improve sleep habits in young Japanese children and that interventions for sleep habits of young children may lead to the enhancement of
children’s social development. Future studies must focus on the effectiveness of the app in other regions with different regional characteristics and neuroscientific investigations on how changes in sleep impact brain development.

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KEYWORDS

infant sleep; app; mHealth; mobile health; behavioral intervention; sleep health; social implementation; mobile phone

Introduction

Background

The Centers for Disease Control and Prevention, the National Public Health agency of the United States, described sleep deprivation as a “public health epidemic” linked to a wide range of medical issues, including hypertension, diabetes, depression, obesity, and cancer [1]. Sleep deprivation can impede not only physical health but also mental health and development.

Sleep problems are quite prevalent among young children, regardless of their cultural origins [2]. An international pediatric task force stated that insufficient sleep among children is a major public health concern [3]. According to a meta-analysis of sleep, cognitive, and behavioral problems in school-aged children (aged 5 to 12 years), inadequate sleep quality or quantity during childhood can affect daytime functioning, cognitive development, and health [4].

Current neuroscience research shows that the process of synaptic pruning occurs during rapid eye movement sleep [5], which demonstrates the importance of sleep from a developmental perspective. Recent cohort studies have shown that children who sleep less during infancy and early childhood are at a higher risk for hyperactivity and lower cognitive functioning later in their lives [6]. In addition, extant literature suggests that the early years (up to 3 years of age) are a sensitive period in which sleep can impact development [6,7]. A Norwegian cohort study investigating the link between sleep in early years and later development showed that short sleep duration and frequent nocturnal awakenings among toddlers aged 1.5 years were associated with the development of both internalizing and externalizing problems at 5 years of age [8]. Sivertsen et al [9] also found that short sleep duration (≤10 hours) and frequent (≥3) nightly awakenings at 1.5 years of age predicted the development of depressive symptoms at 8 years of age. A recent Australian cohort study also reported that sleep problems at 4 to 5 years of age are associated with internalizing difficulties through 12 to 13 years of age [10].

In addition, various studies have demonstrated that children with neurodevelopmental disorders are likely to have more sleep problems and that sleep parameters are associated with the severity of the symptoms of developmental disorders [11-13]. A recent article proposed a novel view on attention-deficit/hyperactivity disorder, whereby a part of the symptoms of attention-deficit/hyperactivity disorder were linked to chronic sleep disorders, with delayed circadian rhythm suggested as the underlying mechanism [14]. Furthermore, several studies on children with neurodevelopmental disorders have indicated that improvements in their sleep problems could lead to improvements in their behavioral problems [15-17].

However, in the context of the evidence regarding the association between sleep problems and developmental trajectories, there is a lack of clarity on whether sleep problems and the predictors of developmental disorders originally coexist or whether sleep problems in early childhood impact developmental trajectories [18].

Therefore, intervention studies examining early childhood are needed to determine whether the improvement of sleep in early childhood can prevent adverse outcomes and enhance healthy developmental trajectories [19]. We hypothesized that improving sleep problems in early childhood would result in better developmental trajectories, which is the ultimate goal of our research.

Furthermore, children’s sleep problems are associated with parental stress, family conflict, and maternal depressive symptoms [20-22] and are a risk factor for maltreatment [23]. The “Common risk assessment tool for child consultation centers and municipalities related to child abuse” issued by the Japanese Ministry of Health, Labour and Welfare in 2017 recommends that early support is needed for children with unstable sleep-wake rhythms and difficulty in sleeping [24]. The research also suggested that interventions for improving children’s sleep and developing good sleep habits in early childhood are likely to improve the quality of life for the whole family.

Previous studies support the substantial impact of cultural factors on children’s sleep habits [25-29]. In addition to cultural factors, caregivers’ lifestyles also impact children’s sleep habits [30]. Japanese infants and young children are reported to have the shortest sleep duration among the infants and young children among the 17 countries where the survey was conducted [31]. Our previous study revealed that 30.8% of preschool children are sleep deprived and that 56.7% of the caregivers of children who sleep <8 hours at night rated their children’s sleep as “good” [30]. It has been suggested that the current situation may be the result of Japan’s unique sleep culture, which values working hard over getting enough sleep; the working environment of caregivers; the living environment; and other complex factors along with a lack of sleep literacy. Furthermore, Japan has witnessed a rapid increase in the use of electronic devices and a shift to a more nighttime lifestyle in recent years, which threaten the sleep health and development of Japanese children. As infancy and early childhood are the sensitive periods for sleep, it is necessary for children to develop adequate sleep habits during their early childhood. However, given the various factors involved, improving the sleep health of Japanese toddlers can be quite challenging.

Recent findings suggest that parental factors both predict the outcomes of and are predicted by behavioral interventions for infant sleep problems [32]. Sivigum et al [33] suggested that
early and customized guidance for caregivers, with a focus on revealing and acknowledging their experiences with sleep problems in their children, is essential in helping caregivers deal with the challenges [33]. Shetty et al [34] focused on daytime parenting and found that permissive or inconsistent daytime parenting practices were associated with more severe sleep problems [34].

Therefore, we can conclude that suggestions for caregivers should include guidance on daytime parenting practices and be tailored to the unique experiences of families by considering sociopsychological factors such as culture, values, family and housing environment, and the working situations of caregivers. This is particularly the case for Asia, where people have a habit of cosleeping; hence, it is necessary to provide culturally sensitive suggestions. Previous findings have suggested that there are various familial factors that can affect children’s sleep, such as sleep environment, wake-up time, delayed or irregular mealtime, screen time, physical activity, and irregular or late bedtime of parents [28,35-39].

In Japan, guidance on sleep and childcare has traditionally been provided through face-to-face consultations at public health care centers. However, as the number of dual-working families has increased, such consultations have become more difficult for caregivers, thereby limiting the availability of guidance. Recent studies have shown the efficacy of web-based and mobile health (mHealth) interventions for sleep problems in infants and young children [31,40,41]. However, these devices developed in Western countries cannot be used in Japan without substantial modifications to account for the cultural differences in sleep habits, such as cosleeping and sleeping on futon mattresses. Considering these background and previous reports, we developed a smartphone app called “Nenne Navi,” which facilitates interaction between caregivers and pediatric sleep experts to improve sleep habits in young Japanese children [42]. This app provides culturally and family-tailored advice to each family to make small behavioral changes in their lifestyles through the Plan-Do-Check-Act cycle (Multimedia Appendix 1). We previously conducted a community-based trial for 1 year. The aim of this study was to examine the app’s long-term continuity and effectiveness in improving children’s sleep habits and development and parental cognition and behavior.

A Priori Hypotheses

The app demonstrates intervention adherence (continuity) for long-term use in the community-based trials and long-term effectiveness in improving the sleep habits of young children and the parenting efficacy of their caregivers.

Methods

Ethics Approval and Consent to Participate

This study was approved by the Osaka University Clinical Research Review Committee (CRB5180007) on January 23, 2017, before the start of the study. All the study procedures were conducted in accordance with the ethical standards of the Declaration of Helsinki. At the beginning of the baseline assessment, the participants received detailed information about the study’s goals and procedures and were informed about the underlying data protection. Written consent was obtained from all the participants individually. All participants received a coupon for books worth JAP ¥5000 (US $42) upon the completion of the trial. The amount was set to be increased to up to US $100 for the app group depending on their contribution. The participants in the app group were notified that they would receive additional rewards according to their app use but were not informed of the exact amount to avoid impacting the results.

Participants

A total of 87 Japanese caregivers (all mothers) with young children (mean 19.50, SD 0.70 months) from the Higashi-Osaka city were recruited over a 6-month period (September 2017 to March 2018) and assigned to either the app use group (intervention group) or the video-only group (control group) based on their preference; those without a preference were randomly assigned to either intervention. The Higashi-Osaka city is an urban area in the Western part of Japan with approximately 3000 births per year. It was confirmed that the sleep-wake patterns of the young children in this city were comparable with the national average in Japan (mean wake-up time: 7:12 AM, SD 0.58; mean bedtime: mean 9:20 PM, SD 0.54; Taniike et al, unpublished data, August 2016). Our study targeted caregivers with children who had completed the developmental health checkup at 1.5 years of age, as the app was designed for this age group. The inclusion criteria were that the children faced at least 1 of the following sleep problems: (1) bedtime later than 10 PM, (2) <9 hours of nighttime sleep, and (3) frequent night awakenings. In addition, the caregivers of the children needed to be fluent in Japanese, not currently be a participant of any interventions for parenting or children’s development, and be willing to participate in the study. The following inclusion criteria had to be met for the app use group: possession of a mobile device (iOS [Apple Inc] or Android [Google LLC]) with internet access and the willingness to install the “Nenne Navi” app on the mobile device. The following inclusion criteria had to be met for the video-only group: ability to access the internet to watch the video content and for record data. A total of 34 participants were excluded, as they did not meet the inclusion criteria. Supported devices included the iPhone, iPad, and iPod touch (Apple Inc) with iOS 8.0 or a later version, and Android devices with Android OS 4.3 or a later version. Both groups received educational video content regarding sleep health literacy. The caregivers in the app use group cooperated in the follow-up evaluation 6 months after the completion of the app use. A flow diagram of this study is shown in Figure 1.
Measures

“Nenne Navi” App: Acceptability and Safety in Use
The Nenne Navi app was developed by pediatric sleep experts at the pediatric sleep clinic at Osaka University Hospital to positively influence caregivers’ behavior to ensure healthy sleep habits among their young children. The pilot trial of the app showed that there were no major problems with the system and that the usability and acceptability of the app was sufficient. Details of the system design were previously reported elsewhere by Yoshizaki et al [42]. The trademark was registered on July 20, 2018, and the registration number is 606435 “Nenne Navi” (Osaka University; MT, IM, Yoko Aoi, and AY). The patent number is 6920731.

The caregivers were asked to respond to approximately 36 questions regarding sleep-related lifestyles such as wake-up time, bedtime, nap time, daytime activities, media use, dinner time, bath time, bedtime routine, and cosleeping habits, as problems with children’s sleep habits are caused by a variety of interrelated factors.

The app was designed with the ability to set individualized goals in accordance with individual users’ home lives; for example, the app sent personalized advice such as “Try to finish dinner before 8:00 p.m.” instead of “Try to have dinner earlier” to deliver specific and optimal goals to caregivers in small progressive steps based on the concept of behavioral therapy. The app does not expect caregivers to obey the advice; conversely, it was designed to send various pieces of advice and suggestions, from which caregivers could choose one to implement temporarily without much effort. Examples of the advice are presented in the study by Yoshizaki et al [42].

One of the features of the app allows caregivers to report the advice they have chosen and whether they have tried it on a monthly basis through the app. This enables the monitoring of caregivers’ spontaneous commitment to behavioral change, and the pediatric sleep experts can check the caregivers’ degree of compliance. A feedback message (of approximately 150 letters in English) was sent to each caregiver every month through the app to provide them with positive feedback on the improvements they have made in their lifestyle compared with the previous months. In addition, an icon in the app that displays an egg will gradually hatch and grow into a beautiful bird as users use the app. The app also has the function of plotting data into a graph. Caregivers can select their parameters of concern (eg, night awakenings and morning mood) in addition to the time their children fall asleep and see the changes visually. In addition to these personalized interventions and supports, the app provides all users with educational videos and tips on basic sleep and parenting literacy, specifically regarding positive daytime activities to create good sleep.

The design of the intervention study is shown in Figure 2.
Sleep Parameters
Data on sleep parameters was collected once a month for 8 consecutive days from baseline to the postintervention stage (1 year after) and at follow-up (1.5 years after) for the app use group, whereas for the video-only group, these data were collected for 8 consecutive days at baseline and 1 year after.

In addition to data on typical sleep parameters such as wake-up time, bedtime, nighttime sleep duration, and sleep onset latency, including their SDs, this study used data on social sleep restriction and social jetlag, as both these factors have been noted to be associated with physical health, mental health, and daytime performance. Social sleep restriction and social jetlag are defined as the difference in sleep duration between weekdays and weekends and shifts in sleep timing between weekdays and weekends, respectively.

Measure of Children’s Development
The parent-rated Kinder Infant Development Scale (KIDS) [43] was administered to all caregivers at the baseline and postintervention stages. The KIDS is a parent-rated questionnaire that was created in Japan to assess various aspects of the development of infants and toddlers, including motor, language, and social relationships.

Questionnaires and Interviews
A questionnaire was administered and semistructured interviews regarding the changes in parenting efficacy after app use were conducted following the trial to identify the effect of the app and the feasibility of its use in the community. The participants from both groups were asked to describe their impression of the educational video content and the changes in parenting efficacy. The participants in the app use group were additionally asked about their impression of the app, such as about the factors that motivated continued use. The participants responded to items asking them to evaluate the app and the video content using a 5-point scale (5=satisfied, 4=moderately satisfied, 3=neutral, 2=moderately dissatisfied, and 1=dissatisfied) and free descriptions. The participants responded to items asking them to evaluate the changes in parenting efficacy using another 5-point scale (5=very improved, 4=moderately improved, 3=unchanged, 2=moderately worsened, and 1=very worsened).

Data Analysis
We conducted a 2-tailed $t$ test to identify the between-group differences in sleep habits and sleep-related lifestyles of the participants in each group at baseline. We then conducted a 2-way ANOVA (group × time) to identify the efficacy of the app in improving children’s sleep habits (ie, bedtime, wake-up time, nighttime sleep, and sleep onset latency) via the community-based trial. A multiple regression analysis was conducted to evaluate the effects of improvement in sleep on young children’s development. Repeated measures analysis of variance was conducted to examine the maintenance of the effects of app use at follow-up. Data analysis was performed using SPSS statistics (version 26.0; IBM Corp).

Results
Demographic Information of the Study Participants
The demographic information of the study participants is presented in Multimedia Appendix 2. There were no between-group differences, except in fathers’ educational status.

Improvement in Sleep-Wake Patterns in Children
The sleep habits and sleep-related lifestyles of the participants at baseline are provided in Table 1.

The app use group displayed significantly later wake-up times, longer sleep onset latency, larger SD for wake-up time, bedtime, and nighttime sleep duration, larger SD for sleep onset latency, and larger social jetlag compared with the video-only group at baseline. Furthermore, the app use group displayed a tendency to have more bedroom feeding habits and delayed wake-sleep rhythm. It is possible that a bias existed in which the caregivers of children with poorer sleep habits preferred the app use group.
### Table 1. Sleep habits and sleep-related lifestyles of the participants in each group at baseline.

<table>
<thead>
<tr>
<th>Variable</th>
<th>App use group, mean (SD)</th>
<th>Video-only group, mean (SD)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wake-up time (time, minute)</td>
<td>8:06 AM (0:55)</td>
<td>7:20 AM (0.48)</td>
<td>&lt;.001</td>
</tr>
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<td>Wake-up time SD (minutes)</td>
<td>38.95 (18.51)</td>
<td>30.26 (21.33)</td>
<td>.08</td>
</tr>
<tr>
<td>Bedtime (time, minute)</td>
<td>9:36 PM (0:59)</td>
<td>9:14 PM (0:49)</td>
<td>.097</td>
</tr>
<tr>
<td>Bedtime SD (minutes)</td>
<td>36.02 (23.71)</td>
<td>23.35 (13.16)</td>
<td>.01</td>
</tr>
<tr>
<td>Sleep onset latency (minutes)</td>
<td>34.45 (21.45)</td>
<td>22.01 (18.45)</td>
<td>.01</td>
</tr>
<tr>
<td>Sleep onset latency SD (minutes)</td>
<td>20.72 (11.70)</td>
<td>11.86 (11.00)</td>
<td>.002</td>
</tr>
<tr>
<td>Nighttime sleep duration (minutes)</td>
<td>593.52 (46.55)</td>
<td>583.59 (38.94)</td>
<td>.35</td>
</tr>
<tr>
<td>Nighttime sleep duration SD (minutes)</td>
<td>53.93 (25.16)</td>
<td>39.23 (21.44)</td>
<td>.01</td>
</tr>
<tr>
<td>Number of awakenings after sleep onset</td>
<td>0.99 (1.03)</td>
<td>0.76 (1.13)</td>
<td>.40</td>
</tr>
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<td>Nap starting time (time, minute)</td>
<td>1:41 PM (1:17)</td>
<td>1:22 PM (0:50)</td>
<td>.23</td>
</tr>
<tr>
<td>Nap starting time SD (minutes)</td>
<td>97.20 (54.71)</td>
<td>80.47 (37.92)</td>
<td>.15</td>
</tr>
<tr>
<td>Nap ending time (time, minute)</td>
<td>3:53 PM (1:20)</td>
<td>3:26 PM (0:57)</td>
<td>.12</td>
</tr>
<tr>
<td>Nap ending time SD (minutes)</td>
<td>86.35 (37.70)</td>
<td>78.09 (38.81)</td>
<td>.38</td>
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<tr>
<td>Nap duration (minutes)</td>
<td>106.52 (35.98)</td>
<td>104.79 (25.07)</td>
<td>.82</td>
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<td>Nap duration SD (minutes)</td>
<td>39.08 (21.37)</td>
<td>38.77 (17.19)</td>
<td>.95</td>
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<td>Total sleep duration (minutes)</td>
<td>700.00 (50.50)</td>
<td>688.35 (42.64)</td>
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<tr>
<td>Total sleep duration SD (minutes)</td>
<td>59.15 (24.78)</td>
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<tr>
<td>Television-viewing time (minutes)</td>
<td>118.70 (100.35)</td>
<td>87.47 (69.98)</td>
<td>.15</td>
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<td>End of television-viewing time after 4 PM (time, minute)</td>
<td>8:37 PM (1:45)</td>
<td>8:31 PM (1:17)</td>
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<td>Smartphone-use time (minutes)</td>
<td>11.82 (18.00)</td>
<td>7.62 (19.06)</td>
<td>.36</td>
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<td>Outdoor play in the morning (%)</td>
<td>5.35 PM (3:13)</td>
<td>5.44 PM (2:33)</td>
<td>.89</td>
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<tr>
<td>Outdoor play in the morning (%)</td>
<td>57.42 (37.65)</td>
<td>68.00 (37.93)</td>
<td>.26</td>
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<td>End of dinner (time, minute)</td>
<td>7:22 PM (0:48)</td>
<td>7:15 PM (0:43)</td>
<td>.52</td>
</tr>
<tr>
<td>End of bathing (time, minute)</td>
<td>7:54 PM (1:27)</td>
<td>7:34 PM (1:41)</td>
<td>.38</td>
</tr>
<tr>
<td>Breastfeeding in the bed (%)</td>
<td>32.48 (45.95)</td>
<td>11.35 (28.76)</td>
<td>.03</td>
</tr>
<tr>
<td>Media use in the bed (%)</td>
<td>2.15 (6.32)</td>
<td>0.85 (4.97)</td>
<td>.35</td>
</tr>
<tr>
<td>Caregiver wake-up time (time, minute)</td>
<td>7:39 AM (0:53)</td>
<td>6:39 AM (0:48)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Caregiver bedtime (time, minute)</td>
<td>11:30 PM (1:20)</td>
<td>10:52 PM (1:20)</td>
<td>.06</td>
</tr>
<tr>
<td>Caregiver sleep onset latency (minutes)</td>
<td>39.59 (26.18)</td>
<td>31.31 (30.91)</td>
<td>.39</td>
</tr>
<tr>
<td>Caregiver nighttime sleep duration (minutes)</td>
<td>449.88 (54.11)</td>
<td>435.62 (77.23)</td>
<td>.24</td>
</tr>
</tbody>
</table>

---

**a** Differences between groups were tested using the 2-tailed t test.

**b** Italicized values indicate significance.

A summary of the results is presented in Figure 3. Two-way ANOVAs were conducted to determine the effects of the group (the app use group and the video-only group) and intervention (baseline and post) on the sleep habit variables. First, significant interactions between the effects of the group and intervention were confirmed for wake-up time (Figure 3A; $F_{1,65}=5.748; P=0.02$) and sleep onset latency (Figure 3E; $F_{1,65}=12.389; P<.001$), with only the app use group showing reductions for both outcomes ($P=0.05$). Next, significant main effects of both the group and intervention were confirmed for social jetlag (Figure 3J; group: $F_{1,65}=4.264; P=0.04$; intervention: $F_{1,65}=4.709; P=0.03$). Furthermore, only the main effect of the intervention was observed for wake-up time SD (Figure 3B; $F_{1,65}=6.413; P=0.01$), whereas only the main effect of the group was observed for bedtime SD (Figure 3D; group: $F_{1,65}=6.991; P=0.01$) and nighttime sleep duration SD (Figure 3H; group: $F_{1,65}=5.510; P=0.02$). Finally, there were no significant main effects or interactions for bedtime (Figure 3C; $F_{1,65}=2.429; P=0.12$), nighttime sleep duration (Figure 3G; group: $F_{1,65}=7.473; P=0.09$), or social sleep restriction (Figure 3I; $F_{1,65}<0.449; P=0.51$).
Feasibility of Using Nenne Navi in the Community

There were no dropouts at the 6-month point, and only 8% (3/36) of the caregivers in the app use group dropped out after 1 year of the intervention. A total of 6% (2/36) of caregivers decided to finish the intervention prematurely, as they determined that they had “improved enough” at the 6-month point, based on the disappearance of night awakening (mean: more than 5 times per night before the intervention to none after), reduction of sleep onset latency as the changes for each of the 2 children who finished intervention prematurely (mean 27.9 minutes to “immediately”), reduction of sleep onset latency (mean: from 20 minutes to 5 minutes), and bedtime refusal. Overall, 3% (1/36) of caregivers dropped out of the intervention owing to internet connectivity issues on her smartphone. The mean score for the evaluation of the app was 4.303 (SD 0.969) and that for the evaluation of the video content was 4.545 (SD 0.782). In the feedback section on the app, the participants mentioned the following as the factors that encouraged continued app use (multiple answers allowed): (1) 91% (30/33) of the caregivers mentioned “caring and encouraging text messages to caregivers,” (2) 64% (21/33) mentioned “individually tailored advice,” (3) 18% (6/33) mentioned “growth of the bird icon,” and (4) 9% (3/33) mentioned “nothing in particular,” and (5) 3% (1/33) mentioned “other reasons.” Regarding their perception of the appropriate duration of app use, 42% (14/33) of the caregivers answered that a period of around 6 months would be appropriate, 52% (17/33) answered “10–12 months,” and 6% (2/33) answered “13 months or longer.” At the postintervention stage, of the 33 caregivers, 1 (3%) caregiver stated, “At first, I thought it would be impossible to achieve the goal of turning off the TV at 7:00 PM. But as I worked on other goals and adjusted my lifestyle, I gradually started to turn off the TV earlier and earlier, and finally I made it!!”

Improvement in Parenting Efficacy

In terms of the improvement in the parenting efficacy of the participants, the mean score was 3.8 (SD 1.1) in the app use group and 3.3 (SD 1.0) in the video-only group. The results of the independent t test comparing the 2 groups were as follows: $t_{62}=1.996$, $P=.05$. In the app use group, 32% (10/31) of the caregivers rated their parenting efficacy after intervention as “very improved” and 32% (10/31) as “moderately improved,” whereas in the video-only group, 6% (2/33) of the caregivers rated their parenting efficacy after intervention as “very improved” and 46% (15/33) as “moderately improved.” A chi-square test was performed to compare the proportion of caregivers in both groups who responded for the score of change in parenting efficacy. The results showed a trend for differences in response between the groups ($\chi^2_{4}=8.3; P=.08; \phi=0.361$). A residual analysis revealed that the caregivers of the app use group selected the “very improved” option significantly more than the video-only group ($P=.01$).

Association Between the Content of and Preference for Advice

Figure 4 shows data on the advice sent by the pediatric sleep expert team to the caregivers and the advice chosen by the caregivers. The app offers a variety of advice concerning the daily lives of children and parenting behavior. There was a discrepancy between the advice that the experts tended to focus on and the advice that the caregivers preferred.
on (send frequently) and the advice that the caregivers tended to choose to try. The most commonly sent advice was about media control at home; however, it was the advice that the caregivers chose the least. The caregivers were most likely to select the advice about controlling dinner time. The “Others” category included advice on household chores (e.g., chores around bedtime should be done after the children have slept or next morning), iron intake for children who are suspected of having restless leg syndrome, receiving help from family members, and adopting measures to maintain a healthy lifestyle. When the advice was sent, the following cultural issues were taken into account: bed sharing with caregivers and siblings, breastfeeding while lying in bed as a bedtime routine, awaiting father’s return home for dinner or bathing, and breastfeeding at midawakening while lying in bed.

Figure 4. The advice was sent by the experts and chosen by the caregivers to try.

Effects of Changes in Sleep Habits on Mental Development

We performed a multiple regression analysis to examine the relationship between the changes in sleep habits and mental development to clarify the effects of the changes in sleep habits from baseline to postintervention stage on children’s development. Developmental age scores in each group, as assessed using KIDS, at baseline and postintervention stage are shown in Multimedia Appendix 3. Table 2 shows the results of the multiple regression analysis. The changes (Δ) in sleep parameters from baseline to the postintervention stage were entered as predictors. Multiple regression analysis showed that the model was significant for social relationships with adults ($F_{1,64}=2.399; P=.02; R^2=0.303$) but not for social relationships with children ($F_{1,64}=1.118; P=.37; R^2=0.169$). Increased sleep onset latency SD and decreased social jetlag were significant predictors of the development of social relationships with adults ($\beta=.426, t_{54}=2.521, P=.02; \beta=-0.302, t=-2.883, P=.03$).
Table 2. Multiple regression analysis of social development with sleep habit variables as predictors.

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>B (SE; 95% CI)</th>
<th>$\beta$</th>
<th>t test (df)</th>
<th>$P$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wake-up time (Δ)</td>
<td>$-2.092 (4.011; -10.130 to 5.946)$</td>
<td>$-0.281$</td>
<td>$-0.522 (54)$</td>
<td>.60</td>
</tr>
<tr>
<td>Wake-up time SD (Δ)</td>
<td>$0.025 (0.037; -0.048 to 0.098)$</td>
<td>$0.107$</td>
<td>$0.681 (54)$</td>
<td>.50</td>
</tr>
<tr>
<td>Bedtime (Δ)</td>
<td>$3.606 (4.085; -4.581 to 11.794)$</td>
<td>$0.434$</td>
<td>$0.883 (54)$</td>
<td>.38</td>
</tr>
<tr>
<td>Bedtime SD (Δ)</td>
<td>$-0.033 (0.035; -0.104 to 0.038)$</td>
<td>$-0.165$</td>
<td>$-0.941 (54)$</td>
<td>.35</td>
</tr>
<tr>
<td>Sleep onset latency (Δ)</td>
<td>$0.043 (0.072; -0.101 to 0.188)$</td>
<td>$0.160$</td>
<td>$0.601 (54)$</td>
<td>.55</td>
</tr>
<tr>
<td>Sleep onset latency SD (Δ)</td>
<td>$0.145 (0.039; 0.068 to 0.223)^a$</td>
<td>$0.426$</td>
<td>$2.521 (54)$</td>
<td>.02</td>
</tr>
<tr>
<td>Nighttime sleep duration (Δ)</td>
<td>$0.042 (0.061; -0.081 to 0.165)$</td>
<td>$0.354$</td>
<td>$0.686 (54)$</td>
<td>.50</td>
</tr>
<tr>
<td>Nighttime sleep duration SD (Δ)</td>
<td>$0.022 (0.035; -0.048 to 0.091)$</td>
<td>$0.119$</td>
<td>$0.633 (54)$</td>
<td>.53</td>
</tr>
<tr>
<td>Social sleep restriction (Δ)</td>
<td>$-0.019 (0.010; -0.040 to 0.001)$</td>
<td>$-0.250$</td>
<td>$-1.912 (54)$</td>
<td>.06</td>
</tr>
<tr>
<td>Social jetlag (Δ)</td>
<td>$-4.166 (1.445; -7.053 to 1.278)$</td>
<td>$-0.302$</td>
<td>$-2.883 (54)$</td>
<td>.03</td>
</tr>
</tbody>
</table>

*Italicized values indicate significance.

Long-term Effects of the App Intervention

A total of 28 (78% of caregivers in the baseline population) caregivers from the app use group participated in the follow-up, including the individual interview months after the end of the intervention. We conducted a repeated measures ANOVA of each sleep parameter at baseline, postintervention, and follow-up time points to examine the follow-up effects of app use. No correction was performed for the missing values. Multimedia Appendix 4 shows the sleep-wake patterns of the children in the app use group at these 3 time points. Wake-up time progressively and significantly advanced from baseline to follow-up. Wake-up time SD, sleep onset latency, sleep onset latency SD, and social jetlag were also significantly shortened between baseline and follow-up. There were no sleep parameters that showed a significant deterioration at follow-up.

As for the caregivers’ subjective responses in the follow-up, about 80% (22/28) of the users who participated in the follow-up answered that “the effect of improving sleep habits is still continuing,” implying a maintenance of the effect of the app. Furthermore, about 30% (8/28) of app users who participated in the follow-up answered that they began to offer advice to other caregivers around them who were facing problems with their children’s sleep.

Discussion

Principal Findings

This study investigated the effectiveness of the interactive smartphone app “Nenne Navi,” which provides culturally tailored and family-tailored suggestions for improving the sleep habits of young Japanese children. The results of a long-term trial with community populations suggested that “Nenne Navi” has a very high continuity and that the use of the app can contribute to the promotion of changes in parenting behavior, healthy sleep habits, and development in children. It is also suggested that the improvement in sleep habits resulting from the use of this app might be maintained after the end of the intervention, although further examination of the long-term effects is needed. One of the goals of remote interventions such as mHealth or computerized cognitive behavioral therapy is to minimize dropouts and maintain intervention adherence—high dropout rates, which can reach up to 80%, have been one of the main issues plaguing remote cognitive behavioral therapy [44-47]. Longer programs were associated with higher dropout rates in previous research [48]. The continuity of Nenne Navi was remarkably high in the community-based trial, as there was no dropout at the 6-month mark, and only 8% (3/36) of the participants in the app use group dropped out after 1 year. This high compliance may be explained by the design of the app, which endeavored to promote the confidence and empowerment of caregivers. Some of the design aspects to which the high intervention compliance can be attributed are (1) a reciprocal intervention design instead of a 1-way instruction based on valid suggestions and information; (2) thorough caregiver support function throughout the intervention, such as encouraging and motivating text messages for caregivers; (3) adequate sleep literacy via educational video content; (4) an intervention system that can increase the caregivers’ proactive commitment by sending advice several times corresponding to each individual situation and letting the user choose 1 item “to try”; (5) providing small-step multiple advice that can help bridge the gap between “proper literacy” and “caregivers’ limitations” while supporting parenting efficacy; and (6) the use of unique design features, such as the growth of the egg icon in response to use and a graphical representation of the parameters selected by individual caregivers. These elements conform to the suggestions of Whittall et al [49]. Surprisingly, as we confirmed the factors that motivated the continued use of the app, many caregivers reported that “caring and encouraging text messages” were the driving force behind their continued use.

Significant between-group differences in sleep-wake patterns were observed at baseline. Overall, the app use group displayed worse sleep habits at baseline. These differences may be explained by a tendency among caregivers more troubled by their children’s sleep problems to prefer being recruited to the app use group. Surveys in Japan have shown that wake-up time does not advance in the natural developmental process without intervention among children in the age range covered in this study [50,51]. Regarding the significant within-group change
from baseline to the postintervention stage, the improvement in wake-up time and sleep onset latency in the app use group from baseline to the postintervention stage was owing to individual intervention and not the natural course.

The improvement in wake-up time SD, sleep onset latency SD, and social jetlag in both groups may have been the result of the education on “constant sleep rhythm” provided by the educational video delivered to both groups, which led to an improvement in rhythm irregularity.

Overall, this app was effective in improving wake-up rhythm and reducing the difficulty in falling asleep. The improved wake-up rhythm could be explained by the fact that it is relatively easy for mothers to wake up their children at a certain time, as they do not need the cooperation of other family members and already have practice in doing this. Intervention on wake-up time would be important because delayed wake-up time leads to delayed timing of nighttime melatonin secretion as well as napping rhythms, which will inevitably lead to reduced sleep pressure and delayed bedtime at night. In addition, improvement in waking time is also considered beneficial for adaptation to social life. Furthermore, the shortened sleep onset latency was attributed to the increased sleep pressure caused by the advancement of the wake-up rhythm, as well as the guidance provided by the app on establishing bedtime routines and sedative ways of spending time before going to bed, which are relatively new concepts in Japan. Nonetheless, effects on bedtime and extension of sleep time were not observed in this study. It might have been difficult to advance bedtime, as many factors are required to accomplish this. For example, several caregivers reported that it was difficult to obtain the cooperation of other family members in controlling the media use to advance bedtime or bath time. In addition, because many children in Japan go to bed together with their caregivers, the bedtime tended to be late, as the caregivers (the mothers in most cases) had to finish all the household chores before sleeping. However, it must be noted that the trial was conducted in a single community in a relatively urban area and, therefore, may reflect living conditions specific to the region, such as a greater exposure to light at night.

Consequently, although the children in the app use group made significant advances in wake-up time without advances in bedtime, their nighttime sleep duration was not shortened because of decreased sleep onset latency. As sleep duration did not change, there may have been no change in social sleep restriction. The development of further strategies to improve bedtime and sleep duration is an important focus area for future intervention studies.

Allen et al [52] conceptualized the elements of adequate or good sleep for children in a review of studies examining sleep regularity, bedtime routines, quiet or noise comfort or lights, media use, activities, and family conflict. They identified that there are many factors that impact children’s sleep. Recent findings suggest that there are multiple barriers for caregivers to adjust parenting behavior to create better sleep habits or reduce sleep problems [49]. The regional characteristics suggest that Japanese caregivers face relatively more barriers to accessing professional help when their children face trouble sleeping, as there are only a few pediatric sleep specialists in Japan. Thus, Japanese caregivers have little access to sleep literacy or solutions to their children’s problems. The dissemination of “children’s sleep literacy” is an urgent and critical social issue. In addition, the need for remote intervention tools has been further heightened by the COVID-19 pandemic. The COVID-19 pandemic has created new barriers for families struggling to raise their young children and might leave many families isolated. Thus, a means for pediatric sleep specialists to safely communicate up-to-date knowledge without face-to-face contact to caregivers can aid in bridging these barriers and bring many benefits to families.

This app helps caregivers to overcome some of the possible barriers through its unique design incorporating integrated support and small-step care intervention strategies. It is necessary for busy caregivers and those who lack adequate help or knowledge regarding childcare to achieve appropriate levels of sleep literacy and receive positive feedback to improve their children’s sleep habits. Many caregivers will benefit from this design aimed at empowering them to change their parenting behavior. Bradway et al [53] pointed out that it is essential to focus on the impact on users’ self-efficacy and engagement when judging the success, usefulness, and potential benefits of mHealth in health intervention research [53]. Our findings also suggest that designing the app to increase user engagement and self-efficacy contributed to high continuity of use and effectiveness.

Interestingly, there was a discrepancy between the advice that the experts selected on the basis of scientific priority and the advice that the caregivers chose to try. The greater discrepancy in the media control goal might accurately reflect the reality of parenting. Sleep and media use in young children have been a concern for many sleep professionals overseas [54,55]. However, in recent years, children have been reported to be exposed to media devices at increasingly younger ages, and the guidelines on screen time published by the American Academy of Pediatrics [56] appear to be ignored by approximately 90% of caregivers [57]. Some studies suggest that excessive media use may negatively impact brain development [57-59]. Media control at home is a major concern in Japan, similar to other high-income countries, and is often not practiced despite caregivers’ knowledge of the potential harm caused by excessive media use. Social transitions, such as an increasing number of nuclear families and dual-earner families, necessitate caregivers to rely on visual media to keep their children busy so that they can focus on household chores. Nonetheless, interviews with caregivers revealed that one of the most effective pieces of advice for improving sleep habits was media control (data not shown). Although the issue may be difficult to solve, this study clarifies that it is an area that professionals should focus on to help “build the bridge” to improve children’s sleep. As this app emphasizes the empowerment of caregivers and their own spontaneous behavioral changes, we designed it to build up “what I can do now” scenarios one by one. Regarding advice that is considered important by experts for improvement but not chosen by caregivers, we may be able to help them by providing practical tips or other support for carrying it out; additionally, we should be considerate of the possibility that...
there may be some limitations (eg, housing conditions) depending on familial situations.

In accordance with the previous reports that sleep in childhood was associated with later socioemotional problems [8,60], we focused on the social relationships with children and adults as a socioemotional developmental index. We found that decreased social jetlag and increased sleep onset latency SD in children predicted significant enhancement of social development. Although there are many indications of the adverse health effects of social jetlag in adolescents and adults [61,62], the results of this study suggest that close attention should be paid to social jetlag in young children from a developmental perspective. A recent study reported that social jetlag is negatively associated with serum brain-derived neurotrophic factor levels, which play an important role in neuronal maintenance, plasticity, and neurogenesis [63]. The age of the participants in this study, from 1.5 years to 2.5 years, is regarded as an age of remarkable socioemotional development (critical or sensitive period) in the trajectories of brain development [64,65]. The age of 2 years has been defined as a time when the restructuring of the parent-child relationship progresses from the perspective of a developmental theory of parent-child attachment [66]. Our results suggested the possibility that a reduction in social jetlag during this period might play a role in the enhancement of social development. Further research is needed to explain why the social jetlag could be related to social development in young children. Our results also suggested that the increased sleep onset latency SD might be also related to social development with adults. One possible explanation for this association is that as caregivers begin to modify their living situations and bedtime routines to accommodate better sleep, sleep onset latency might range from being very short (successful days) to long (unsuccessful days for any reason), which could have contributed to the current results. This association has not yet been clarified in many aspects and needs to be further investigated in the future.

In Japan, children’s sleep habits are strongly influenced by the sleep habits of their caregivers owing to the cosleeping lifestyle. Fukumizu et al [67] suggested that the cosleeping habit and bedtime irregularity were associated with sleep-related nighttime crying in Japanese children. It is necessary to increase awareness among families and help parents make changes in parenting to ensure that their children are not negatively impacted by irregular sleep habits. The relationship between increased sleep onset latency SD and a promotion of social development with adults remains to be clarified; however, there are some possible explanations. First, it may have been related to caregivers’ efforts to change parenting behaviors to help children sleep. For example, some caregivers discontinued breastfeeding as a bedtime routine and started reading picture books instead. Although the range of sleep onset latency increased and then varied temporarily, it may have had a positive impact on the parent-child relationship. Alternatively, children who were sleep deprived and fell asleep immediately at a later bedtime at baseline went to bed earlier with varied sleep onset latency.

The use of an interactive design in the app demonstrated its similarity to precision medicine, which can identify the issues in each family and provide optimized suggestions. Recent findings suggested that there are multiple barriers or reasons for caregivers not seeking help for children’s sleep problems, indicating that deferential help-seeking interventions are needed depending on the barriers or problem severity [68]. Increasing the choice of caregiver education and interventions, such as video-based caregiver education, app-based individualized remote interventions adopted in this study, traditional face-to-face interventions, telemedicine, and specialized outpatient services, will benefit more families.

**Study Strengths and Limitations**

This study adopted a community-based approach, which is closer to the real world and could be applied to diverse social service settings and target audiences. This study shows that the app is successfully designed for reciprocal interaction between caregivers and pediatric sleep experts to promote caregivers’ behavioral changes to ensure healthy sleep habits among young children. The design of interactive interventions that allow for seamless caregiver, with a specific focus on culturally and family-tailored interventions, and consistent empowerment and support for caregivers resulted in a very high continuity of use while enhancing parenting efficacy. The techniques used in this study may be applicable to other medical or health care domains.

Nonetheless, this study had some limitations. The primary limitation of this study is the moderate sample size. Another limitation is that randomization was not adopted owing to the municipality’s preference for the equality of its citizens. As the design of randomized controlled trials could not be adopted, we cannot exclude the possibility that the improvement in sleep variables in the app use group included the effect of regression to the mean. Therefore, it would be difficult to determine the general effectiveness of the app in this study. We assume that a certain intervention effect was observed after the intervention because significant differences in many sleep variables relative to the video-only group disappeared; however, it is essential to confirm the effect of improvement by randomized controlled trials in the future. Therefore, we should be careful not to overgeneralize the results of this study. Data at the follow-up point were obtained only from the app use group; therefore, the sleep habits of the video-only group at that point are unknown. In addition, because the data in this study were reported by the caregivers, there is a possibility of reporting bias, although the accuracy of the sleep pattern data entered into the app was confirmed in a previous study by Yoshizaki et al [42]. Furthermore, this community-based trial was conducted in a single community in an urban area. We also note that it is still unclear why changes in sleep parameters predicted accelerated development. Although this study did not include an analysis of the association between the objective parameters of app use such as access history and adherence, the focus on objective parameters should be important for understanding adherence and future development of the app. Further studies should be conducted considering these limitations.

**Conclusions**

This study confirmed the long-term continuity of the use of the app and its efficacy in improving sleep habits. In addition, its effects on follow-up maintenance with long-term intervention in the community-based trial was also confirmed. The use of...
the Nenne Navi app was associated with improved sleep habits and parenting behavior, suggesting an enhanced parenting efficacy in caregivers. The participants' feedback demonstrated that this effect was supported by the advice that empowered caregivers while encouraging family-tailored, small-step changes in parenting behavior.

The app is expected to be used in sleep medicine and parental education in Japan and is expected to contribute to the expansion of sleep health literacy among families with young children. This app will continue to be implemented in the community as a culturally and individually sensitive, caregiver-supportive sleep education tool. Furthermore, the app could ultimately contribute to improvements in sleep habits and healthy development among Japanese children. Further research must focus on neuroscience to confirm whether this early sleep intervention would lead to more desirable brain development.

Acknowledgments
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Conflicts of Interest
AY, EM, IH, IM, and MT received licensing fees of this app from Panasonic Advanced Technology Development Co, Ltd. AY, IM, and MT received patent royalties’ fees of this app from Panasonic Advanced Technology Development Co, Ltd.

Multimedia Appendix 1
Screenshots and the interactive Plan-Do-Check-Act cycle of the app. (A) Snapshot of the app. (B) Screenshots of the top page and data input page. (C) e-Learning content. (D) Interactive Plan-Do-Check-Act cycle of the app.

Multimedia Appendix 2
Demographic information of the study participants.

Multimedia Appendix 3
Developmental age scores for the Kinder Infant Development Scale in each group at the baseline and postintervention stages.

Multimedia Appendix 4
Children's sleep-wake patterns by group at the baseline, postintervention, and follow-up stages.

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65. Early Years Study 1, Reversing the Real Brain Drain. Early Years Study. 1999. URL: https://earlyyearsstudy.ca/early-years-study-1/ [accessed 2022-06-15]


Abbreviations

KIDS: Kinder Infant Development Scale
mHealth: mobile health

https://mhealth.jmir.org/2023/11/e40836
Original Paper


Roman Shrestha1,2, PhD, MPH; Frederick L Altice3, MD; Antoine Khati1, MD; Iskandar Azwa3, MD; Kamal Gautam1, MPH; Sana Gupta4; Patrick Sean Sullivan4, PhD; Zhao Ni5, PhD; Adeeba Kamarulzaman3, MD; Panyaphon Phiphatkunarnon6, MSc; Jeffrey A Wickersham2, PhD

1Department of Allied Health Sciences, University of Connecticut, Storrs, CT, United States
2AIDS Program, Yale School of Medicine, New Haven, CT, United States
3Faculty of Medicine, University of Malaya, Kuala Lumpur, Malaysia
4Department of Epidemiology, Rollins School of Public Health, Emory University, Atlanta, GA, United States
5Yale School of Nursing, West Haven, CT, United States
6Love Foundation, Bangkok, Thailand

Corresponding Author:
Roman Shrestha, PhD, MPH
Department of Allied Health Sciences
University of Connecticut
358 Mansfield Road Unit 1101
Storrs, CT, 06269
United States
Phone: 1 8604862834
Email: roman.shrestha@uconn.edu

Abstract

Background: HIV disproportionately affects men who have sex with men (MSM). In Malaysia, where stigma and discrimination toward MSM are high, including in health care settings, mobile health (mHealth) platforms have the potential to open new frontiers in HIV prevention.

Objective: We developed an innovative, clinic-integrated smartphone app called JomPrEP, which provides a virtual platform for Malaysian MSM to engage in HIV prevention services. In collaboration with the local clinics in Malaysia, JomPrEP offers a range of HIV prevention (ie, HIV testing and pre-exposure prophylaxis [PrEP]) and other support services (eg, referral to mental health support) without having to interface face to face with clinicians. This study evaluated the usability and acceptability of JomPrEP to deliver HIV prevention services for MSM in Malaysia.

Methods: In total, 50 PrEP-naive MSM without HIV in Greater Kuala Lumpur, Malaysia, were recruited between March and April 2022. Participants used JomPrEP for a month and completed a postuse survey. The usability of the app and its features were assessed using self-report and objective measures (eg, app analytics, clinic dashboard). Acceptability was evaluated using the System Usability Scale (SUS).

Results: The participants’ mean age was 27.9 (SD 5.3) years. Participants used JomPrEP for an average of 8 (SD 5.0) times during 30 days of testing, with each session lasting an average of 28 (SD 3.9) minutes. Of the 50 participants, 42 (84%) ordered an HIV self-testing (HIVST) kit using the app, of whom 18 (42%) ordered an HIVST more than once. Almost all participants (46/50, 92%) initiated PrEP using the app (same-day PrEP initiation: 30/46, 65%); of these, 16/46 (35%) participants chose PrEP e-consultation via the app (vs in-person consultation). Regarding PrEP dispensing, 18/46 (39%) participants chose to receive their PrEP via mail delivery (vs pharmacy pickup). The app was rated as having high acceptability with a mean score of 73.8 (SD 10.1) on the SUS.
Conclusions: JomPrEP was found to be a highly feasible and acceptable tool for MSM in Malaysia to access HIV prevention services quickly and conveniently. A broader, randomized controlled trial is warranted to evaluate its efficacy on HIV prevention outcomes among MSM in Malaysia.

Trial Registration: ClinicalTrials.gov NCT05052411; https://clinicaltrials.gov/ct2/show/NCT05052411

International Registered Report Identifier (IRRID): RR2-10.2196/43318

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KEYWORDS
men who have sex with men; mHealth; HIV prevention; pre-exposure prophylaxis; mobile phone; Malaysia; MSM; mobile health; HIV; prevention; usability; acceptability; sexual minority; gay; homosexual

Introduction

Men who have sex with men (MSM) are disproportionately affected by HIV in Malaysia and accounted for 63% of new HIV diagnoses in 2021, a proportion that has been increasing over the past decade [1,2]. This pattern requires implementation of more effective HIV prevention in MSM, yet in Malaysia, as in many low- and middle-income countries (LMICs), MSM often do not adequately access evidence-based HIV prevention (and treatment). Gaps in prevention and treatment are due, in part, to high levels of social stigma and discrimination against MSM. In Malaysia, these factors are heightened further because same-sex sexual behaviors are criminalized [2-4]. Other factors also contribute to low uptake of services, including sexual networks that have evolved through social networking apps. Transmission potential is heightened by behavioral or biological factors, including condomless sex, multiple concurrent sexual partners, substance use, and mental health problems (eg, depression, anxiety) that act synergistically to increase the HIV risk in this group [5-12].

Routine HIV testing and expanded use of pre-exposure prophylaxis (PrEP) would drastically reduce the population-level burden of HIV [13-16]. Uptake of these evidence-based tools, however, is suboptimal among Malaysian MSM. For example, recent data suggest that 55% of MSM reported not having tested for HIV in the past 6 months, and approximately 30% reported they had never been tested [17-19]. Additionally, only 18.3% of MSM with indications for PrEP reported ever using it, despite high awareness and willingness to use PrEP [20,21]. This low uptake is partly explained by the need to maintain meaningful engagement with the health care system to access these services. Yet, it is often difficult for MSM in Malaysia to find culturally appropriate health care services due to known barriers, such as discomfort and distrust associated with disclosing sexual behavior to providers for fear of ramifications [22]. As such, there is a need for innovative strategies to improve access to HIV prevention services for Malaysian MSM.

Mobile health (mHealth), particularly smartphone apps, holds great promise for HIV prevention [18,23-26], especially when linked to accessible HIV testing and PrEP. App-based interventions can help overcome multilevel barriers, given their ability to anonymously reach and engage populations that are disenfranchised from existing prevention efforts and offer “real-time” delivery and rapid scalability of programs at relatively low implementation costs. In Malaysia, smartphone use among MSM is nearly universal, and MSM report a strong preference for app-based HIV prevention programs [18,19]. Although app-based interventions are evolving and promote the HIV prevention continuum, most, if not all, are limited to high-income countries and none provide comprehensive HIV prevention services [27]. Furthermore, many of these emerging apps deploy an online-to-offline (O2O) strategy [28,29], where clients eventually must be seen in person. In these cases, the anonymity afforded through the online experience ends during the clinical encounter where individuals must be linked to their testing results and medication prescriptions. An important innovation in the traditional O2O and clinic-based models would be to keep the entire care process in the virtual space (online). However, such strategies have yet to be developed and assessed.

To address this unmet need, we developed JomPrEP (where “Jom” means “let us” in Bahasa Malaysia), a clinic-integrated smartphone app, designed to provide HIV prevention services for MSM in Malaysia. The development of JomPrEP has been described previously [30]. In brief, it is adapted from HealthMindr, an app previously demonstrated to increase HIV testing and PrEP uptake among MSM in the United States [25]. In collaboration with local Malaysian clinics, JomPrEP offers a virtual platform for Malaysian MSM to access a range of HIV prevention (ie, HIV testing and PrEP) and other support services (eg, referral to mental health support) without having to interface face to face with clinicians. It includes several on-demand features, including scheduling and managing appointments in person or through e-consultation, communicating with the clinical team (ie, chat), home-based testing, accessing test results, ordering health products, discrete door-to-door delivery, timely notifications, a points-based reward system for completing activities within the app, and a multimedia resource center. Here, we report findings from beta testing of the recently developed JomPrEP app to evaluate its usability and acceptability.

Methods

Study Design and Settings

We conducted beta testing of JomPrEP to assess its usability and acceptability among MSM living in the Greater Kuala Lumpur region, Malaysia. Beta testing of an app helps to identify any final areas for improvement [31]. We hypothesized that beta testing for 30 days of observation (N=50) would allow us to evaluate the app's design, functionality, and usability. The
sample size of 50 was determined based on the pragmatics of recruitment and the need to examine feasibility [32-34].

We partnered with the Centre of Excellence for Research in AIDS (CERiA) at the University of Malaya, Kuala Lumpur, Malaysia, to conduct this study. Working closely with several other local and international institutions, CERiA conducts innovative and interdisciplinary research that combines epidemiological, biomedical, and sociobehavioral approaches, focusing on the implementation of HIV prevention and treatment. As part of JomPrEP integration with existing clinics, we partnered with 2 local clinics—the Red Clinic (private clinic) and the Community Health Care Clinic (nongovernmental organization [NGO]-based clinic)—to provide clinical services (eg, HIV testing, sexually transmitted infection [STI] testing, PrEP services) virtually via the app.

Study Participants and Recruitment

Eligibility criteria included (1) being 18 years or older; (2) identifying as a cis-gender man; (3) self-reporting an HIV-negative or HIV status unknown at screening; (4) not having used PrEP previously (ie, PrEP naive); (5) self-reporting evidence of being at risk for HIV acquisition, as defined by the World Health Organization PrEP clinical guidelines [35]; (6) owning a smartphone; and (7) currently residing in the Greater Kuala Lumpur region.

In total, 50 participants were recruited between March and April 2022 using in-person and online recruitment strategies. For in-person recruitment, flyers were distributed to potential participants as well as posted at local partner organizations (eg, clinics, lesbian, gay, bisexual, transgender [LGBT]–friendly community-based organizations). Additionally, we used various general and MSM-specific social media platforms as venues for participant recruitment. These included placing advertisements in geosocial networking (GSN) apps popular among MSM in Malaysia (ie, Hornet) as well as posting study flyers on Malaysian MSM–focused Facebook pages. Interested individuals who clicked on an advertisement were directed to the study website [36], where they were presented with a brief description of the study and web-based screening.

Procedures

After meeting enrollment criteria, eligible participants were asked to provide electronic informed consent for study participation, followed by undergoing a baseline assessment. Study staff then assisted enrolled participants with downloading JomPrEP and provided them with brief instructions on the purpose of the app and an overview of how to use it. To restrict access to JomPrEP to the study participants, participants were provided with a single-use registration code needed to gain access to the app. Upon downloading the app, participants were asked to complete an onboarding process, which included creating log-in credentials. They were then redirected to the JomPrEP landing screen (home screen), which contains several icons representing key app functions (Table 1).

Screenshots of the app are available in Multimedia Appendix 1. Participants were requested to keep and use the app for 30 days and encouraged to use all app features. On day 30, participants completed a posttest survey and were asked to provide a synthesis of issues regarding the app (ie, exit interviews). For exit interviews, 20 (40%) participants were randomly sampled and interviews were conducted until data saturation was reached. The 1-on-1 sessions were conducted online via licensed videoconferencing software. Participants were given the choice of turning on or off their cameras and were asked to use a pseudonym/nickname.

Participants received point-based rewards (known as JomPrEP points [JPP]) for completing specific activities or meeting milestones via the app (eg, 100 JPP for baseline and follow-up assessment each, 50 for completing app onboarding, 20 for an HIVST in-app order, 50 for completing a lab test, 50 for completing an e-consultation for PrEP, 30 for an in-app PrEP order, 50 for optimal PrEP adherence; maximum points that could be earned: 740 or US $18.50). Participants were allowed to redeem points for cash at any point during the study period (10 JPP=RM 1, or US $0.24).
<table>
<thead>
<tr>
<th>Features</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customizable Home page</td>
<td>• Visual presentation using avatars and pseudonyms</td>
</tr>
<tr>
<td>HIVST&lt;sup&gt;a&lt;/sup&gt;</td>
<td>• Allows users to order an HIVST kit (Orasure)</td>
</tr>
<tr>
<td></td>
<td>• Allows users to upload HIVST results for verification purposes to facilitate posttest linkage to HIV prevention or treatment services</td>
</tr>
<tr>
<td></td>
<td>• Includes multimedia (ie, text-, picture-, and video-based) content on how to use the HIVST kit and interpret the result</td>
</tr>
<tr>
<td>PrEP&lt;sup&gt;b&lt;/sup&gt; Express</td>
<td>• Provides users with a fast and convenient way to start PrEP (and state on it)</td>
</tr>
<tr>
<td></td>
<td>• Includes a sequential pathway for the users to get on PrEP: HIV risk assessment (provides tailored recommendations based on the user’s response); choose preferred clinic (allows users to choose between the participating clinics for PrEP); choose PrEP type (allows users to choose between different PrEP prescription modalities, ie, same day&lt;sup&gt;c&lt;/sup&gt; vs traditional&lt;sup&gt;d&lt;/sup&gt;); schedule appointments (allows users to choose their preferred date and time for phlebotomy and e-consultation&lt;sup&gt;e&lt;/sup&gt;); PrEP medication delivery (allows users to choose their preferred method of getting PrEP: pickup at the pharmacy vs discrete door-to-door delivery)</td>
</tr>
<tr>
<td>Orders</td>
<td>• Allows users to monitor past and current orders (HIVST kit, PrEP)</td>
</tr>
<tr>
<td></td>
<td>• Allows users to track their current orders in real time (via application programming interface [API] integration of courier tracking)</td>
</tr>
<tr>
<td></td>
<td>• Provides notifications on the status of their orders</td>
</tr>
<tr>
<td>Labs</td>
<td>• Allows users to view their lab test results</td>
</tr>
<tr>
<td></td>
<td>• Allows users to receive timely notifications about new lab results</td>
</tr>
<tr>
<td>Appointments</td>
<td>• Allows users to view details about past and future appointments and make any necessary changes (eg, reschedule, cancel)</td>
</tr>
<tr>
<td></td>
<td>• Allows users to meet with a doctor virtually (ie, e-consultation)</td>
</tr>
<tr>
<td>Mental Health</td>
<td>• Allows users to self-screen for depression and receive results</td>
</tr>
<tr>
<td></td>
<td>• Provides users with community resources and support services (ie, a list of mental health service providers)</td>
</tr>
<tr>
<td></td>
<td>• Provides users with a personalized referral letter to mental health services to facilitate rapid linkage&lt;sup&gt;f&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>• Allows users to keep track of previous mental health–screening results and access referral letters</td>
</tr>
<tr>
<td>MedManager</td>
<td>• Allows users to set and receive personalized medication reminders</td>
</tr>
<tr>
<td></td>
<td>• Provides users with reminders to refill their prescriptions</td>
</tr>
<tr>
<td></td>
<td>• Allows users to view visual reports of their medication adherence</td>
</tr>
<tr>
<td>MoodTracker</td>
<td>• Allows users to keep track of their mood daily</td>
</tr>
<tr>
<td></td>
<td>• Provides users with a visual display of their mood over time</td>
</tr>
<tr>
<td>Messages (ie, chat)</td>
<td>• Allows users to send and receive nonurgent medical questions to the clinic and research staff</td>
</tr>
<tr>
<td>Resources</td>
<td>• Provides users with multimedia (text-, picture-, video-based) content of an array of relevant information (eg, HIV, PrEP, substance use, mental health)</td>
</tr>
<tr>
<td>News</td>
<td>• Provides users with the latest health news updated regularly</td>
</tr>
<tr>
<td>Reward points</td>
<td>• Allows users to accumulate points for completing activities in the app</td>
</tr>
<tr>
<td></td>
<td>• Allow users to track and redeem points for cash or in-app purchases</td>
</tr>
<tr>
<td>JomPrEP Clinic Dashboard</td>
<td>• Includes a web-based dashboard for the clinics affiliated with the JomPrEP app</td>
</tr>
<tr>
<td></td>
<td>• Allows staff members of the affiliated clinics (ie, doctors, nurses, pharmacists, front-desk staff) to access the dashboard to facilitate patient care for JomPrEP app users</td>
</tr>
<tr>
<td></td>
<td>• In the absence of an electronic health record (EHR) in the local setting, functions more like the EHR system</td>
</tr>
</tbody>
</table>

<sup>a</sup>HIVST: HIV self-testing.

<sup>b</sup>PrEP: pre-exposure prophylaxis.

<sup>c</sup>Receive PrEP at the first doctor visit (no need to wait for lab results).

<sup>d</sup>Get PrEP after lab results are complete (need a follow-up doctor visit to review lab results).

<sup>e</sup>Applies only to those who choose traditional PrEP.

<sup>f</sup>Includes a referral letter for mental health.
Ethical Considerations

The Institutional Review Board at the University of Connecticut approved this study (H22-0049), with an institutional reliance agreement with the University of Malaya. Eligible participants provided electronic informed consent for study participation.

Assessments

Participant Characteristics

All assessments (ie, baseline and follow-up) were conducted virtually and self-administered using Qualtrics. We collected participant demographic and baseline characteristics, including age, ethnicity, educational status, relationship status, income, housing status, depressive symptoms [37], substance use and sexual history, HIV/STI-testing practices, and past use of PrEP and postexposure prophylaxis (PEP).

JomPrEP App Evaluation

After 30 days of use, participants were asked to assess the app’s features, usability, design, content, and functionality using 2 Likert scales. JomPrEP acceptability was assessed using the System Usability Scale (SUS) [38], a validated measure that assesses the subjective usability of an app. Scores range from 0 to 100, with scores of ≥50 indicating that the app is acceptable [38]. We also collected app analytics, such as the number of log-ins, session duration, pages visited, and frequency and duration of use of app components, to determine usability. Additionally, data on the uptake of HIV testing and PrEP, mental health screening and referral to mental health support services, and use of the HIVST kit for those who placed in-app orders were extracted from the web-based JomPrEP Clinic Dashboard.

Finally, we conducted exit interviews with 20 (40%) participants to obtain feedback on app functionality, technical performance, errors and software bugs encountered, overall experience using the app, feedback for further refinement, and subjective impact of the app on HIV testing and PrEP uptake. One-on-one interviews were conducted by research staff virtually using videoconferencing technology. Interviews were recorded and transcribed for analysis.

Analytical Plan

All quantitative data were managed and analyzed using IBM SPSS Statistics version 28. Means for continuous variables and frequencies for categorical variables were calculated to describe the participants at baseline. App usability and acceptability were based on descriptive statistics from the app analytics and acceptability measure. For example, evaluation responses are reported as the percentage of users who completed the posttest survey. SUS results are reported as an aggregate score, with a score of ≥50 indicating that the app is acceptable [39,40]; the percentage of participants with scores ≥50 is also reported. Descriptive statistics of app analytics were used to examine app engagement and are reported as the mean with the range for time and action measurements. For qualitative data, all the exit interviews were audio-recorded, transcribed, and analyzed. The comments and issues were grouped and categorized according to common themes relative to specific app functions by 3 coders (including 2 senior coders) and agreed upon by all authors. Dedoose version 9.0.54 was used throughout to assist in data management and analysis.

Results

Participant Characteristics

The mean age of the 50 participants was 27.9 years (range 21-45 years), with most being single (36/50, 72%), Malay (26/50, 52%), university graduates (34/50, 68%) and living in a house/apartment with other people (36/50, 72%). Almost all participants reported having been tested for HIV (49/50, 98%), and 39/50 (78%) participants had done so in the past 6 months. Of all 50 participants, 26 (52%) reported using HIVST and only 5 (10%) had used PrEP previously. Regarding sexual behaviors in the past 6 months, 47/50 (94%) participants reported anal sex with another man, while only 16/50 (32%) participants reported consistent condom use, 4/50 (8%) reported having engaged in sexualized drug use, and 9/50 (18%) reported having engaged in group sex (Table 2).
Table 2. Characteristics of participants (N=50).

<table>
<thead>
<tr>
<th>Variables</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years), mean (SD)</td>
<td>27.9 (5.3)</td>
</tr>
<tr>
<td>Ethnicity (Malaya), n (%)</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>24 (48)</td>
</tr>
<tr>
<td>Yes</td>
<td>26 (52)</td>
</tr>
<tr>
<td>University graduate, n (%)</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>16 (32)</td>
</tr>
<tr>
<td>Yes</td>
<td>34 (68)</td>
</tr>
<tr>
<td>Relationship status, n (%)</td>
<td></td>
</tr>
<tr>
<td>Single</td>
<td>36 (72)</td>
</tr>
<tr>
<td>Partner</td>
<td>14 (28)</td>
</tr>
<tr>
<td>Monthly income (RM/US $), mean (SD)</td>
<td>3553.40 (2985.90)/837.97 (704.14)</td>
</tr>
<tr>
<td>Living status, n (%)</td>
<td></td>
</tr>
<tr>
<td>Alone</td>
<td>14 (28)</td>
</tr>
<tr>
<td>Living with others</td>
<td>36 (72)</td>
</tr>
<tr>
<td>Tested for HIV (past 6 months), n (%)</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>11 (22)</td>
</tr>
<tr>
<td>Yes</td>
<td>39 (78)</td>
</tr>
<tr>
<td>Ever used an HIVST kit, n (%)</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>24 (48)</td>
</tr>
<tr>
<td>Yes</td>
<td>26 (52)</td>
</tr>
<tr>
<td>Previously diagnosed with STI, n (%)</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>27 (54)</td>
</tr>
<tr>
<td>Yes</td>
<td>23 (46)</td>
</tr>
<tr>
<td>Ever used PrEP, n (%)</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>45 (90)</td>
</tr>
<tr>
<td>Yes</td>
<td>5 (10)</td>
</tr>
<tr>
<td>Ever used PEP, n (%)</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>46 (92)</td>
</tr>
<tr>
<td>Yes</td>
<td>4 (8)</td>
</tr>
<tr>
<td>Perceived HIV risk, n (%)</td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>6 (12)</td>
</tr>
<tr>
<td>Low</td>
<td>25 (50)</td>
</tr>
<tr>
<td>Moderate</td>
<td>15 (30)</td>
</tr>
<tr>
<td>High</td>
<td>4 (8)</td>
</tr>
<tr>
<td>Ever injected drugs, n (%)</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>49 (98)</td>
</tr>
<tr>
<td>Yes</td>
<td>1 (2)</td>
</tr>
<tr>
<td>Engaged in anal sex (past 6 months), n (%)</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>3 (6)</td>
</tr>
<tr>
<td>Yes</td>
<td>47 (94)</td>
</tr>
<tr>
<td>HIV serodiscordant relationship (past 6 months), n (%)</td>
<td></td>
</tr>
</tbody>
</table>
Frequency

Variables | Frequency
---|---
No | 47 (94)
Yes | 3 (6)

Consistent condom use (past 6 months), n (%) | Frequency
---|---
No | 34 (68)
Yes | 16 (32)

Engaged in group sex (past 6 months), n (%) | Frequency
---|---
No | 41 (82)
Yes | 9 (18)

Engaged in sexualized drug use^[f] (past 6 months), n (%) | Frequency
---|---
No | 46 (92)
Yes | 4 (8)

---

^aIncludes college, university, and professional degrees.

^bHIVST: HIV self-testing.

^cSTI: sexually transmitted infections (e.g., gonorrhea, chlamydia, syphilis).

^dPrEP: preexposure prophylaxis.

^ePEP: postexposure prophylaxis.

^[f]Use of psychoactive substances (e.g., amphetamines, 3,4-methylenedioxymethamphetamine [MDMA]) before or during sexual activity.

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**Uptake of HIV Prevention Services**

During the 30-day beta-testing phase of JomPrEP, 42/50 (84%) participants ordered an HIVST kit using the app. Almost all (46/50, 92%) participants used the app to get on PrEP. Specifically, 30/46 (65%) participants chose same-day PrEP versus traditional PrEP, and the majority of them picked up the PrEP medication at the pharmacy (28/46, 61%). Additionally, 44/50 (88%) participants used the online assessment tool to screen for depression, and 39/44 (89%) of them met the criteria for moderate-to-severe depressive symptoms [37] and were provided with a referral letter (Table 3).

**Table 3.** Participants’ uptake of HIV testing and PrEP^[a] services using JomPrEP (N=50).

<table>
<thead>
<tr>
<th>Service usage</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>HIV testing</strong></td>
<td></td>
</tr>
<tr>
<td>Ordered HIVST^[b] kit</td>
<td>42 (84)</td>
</tr>
<tr>
<td>Verified HIVST results^[c]</td>
<td>40 (95)</td>
</tr>
<tr>
<td><strong>Linked to PrEP services (n=46, 92%)</strong></td>
<td></td>
</tr>
<tr>
<td>Traditional^[d] PrEP delivery</td>
<td>16 (35)</td>
</tr>
<tr>
<td>Same-day^[e] PrEP delivery</td>
<td>30 (65)</td>
</tr>
<tr>
<td>Completed phlebotomy</td>
<td>46 (100)</td>
</tr>
<tr>
<td>Completed e-consultation^[f]</td>
<td>16 (35)</td>
</tr>
<tr>
<td>Completed in-person consultation</td>
<td>30 (65)</td>
</tr>
<tr>
<td>Picked-up PrEP medication at pharmacy</td>
<td>28 (61)</td>
</tr>
<tr>
<td>PrEP medication delivered at home</td>
<td>18 (39)</td>
</tr>
<tr>
<td>Mental health screening</td>
<td>44 (88)</td>
</tr>
</tbody>
</table>


^[b]HIVST: HIV self-testing.

^[c]HIVST result verified by providing an image of the result via the app.

^[d]Receive PrEP after lab results are complete (need a follow-up doctor visit to review lab results).

^[e]Receive PrEP at the first doctor visit (no need to wait for lab results).

^[f]Applies only to those who choose same-day PrEP.
**JomPrEP App Evaluation**

During the beta-testing phase, 29/50 (58%) participants were Android users, while the remainder (21/50, 42%) were iOS users. Usability measures by participants included app use, with an average of 8 (SD 5.0, range 2-18) unique visits over 30 days, with an average duration of 28 (SD 38.9) minutes per session. The app had a mean of 34.9 (SD 14.7) daily users, with 939.3 (SD 597.9) daily page views, 63.4 (SD 28.5) daily sessions on average, and consistent returning visits (eg, >10: 29/50, 58%; 6-10: 22/50, 44%).

The mean acceptability score was 73.8 (SD 10.1) on the SUS, well above the minimum criteria (≥50) set for the acceptability of the app [39,40], with all participants reporting acceptability scores of >50. Almost all participants reported that they were satisfied with JomPrEP (46/50, 92%) and that the app was useful in addressing their HIV prevention needs (49/50, 98%); see Table 4.

When participants were asked about future app use, most said they were likely to continue using the app as part of their HIV prevention plan (42/50, 84%), would download the app if publicly available (43/50, 86%), and would recommend the app to their friends or colleagues (50/50, 100%). Most participants felt confident in in-app security (43/50, 86%), including autologout after 5 minutes of inactivity (44/50, 88%), an email and password log-in (42/50, 84%), a 4-digit personal identification number (36/50, 72%), and the app name and icon not associated with HIV (32/50, 64%); see Table 5.

Participants found JomPrEP to be easy to use and felt confident that they would be able to learn how to use it quickly and without technical assistance (Table 6).

**Table 4.** Participants’ rating of satisfaction with using JomPrEP features (N=50).

<table>
<thead>
<tr>
<th>Activity (“How satisfied are you with the following features of the JomPrEP app?”)</th>
<th>Participants, n (%)&lt;sup&gt;a&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ordering an HIVST&lt;sup&gt;b&lt;/sup&gt; kit</td>
<td>47 (94)</td>
</tr>
<tr>
<td>Ordering PrEP&lt;sup&gt;c&lt;/sup&gt; medication</td>
<td>46 (92)</td>
</tr>
<tr>
<td>Reward system (earning and redeeming points)</td>
<td>43 (86)</td>
</tr>
<tr>
<td>Completing the mental health screener</td>
<td>42 (84)</td>
</tr>
<tr>
<td>Chat with clinical or research staff</td>
<td>42 (84)</td>
</tr>
<tr>
<td>Booking appointments (blood draw, consultation with doctor)</td>
<td>42 (84)</td>
</tr>
<tr>
<td>Keeping track of upcoming and past appointments</td>
<td>42 (84)</td>
</tr>
<tr>
<td>Tracking order status (ie, HIVST, PrEP)</td>
<td>40 (80)</td>
</tr>
<tr>
<td>MoodTracker (track mood daily)</td>
<td>40 (80)</td>
</tr>
<tr>
<td>Online consultation with the doctor (e-consultation)</td>
<td>40 (80)</td>
</tr>
<tr>
<td>Reviewing laboratory test results</td>
<td>38 (76)</td>
</tr>
<tr>
<td>Resources/News Center</td>
<td>36 (72)</td>
</tr>
<tr>
<td>Notifications from the app</td>
<td>36 (72)</td>
</tr>
<tr>
<td>MedManager (receive medication reminders, track medication use)</td>
<td>30 (60)</td>
</tr>
</tbody>
</table>

<sup>a</sup>Very satisfied and extremely satisfied (not included: not at all satisfied, slightly satisfied, moderately satisfied).

<sup>b</sup>HIVST: HIV self-testing.

<sup>c</sup>PrEP: preexposure prophylaxis.
### Table 5. Participants’ rating of the usefulness of JomPrEP features (report their use; N=50).

<table>
<thead>
<tr>
<th>Activity (“How much do you agree that the use of the JomPrEP app…”)</th>
<th>Participants, n (%)&lt;sup&gt;a&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assisted in getting tested for HIV</td>
<td>50 (100)</td>
</tr>
<tr>
<td>Assisted in getting started on PrEP&lt;sup&gt;b&lt;/sup&gt;</td>
<td>50 (100)</td>
</tr>
<tr>
<td>Made access to medical records easier (ie, test results, appointments)</td>
<td>49 (98)</td>
</tr>
<tr>
<td>Made access to HIV testing much easier</td>
<td>49 (98)</td>
</tr>
<tr>
<td>Helped to understand the risk of getting HIV</td>
<td>46 (92)</td>
</tr>
<tr>
<td>Motivated to get on PrEP</td>
<td>46 (92)</td>
</tr>
<tr>
<td>Motivated to get tested for STIs&lt;sup&gt;c&lt;/sup&gt;</td>
<td>46 (92)</td>
</tr>
<tr>
<td>Helped to understand whether PrEP would be a good fit</td>
<td>46 (92)</td>
</tr>
<tr>
<td>Helped to get in touch with the clinic staff (via chat messages)</td>
<td>44 (88)</td>
</tr>
<tr>
<td>Helped to get the latest information about HIV</td>
<td>43 (86)</td>
</tr>
<tr>
<td>Helped to understand mental health needs</td>
<td>42 (84)</td>
</tr>
<tr>
<td>Made access to PrEP much easier</td>
<td>40 (80)</td>
</tr>
</tbody>
</table>

<sup>a</sup>Agree and strongly agree (not included: strongly disagree, disagree, neither agree nor disagree).

<sup>b</sup>PrEP: preexposure prophylaxis.

<sup>c</sup>STI: sexually transmitted infection.

### Table 6. Participants’ rating of the level of difficulty of JomPrEP app features (N=50).

<table>
<thead>
<tr>
<th>Activity (“How easy or hard was it to do the following tasks on the JomPrEP app?”)</th>
<th>Participants, n (%)&lt;sup&gt;b&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ordering an HIVST&lt;sup&gt;b&lt;/sup&gt; kit</td>
<td>49 (98)</td>
</tr>
<tr>
<td>Ordering PrEP&lt;sup&gt;c&lt;/sup&gt; medication</td>
<td>47 (94)</td>
</tr>
<tr>
<td>Booking appointments (blood draw, consultation with doctor)</td>
<td>46 (92)</td>
</tr>
<tr>
<td>Reward system (earning and redeeming points)</td>
<td>44 (88)</td>
</tr>
<tr>
<td>Completing a mental health screener</td>
<td>43 (86)</td>
</tr>
<tr>
<td>Customizing profile page (eg, avatar, password, address, name)</td>
<td>43 (86)</td>
</tr>
<tr>
<td>Tracking the order status (ie, HIVST, PrEP)</td>
<td>43 (86)</td>
</tr>
<tr>
<td>Creating an account (onboarding process)</td>
<td>40 (80)</td>
</tr>
<tr>
<td>Reviewing laboratory test results</td>
<td>40 (80)</td>
</tr>
<tr>
<td>MoodTracker (track mood daily)</td>
<td>40 (80)</td>
</tr>
<tr>
<td>Chat with clinical or research staff</td>
<td>38 (76)</td>
</tr>
<tr>
<td>Find relevant information about HIV prevention</td>
<td>35 (70)</td>
</tr>
<tr>
<td>Online consultation with a doctor (e-consultation)</td>
<td>33 (66)</td>
</tr>
<tr>
<td>MedManager (receive medication reminders, track medication use)</td>
<td>25 (50)</td>
</tr>
</tbody>
</table>

<sup>a</sup>Very easy (not included: very difficult, difficult, neutral).

<sup>b</sup>HIVST: HIV self-testing.

<sup>c</sup>PrEP: preexposure prophylaxis.

### Exit Interviews

In follow-up exit interviews (n=20, 40%), participants indicated a high level of acceptability for the content, interface, and features of JomPrEP. Participants found the app to be user friendly, easy to navigate, and with a good layout. Participants also appreciated the ability to earn reward points for using specific app features, facilitating user engagement and retention.

…it’s straightforward, it’s user friendly, it’s easy to use…I think the critical part for me is actually the ease of use of the app.

Because of convenience. It’s like having a mini-doctor. It’s much easier for you to get tested, instead of going to a clinic and stuff.

The point and rewards system are very interesting and attractive.
Participants noted that ordering HIVST kits via the app was straightforward and that the multimedia instructions helped them use HIVST kits and interpret test results.

I tried self-test kits from other sources, comparing the experience using this and also ordering elsewhere, I think JomPrEP was very prompt, the delivery was, I think, the next day and self-test kit was easy to use. The feature I used most in the app is the one that allowed me to order a self-testing kit. It’s super convenient because first, order placement is very easy to do and the second one because the delivery is very fast...And they have very clear instructions on how to do it and get the result. Instructions to do the screening at home are very clear. And to upload the result is easy as well.

Furthermore, participants endorsed that the app helped them initiate PrEP use and maintain optimal adherence by facilitating a safe and stigma-free virtual platform to access PrEP services. Participants commented on the relevant information presented in the app, and many noted that they “didn’t know anything about [PrEP] until [they] used the app.”

There’s a lot of information that makes me want to take PrEP more, because of the useful information and why I need to take the PrEP. This app is very like a one-stop center to take the PrEP...inside, you can book a consultation, view your result and you can directly order the PrEP. So, this helped me more easily to get the PrEP.

I have been thinking of getting PrEP but didn’t know much about it (process, the cost, etc). The app makes everything more transparent. And when you take it, there’s a reminder every day so you can set up the clock, so you don’t forget.

When I first came here, I am not originally from here, I was trying to find PrEP, and I had a hard time finding it. When I used this app, it made things much easier. I don’t need to worry if the clinic is judgmental.

Participants also provided suggestions to improve the app and specific feedback on additional resources and features that they found interesting and helpful. For example, participants suggested that the app include an option to make an appointment with a mental health counselors and support groups and the ability to connect with other JomPrEP users through private messaging or discussion forums. Participants shared occasional issues with lagging app response time, difficulty setting up reminder notifications, and missing notifications. A few participants indicated that the test result feature of the app was a little challenging to use and required multiple clicks to view the results. A few participants also noted that some of the information in the app is repetitive or is not updated frequently. One participant recommended that the app allow the users to make the app more discreet (eg, the ability to change app icons).

Participants indicated that they would continue to use the JomPrEP app after the final version is released to the public.

Yes, definitely. I would use it because it’s easier to put my appointment and view my lab results. I don’t have to have it in a hardcopy form, easily accessible to my smartphone, and I could easily order my HIV self-testing kit as well.

I will continue to use it. And I think the JomPrEP app is very useful for me in terms of ordering the PrEP and booking e-consultations.

Discussion

Principal Findings

Using innovative tools, such as mHealth, in public health programming and the health care system can help bridge gaps in the adoption of needed health and prevention services, particularly among underserved populations [41-44]. In this study, we sought to investigate the usability and acceptability of JomPrEP, a clinic-integrated smartphone app, as an additional platform to promote routine HIV testing and PrEP uptake among MSM in Malaysia. Our findings demonstrated that Malaysian MSM will use a smartphone app to virtually access HIV prevention services and that such an app is acceptable to this at-risk group, as indicated by the participants’ empiric use of the app.

Comparison With Prior Work

Prior studies have demonstrated several apps for HIV prevention and treatment efforts to be promising and cost-effective strategies to reach and engage stigmatized and hidden populations, such as MSM [25,45-47]. In Malaysia, the use of mobile technology over the past decades has grown markedly, particularly among MSM, with a mobile phone penetration rate of 97.5% and an internet penetration rate of 71.1% [18,19,48]. Importantly, our beta testing of JomPrEP revealed that an overwhelming majority of men used the app to receive HIV prevention services: ordering an HIVST kit (84%) and getting on PrEP (94%). Participants reported that they were satisfied and comfortable using JomPrEP and would recommend it to friends or colleagues. These findings indicate the potential utility of JomPrEP for Malaysian MSM to promote HIV prevention services.

One of the key innovations on JomPrEP includes incorporating on-demand features, such as home-based HIVST, e-consultations, and discrete door-to-door delivery, to provide a scalable model for remote HIV prevention services delivery in the LMIC setting. Although the users would still be required to visit a laboratory for clinical testing, this would not require them to be face-to-face with their clinicians. Moreover, the platform allows users to self-assess their HIV risk, consult online with clinicians from the participant clinics, and have their medication delivered to their preferred location, thus minimizing the need for in-person interactions with the clinician. This represents a significant and much-needed innovation over traditional clinic-based and O2O models of HIV service delivery to keep at-risk individuals wedded into the virtual clinical ecosystem and boost the uptake of clinical services [28,29]. This is particularly important in LMIC settings, such as Malaysia, as the virtual platform allows users to bypass barriers to care for marginalized populations and feel safer and less...
vulnerable to potential legal or social harm (eg, by reducing face-to-face interactions with providers).

Prior research has documented low user retention and a lack of sustained use after adoption as key challenges to the effectiveness of existing app-based interventions [49]. Obtaining high engagement and retention is necessary to maintain the integrity and long-term sustainability of effective mHealth interventions [50]. Strategies to integrate other features that do not include individual input, such as passive data collection using inputs from their smartphones or unobtrusive wearable devices, may strengthen the features of the app.

Results from our beta testing, however, revealed that MSM were actively engaged in the app and that retention was excellent through the beta testing. Although it is possible that the perfect retention rate could be because of the shorter follow-up time, it is likely that the incorporation of additional components, such as the ability to customize profiles, personalized messages, and gaming elements (ie, the ability to “level up,” earn and redeem points), may have allowed for enhanced user engagement. In recent years, the utility of gamification features (eg, challenges, tasks, rewards, badges, leaderboards) in nontraditional gaming contexts has increased significantly, thus providing opportunities for greater user engagement in mHealth interventions [51,52].

As confirmed in the exit interviews, the overall high engagement and usage of key features of JomPrEP suggest that an app-based intervention, such as JomPrEP, has a high degree of feasibility to ensure equitable access to HIV testing and PrEP services for MSM in Malaysia.

Although there was consensus on the usability and acceptability of JomPrEP, with no significant differences between different subgroups of Malaysian MSM, the app would benefit from continued refinement to address some of the shortcomings identified by men. For example, most participants who completed screening for depressive symptoms (88%) received referral letters to seek care offline (ie, outside the app). Given the focus of JomPrEP to offer holistic HIV prevention services within the online ecosystem, it would be important for the app to incorporate online consultation with mental health counselors and linkage to support groups via the app. Additionally, as part of the continued effort to ensure the safety and security of users, it would be important that JomPrEP incorporate added security measures, including 2-factor authentication and a discreet app icon (DAI). The availability of a DAI allows users to replace the default JomPrEP app log on their phone with another symbol (of their choice). This will help protect users when there is a possibility that someone may accidentally look at users’ phones and recognize that they have an app that might link them to the HIV or lesbian, gay, bisexual, transgender, queer, and others (LGBTQ+) community. A study conducted with MSM of Malaysia also highlighted the importance of privacy and confidentiality features in the mobile apps targeted for HIV prevention and treatment to minimize harm and safeguard users’ privacy and confidentiality [53]. Furthermore, it is important that the app be available for users outside of Kuala Lumpur, the capital city, and be linked to both private and government clinics/hospitals. This will ensure widespread implementation of JomPrEP to scale-up HIV prevention services for MSM across Malaysia.

Limitations
The results of this study should be viewed in the context of the limitations. First, this pilot study included a small sample size and short-term follow-up (ie, 30-days) and used a single-arm design that is commonly used in beta testing; therefore, it was not powered or designed to evaluate efficacy. Second, our participants were subject to selection bias across several dimensions. For example, we recruited men using Facebook or a dating app (ie, Hornet) who may have been more comfortable using mobile apps than other men (ie, hidden MSM). Moreover, participants were already engaged, at least in part, due to their prior high levels of HIV testing. Participants were enrolled in the Greater Kuala Lumpur area only, potentially limiting the generalizability of the findings. Third, social desirability bias may have led participants to speak more positively about their app experience during the survey and exit interviews. This was in part observed by participants who responded favorably to app features, but our usability testing had not confirmed they used the specific feature. Finally, HIVST kits and PrEP services were free to the participants, which may have led to an overestimation of the actual uptake of HIV testing and PrEP services.

Future Directions
Further research is warranted to examine the implementation of JomPrEP in a more real-world setting. Regardless of these limitations, we believe that our findings carry important implications for efforts to improve the uptake of HIV testing and PrEP services among Malaysian MSM using an app-based intervention.

Conclusion
Overall, the JomPrEP app represents a feasible and acceptable tool for Malaysian MSM to access HIV prevention services. Importantly, it incorporates several on-demand features to support the remote delivery of HIV prevention services, thus representing a significant innovation on traditional clinic-based and O2O service delivery models [28,29]. The reported outcomes are promising and indicate the benefits of systematically implementing this platform to foster HIV prevention efforts in LMICs, such as Malaysia, where MSM are disenfranchised from existing prevention efforts [2-4]. A large-scale randomized controlled trial is warranted to establish the efficacy of JomPrEP among this at-risk group.

Acknowledgments
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Data Availability
The data sets generated and analyzed during this study are available from the corresponding author on reasonable request.

Conflicts of Interest
None declared.

Multimedia Appendix 1
JomPrEP app screenshots.

References


Abbreviations

CERiA: Centre of Excellence for Research in AIDS
DAI: discreet app icon
EHR: electronic health record
HIVST: HIV self-testing
JPP: JonPrEP points
LMIC: low- and middle-income country
mHealth: mobile health
MSM: men who have sex with men
O2O: online-to-offline
PEP: postexposure prophylaxis
PrEP: pre-exposure prophylaxis
STI: sexually transmitted infection
SUS: System Usability Scale
Acceptability and Utility of a Smartphone App to Support Adolescent Mental Health (BeMe): Program Evaluation Study

Judith J Prochaska1, MPH, PhD; Yixin Wang1, PhD; Molly A Bowdring1, PhD; Amy Chieng1, BA; Neha P Chaudhary2, MD; Danielle E Ramo2, PhD

1Stanford Prevention Research Center, Department of Medicine, Stanford University, Palo Alto, CA, United States
2BeMe Health, Miami, FL, United States

Abstract

Background: Adolescents face unprecedented mental health challenges, and technology has the opportunity to facilitate access and support digitally connected generations. The combination of digital tools and live human connection may hold particular promise for resonating with and flexibly supporting young people’s mental health.

Objective: This study aimed to describe the BeMe app-based platform to support adolescents’ mental health and well-being and to examine app engagement, usability, and satisfaction.

Methods: Adolescents in the United States, aged 13 to 20 years, were recruited via the web and enrolled between September 1 and October 31, 2022. App engagement, feature use, clinical functioning, and satisfaction with BeMe were examined for 30 days. BeMe provides content based on cognitive behavioral therapy, dialectical behavior therapy, motivational interviewing, and positive psychology; interactive activities; live text-based coaching; links to clinical services; and crisis support tools (digital and live).

Results: The average age of the sample (N=13,421) was 15.04 (SD 1.7) years, and 56.72% (7612/13,421) identified with she/her pronouns. For the subsample that completed the in-app assessments, the mean scores indicated concern for depression (8-item Patient Health Questionnaire mean 15.68/20, SD 5.9; n=239), anxiety (7-item Generalized Anxiety Disorder Questionnaire mean 13.37/17, SD 5.0; n=791), and poor well-being (World Health Organization–Five Well-being Index mean 30.15/100, SD 16.1; n=1923). Overall, the adolescents engaged with BeMe for an average of 2.38 (SD 2.7) days in 7.94 (SD 24.1) sessions and completed 11.26 (SD 19.8) activities. Most adolescents engaged with BeMe’s content (12,270/13,421, 91.42%), mood ratings (13,094/13,421, 97.56%), and interactive skills (10,098/13,421, 75.24%), and almost one-fifth of the adolescents engaged with coaching (2539/13,421, 18.92%), clinical resources (2411/13,421, 17.96%), and crisis support resources (2499/13,421, 18.62%). Overall app engagement (total activities) was highest among female and gender-neutral adolescents compared with male adolescents (all \(P<.001\)) and was highest among younger adolescents (aged 13-14 years) compared with all other ages (all \(P<.001\)). Satisfaction ratings were generally high for content (eg, 158/176, 89.8% rated as helpful and 1044/1139, 91.66% improved coping self-efficacy), activities (5362/8468, 63.32% helpful and 4408/6072, 72.6% useful in coping with big feelings), and coaching (747/894, 83.6% helpful and 747/894, 83.6% improved coping self-efficacy). Engagement (total activities completed) predicted the likelihood of app satisfaction (\(P<.001\)).

Conclusions: Many adolescents downloaded the BeMe app and completed multiple sessions and activities. Engagement with BeMe was higher among female and younger adolescents. Ratings of BeMe’s content, activities, and coaching were very positive for cognitive precursors aimed at reducing depression and anxiety and improving well-being. The findings will inform future app development to promote more sustained engagement, and future evaluations will assess the effects of BeMe on changes in mental health outcomes.
adolescents; mobile app; depression; anxiety; resilience; digital intervention; digital mental health; mobile phone

Introduction

Background

The state of adolescent mental health has been steadily declining, and the COVID-19 pandemic ushered in a new set of challenges. Across the 10 years preceding the pandemic, feelings of persistent sadness and hopelessness as well as suicidal thoughts and behaviors increased by approximately 40% among young people, according to the Centers for Disease Control and Prevention’s Youth Risk Behavior Surveillance System [1,2]. In 2021, about 4 in 10 American high school students reported feeling persistently sad or hopeless over the last year, and 1 in 11 attempted suicide [3]. Since 2019, emergency department visits for mental health conditions among adolescents aged 13 to 17 years have increased annually [4]. A 2021 report from the Surgeon General called adolescent mental health a national crisis and made a series of recommendations to support youth, including empowering youth and their families to recognize, manage, and learn from difficult emotions; ensuring that every child has access to high-quality, affordable, and culturally competent mental health care; and promoting equitable access to technology that supports the well-being of children and youth [5].

Adolescence is the developmental period that begins with the onset of puberty and is defined by the American Academy of Pediatrics as spanning ages 11 to 21 years; it is a phase during which a young individual transitions from childhood to adulthood [6]. Throughout this developmental period, adolescents experience unique stressors, including social transitions, physical and emotional changes, and other potentially overwhelming life challenges, which may benefit from adolescent-targeted psychological guidance and support. Although there are a multitude of psychotherapeutic approaches that have a strong evidence base for enhancing adolescent mental health [7-9], many young people experience barriers in accessing traditional in-person therapy (eg, stigma, finances, transportation barriers, and inconvenient appointment times) [10-12], and half of the children diagnosed with a mental health condition in the United States do not receive treatment [13]. Therefore, alternative methods for care service delivery are required.

Digital health tools have a significant potential to increase adolescents’ access to mental health support. Although early studies on web-based mental health services failed to demonstrate effectiveness in increasing help-seeking behavior among adolescents [14], the surge in mobile app development over the past decade has changed the landscape of digital mental health. Recent estimates suggest that there are >40,000 health and medical apps on leading app sites [15]. With 95% saturation of smartphone use among adolescents [16], mobile apps in particular may have the ability to provide desirable, accessible, and affordable support to adolescents when and where they are most likely to consume this support.

A recent systematic review indicated that most existing digital interventions (mobile and otherwise) are not evidence based, and there is inconclusive support for their effectiveness on mental health concerns other than anxiety and depression [17]. However, a separate, recent review and meta-analysis of 80 studies describing 83 mobile health interventions based on evidence-based principles found symptom improvement for a variety of psychological disorders, improved general well-being, and reduced distress [18]. Indeed, evidence-based digital services may offer the best opportunity to enhance outcomes among adolescents. For example, brief coping skills delivered digitally have been shown to improve mood and support young people in managing difficult moods without finding them unbearable, thereby preventing mental health challenges [19].

In addition, positive psychology skills focused on enhancing positive emotions and reducing negative emotions, when delivered via a smartphone app, can buffer older adolescents against loneliness and depression, improve sleep quality, and aid adjustment to college [20].

Mixed findings in the literature for adolescent mental health digital interventions may also be partly because of the combined assessment of bot coaching with human support [18]. The combination of digital tools and live human connection may hold particular promise for resonating with and flexibly supporting adolescent mental health. The addition of synchronous human support through skills-based coaching appears to improve adherence to and outcomes from digital mental health interventions as well as lower dropout among adolescents [17]. For example, live counselor contact was associated with improved clinical outcomes from a smoking cessation intervention delivered via Facebook to young adults [21]. Peer-to-peer counseling from paraprofessionals in a digital environment aided the delivery of evidence-based skills to undergraduate college students [22]. Tools that combine digital coping–skills delivery with live human connection for extra support and crisis management have the potential to help adolescents across a range of mental health challenges.

Despite the profound potential of digital health tools to address gaps in adolescent mental health care, initiation and continued app engagement remains suboptimal. Although some digital mental health tools have reported positive user engagement and adherence under certain conditions [17,23], many apps fail to retain users beyond initial registration [24], with evidence of poor user experience and negative perceptions of app usefulness among adolescents [25,26]. In recent years, there has been increased advocacy for the critical importance of involving people with lived experience in treatment development and, specifically, involving young people in the development of digital health products for adolescents [27,28]. Focus groups with adolescents have identified interest in strengths-based mobile health coaching and structured, supported web-based peer-to-peer interactions [29]. For digital mental health tools,
adolescents have also identified interest in self-directed learning, multimedia (eg, audio and video components), and content diversity as opposed to focusing on a singular health issue [30]. Designing the look and functionality of mobile mental health tools according to adolescent preferences is likely to enhance reach and engagement.

With a purposeful focus on adolescent experience in its app design, BeMe Health, a digital mental health company, engages a Teen Advisory Board in partnership with adolescent clinical scientists and technology product and safety experts. The BeMe app was designed to support adolescent mental health by combining digital support through content and interactive care activities, live human connection through skills-based coaching with paraprofessionals, early identification and facilitation of clinical services as needed, and in-app digital crisis support tools linked to live crisis support as needed. Skills and coaching support in the BeMe app are based on interventions that have a strong and sound evidence base with adolescents, including cognitive behavioral therapy [31], dialectical behavior therapy [32], acceptance and commitment therapy [33], mindfulness-based self-compassion [34], positive psychology [35], and motivational interviewing [36].

**Objectives**

The goal of this first large-scale evaluation of the BeMe app was to assess acceptability and utility among adolescents throughout the United States. We examined adolescent use patterns over 30 days on the BeMe platform, satisfaction and perceived helpfulness across BeMe’s features, and predictors of app engagement.

**Methods**

**Participant Recruitment**

Deidentified data were obtained within the BeMe app from adolescents aged 13 to 20 years between September 1 and October 31, 2022, when the beta version of the app included all basic features to characterize and support adolescent mental health. Participant use of the BeMe app was tracked for 30 days from the day of enrollment. Participants learned about BeMe from various channels, including unpaid posts on social media platforms, social media or other web-based platform advertisements (maximum daily budget was US $10000), or from organic channels such as word of mouth from other adolescents. Social media posts included adolescent-centric images and phrases that shared BeMe’s focus on adolescent mental health and highlighted specific features (eg, coaching). Posts were linked to BeMe’s website (BeMe [37]) that shared links to download the app in the iOS or Android app stores.

Upon downloading the app, adolescents registered on the app and were asked to read and accept BeMe’s Terms of Service and Privacy Policy, written in adolescent-facing language and at a 5th-grade reading level. The terms of service (Multimedia Appendix 1) indicated that the data would be used to improve BeMe’s services. The adolescents then completed a profile and were instructed to use the app freely. Assessments were embedded throughout the app experience. To avoid coercion that would affect app engagement and because all metrics used in this study were embedded in the intervention rather than requiring separate time to be spent on completion, adolescents were not given any compensation for using BeMe. Prior research with adolescents and parents has questioned whether the use of incentives for adolescents might lead to invalid results through misrepresentation [38-40].

**Ethical Considerations**

The project was deemed to be a program evaluation exempt from review by Stanford’s Institutional Review Board. Program evaluations follow a systematic method for collecting and analyzing information with the intent of answering questions about the effectiveness and efficiency of a specific program, in this case a digital health program.

**Intervention**

**Overview**

The BeMe platform was designed to improve well-being and address the mental health needs of all teens across the specific need and acuity spectra. BeMe was designed to provide both preventive skills that promote resilience and thriving among all teens as well as provide interventions for common clinical symptoms such as depression and anxiety; support healthy habit formation and behavior change (eg, improve sleep and reduce or quit substance use); and support linkage to clinical services and crisis support for those teens who need it. BeMe accepts any teen on its platform (there are no exclusion criteria for enrollment other than age), and it functions as a primary, secondary, and tertiary prevention program depending on adolescents’ needs at enrollment.

BeMe was designed by a combination of adolescent advisors and experts in the fields of behavioral science, adolescent clinical intervention, medicine, crisis support, mobile apps, and child- and adolescent-focused technology products. During the design phase, BeMe’s Teen Advisory Board had 68 members across the United States, all of whom had lived experience with the topics addressed in the app and some with clinical symptoms of anxiety, depression, or other common mental health concerns. The adolescents informed the look, tone, and design of BeMe’s overall app as well as its specific features. BeMe’s app was open to users aged ≥13 years in accordance with data privacy and protection regulations. Caregiver consent was not required for enrollment in the BeMe app; however, it was required for an adolescent to engage in clinical services through the BeMe app. The beta version of the BeMe app contained the following 5 main features (refer to Multimedia Appendix 2 for samples): content, activities, coaching, clinical services, and crisis support.

**Content**

Content emphasized coping and resilience-building skills based on evidence-based strategies, including cognitive behavioral therapy [31], dialectical behavior therapy [32], acceptance and commitment therapy [33], mindfulness-based self-compassion [34], positive psychology [35], and motivational interviewing [36]. Content included resilience and coping skills for all adolescents, skills for coping with specific mental health conditions (eg, depression and anxiety), and skills specific to adolescent-centric identities and challenges (eg, dealing with a
breakup, challenges with friends or caregivers, and school stress). Content was multimodal, including text screens, videos with and without music or voice-overs, carousels with text or images, and images with dynamic features. Content was tagged based on the primary focus of each piece (ie, validation, general psychoeducation, skill building, and inspiring joy), the evidence-based strategy it drew upon, and the theme (eg, friend fights) and was assigned a learning objective (eg, to improve communication). The tagging system enabled the labeling of specific content pieces from the overall content library so that adolescents could navigate to different types of content based on preferences and needs.

**Activities**

Activities provided interactive tools for practicing resilience and coping skills. Designed collaboratively by BeMe and its Teen Advisory Board, activities included: (1) mood ratings, (2) interactive skills, and a (3) a community-based skill. Mood ratings included both simple and more complex interactive versions. Simple mood ratings included a single item with 4 responses ranging from positive (“I’m great”) to negative (“I’m really struggling”). Interactive ratings used the phone’s camera and digital stickers to encourage teens to take a selfie and label their mood and shared these data back with adolescents in a separate journal section of the app. Interactive skills based on cognitive and behavioral coping skills, mindfulness practice, and positive psychology skills, including those described by Bruehlman-Senecal et al [20] and others. A community-based skill was designed to practice sending and receiving “good vibes” with other adolescents (to promote a sense of community without actual social features).

**Coaching**

Coaching was delivered by BeMe coaches live in the app via text messaging. The coaches were graduate- and undergraduate-level paraprofessionals trained in a program developed by BeMe’s clinical leadership team. Training included a combination of didactic training, role playing, and supervisor observation before working on the platform as well as ongoing weekly individual and group supervision and live supervision during all shifts. Adolescents could message at any time of the day or night with a preset message or an open-ended message of their choice. During the study period, BeMe coaches responded to adolescents for 14 hours per day. All adolescents could message an unlimited number of times on any topic of their choice during the study period. After a coaching session, adolescents received a feedback form with session ratings. Coaches tagged conversations with any number of topics designed by BeMe’s clinical leadership, or as “other.”

**Clinical Services**

Adolescents could connect to a licensed therapist through the BeMe app. Successful linkage to treatment required registration, verified parental consent, and scheduling via telephone or text messages.

**Crisis Support**

Adolescents could self-navigate or be directed by a coach to crisis support services, including 3 live options: a crisis hotline staffed 24/7, the Crisis Text Line, or the Trevor Project Crisis Support services. Adolescents could also complete a digital safety plan based on evidence-based suicide prevention support tools for adolescents [41].

The beta version was not designed to be used in any specific pattern or length. Adolescents were given free access to the app and could navigate through any or all features as they chose.

**Measures**

**Sample Characteristics**

Upon enrollment in the BeMe app, adolescents reported their age, preferred pronouns, interests from a list codeveloped with BeMe’s Teen Advisory Board, and “onboarding topics” adolescents indicated that they would like to explore on the BeMe app. Adolescents could select any number of interests and topics.

**Clinical Functioning**

At any point in their BeMe journey, adolescents could opt to complete assessments of their clinical functioning regarding anxiety, depression, stress, and overall well-being. The tools were selected based on their evidence of use with adolescents. There was no particular time in the engagement process in which the assessments were administered, and participants self-selected to complete any, all, or none of the assessments and could repeat the assessments. The first instance of a completed assessment was analyzed in this study to characterize adolescent functioning. With reference to the past 2 weeks, adolescents completed the 7-item Generalized Anxiety Disorder Questionnaire [42] with scores ranging from 0 to 21; scores from 5 to 9 indicated mild anxiety, scores from 10 to 14 indicated moderate anxiety, anxiety from 15 to 19 indicated moderately severe anxiety, anxiety >19 indicated severe anxiety, and anxiety >20 indicated extreme anxiety. Adolescents could also complete the 8-item Patient Health Questionnaire (PHQ-8) adolescent version [43]. Again, with reference to the past 2 weeks, PHQ-8 total scores ranged from 0 to 24; scores from 5 to 9 indicated mild depression, 10 to 14 indicated moderate depression, 15 to 19 indicated moderately severe depression, and >19 indicated severe depression. The 4-item Perceived Stress Scale [44] assessed participants’ self-reported stress level over the past month on a scale ranging from 0 (“never”) to 4 (“very often”); total score range 0-16. The World Health Organization–Five Well-being Index (WHO-5), widely used with adolescents [45], was used to assess overall well-being during the past 2 weeks. The WHO-5 scores range from 0 to 25 and are multiplied by 4 to yield a well-being score between 0 and 100. Scores ≤50 indicate poor well-being, and scores >28 indicate depression, including in adolescent samples [46].

**Engagement**

Engagement was measured at the individual user level and the app feature level. Heterogeneity in engagement metrics has been reported in previous studies on mental health apps [47]. In this study, we used standard engagement metrics to report on at least minimal use (ie, days with any engagement on the app), number of times on the app (ie, number of unique sessions), and number of unique features used (ie, activities) [48]. Engagement was
also calculated at the app feature level as the number of times each feature was used in a month among those who engaged in that feature. Content engagement was defined as the completion of the entirety of a piece of content (eg, scrolling through all screens of a carousel or watching an entire video). Engaged content was summarized by an intervention skillset coded as acceptance and commitment therapy, behavioral activation, cognitive and behavioral therapy, dialectical behavioral therapy, emotion regulation and distress tolerance skills, interpersonal effectiveness skills, mindfulness practice, motivational interviewing techniques, positive psychology skills, and trauma-informed care skills. Activity engagement was summarized for drawing practice, mindfulness skills, distress tolerance or emotion regulation skills with the phone’s camera, or movement-based skills with the phone’s camera. Interactive mood rating feature moods were tallied for each of the 21 moods across all activities completed. The mood list was developed by the study’s last authors (NC and DR) in collaboration with BeMe’s Teen Advisory Board. The coaching topics were coded by the BeMe coaches at the end of each session. Topic data were only available for approximately half of the study period (October 7, 2022, to November 30, 2022), so the sample of coaching sessions available for analysis was not the full sample of completed sessions during this time. The number of times clinical supports and safety plan resources (digital safety plan and crisis support services) were accessed was tallied. For the adolescents who completed a digital safety plan, we computed the average number of endorsed reasons for living, crisis warning signs, ways to make their environment safe, and coping skills.

**Satisfaction and Helpfulness**

Satisfaction and helpfulness were measured at the feature level. After select pieces of content created by BeMe, adolescents were asked to rate the content on perceived helpfulness and confidence that they would use the skill outside of the BeMe app (self-efficacy). After select pieces of content, adolescents rated whether they felt hopeful (hope), learned something about themselves (self-identity), the content was helpful to their self-esteem (self-esteem), felt less alone (social connection), or felt relaxed and grounded (relaxation; all yes or no). Activities were rated similarly based on perceived helpfulness and utility in coping with a big feeling. The percentage of polls with yes responses was tallied for each response type. Coaching sessions were rated on a 6-point scale (0-5 stars), perceived helpfulness, and self-efficacy (yes or no).

**Analyses**

**Sample Characteristics and Use Patterns**

Descriptive statistics were used to characterize adolescent demographics for the full sample, clinical functioning among the subset that self-selected to complete the assessments, and overall app engagement patterns.

**Relationship Between Individual Characteristics and Engagement**

Logistic regression was used to evaluate predictors of overall app engagement (ie, total activities accessed). The dependent variable was the number of activities completed in 30 days, coded as high or low based on the sample median (7 activities). The independent variables (IVs) were pronouns, age, and overall well-being (WHO-5 total score). P values and CIs determine whether the association between overall app engagement and each term in the model is statistically significant. All IVs were included in the model at once because we lacked an underlying theory to guide model selection. This approach was adopted to prevent bias toward small P values and large parameter estimates [49].

**Satisfaction With BeMe’s Content and Features**

Engagement with content and activities was evaluated at the feature level, and the proportion of “yes” responses was computed for each content or activity type. Coaching satisfaction was evaluated among the proportion of adolescents who engaged with coaching at least once. The patterns of engagement, topics, and ratings were computed for this subsample.

**Relationship Between Individual Characteristics and Satisfaction**

A logistic regression model was used to evaluate the predictors of satisfaction and helpfulness. The dependent variable was the presence of at least 1 “yes” response on a postactivity survey (eg, after a piece of content or activity). IVs were pronouns, age, the WHO-5 total score, and total activities completed dichotomized, consistent with the strategy described in Relationship Between Individual Characteristics and Engagement. P values and CIs determine whether the association between satisfaction and helpfulness and each term in the model was statistically significant.

**Power Estimation**

Planned analyses included at least 2 regression models (1 predicting engagement and 1 predicting satisfaction), with up to 6 IVs, including age, preferred pronouns, depression, anxiety, overall well-being, and perceived stress. A multivariate regression analysis with 6 IVs testing a partial $R^2$ of 0.1 in each IV with an error probability of 0.05 and 95% power requires a sample size of at least 195. A sample size of up to 2000 was deemed sufficient to detect a small effect size for each IV in the 2 models. Relatively low sample sizes in depression, anxiety, and well-being measures compared with other IVs yielded their exclusion from the final models; thus, we expect the final sample size of >13,000 to be adequately powered to report both the final regression models and a series of frequency and proportion results shared in this study.

**Results**

**Sample Characteristics and Use Patterns**

In the 2-month enrollment period, 13,421 adolescents were enrolled in the BeMe app. The characteristics of the sample are presented in Table 1.
Table 1. Sample characteristics (N=13,421).

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age (years)</strong></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>15.04 (1.7)</td>
</tr>
<tr>
<td>Median (IQR)</td>
<td>15 (14-16)</td>
</tr>
<tr>
<td>13-14, n (%)</td>
<td>5977 (44.53)</td>
</tr>
<tr>
<td>15-16, n (%)</td>
<td>4537 (33.81)</td>
</tr>
<tr>
<td>17-18, n (%)</td>
<td>2425 (18.07)</td>
</tr>
<tr>
<td>19-20, n (%)</td>
<td>482 (3.59)</td>
</tr>
<tr>
<td><strong>Pronouns, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>She/her</td>
<td>7612 (56.72)</td>
</tr>
<tr>
<td>He/him</td>
<td>1468 (10.94)</td>
</tr>
<tr>
<td>They/them</td>
<td>1391 (10.36)</td>
</tr>
<tr>
<td>Other/no response</td>
<td>2950 (21.98)</td>
</tr>
<tr>
<td><strong>Interests, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Music</td>
<td>10,966 (81.71)</td>
</tr>
<tr>
<td>Art</td>
<td>7821 (58.27)</td>
</tr>
<tr>
<td>Food</td>
<td>7231 (53.88)</td>
</tr>
<tr>
<td>Animals</td>
<td>7102 (52.92)</td>
</tr>
<tr>
<td>Beauty</td>
<td>6721 (50.08)</td>
</tr>
<tr>
<td>Fashion</td>
<td>6193 (46.14)</td>
</tr>
<tr>
<td>Reading</td>
<td>5941 (44.27)</td>
</tr>
<tr>
<td>Nature</td>
<td>5750 (42.84)</td>
</tr>
<tr>
<td>Photography</td>
<td>5395 (40.20)</td>
</tr>
<tr>
<td>Writing</td>
<td>5383 (40.11)</td>
</tr>
<tr>
<td>Gaming</td>
<td>5362 (39.95)</td>
</tr>
<tr>
<td>LGBTQIA²</td>
<td>5331 (39.72)</td>
</tr>
<tr>
<td>Travel</td>
<td>4874 (36.32)</td>
</tr>
<tr>
<td>Dance</td>
<td>4408 (32.84)</td>
</tr>
<tr>
<td>Anime</td>
<td>4157 (30.97)</td>
</tr>
<tr>
<td>Sports</td>
<td>3858 (28.75)</td>
</tr>
<tr>
<td>Science</td>
<td>2547 (18.98)</td>
</tr>
<tr>
<td>Entrepreneurship</td>
<td>1327 (9.89)</td>
</tr>
<tr>
<td>Climate</td>
<td>1131 (8.43)</td>
</tr>
<tr>
<td>Auto</td>
<td>768 (5.72)</td>
</tr>
<tr>
<td><strong>Goals for using BeMe, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Boosting happiness</td>
<td>10,049 (74.88)</td>
</tr>
<tr>
<td>Building relationships</td>
<td>9000 (67.06)</td>
</tr>
<tr>
<td>Dealing with stressors</td>
<td>9337 (69.57)</td>
</tr>
<tr>
<td>Discovering identity</td>
<td>6757 (50.35)</td>
</tr>
<tr>
<td>Finding ways to cope</td>
<td>8025 (59.79)</td>
</tr>
<tr>
<td>Living mindfully</td>
<td>5706 (42.52)</td>
</tr>
<tr>
<td>Managing mood</td>
<td>9314 (69.40)</td>
</tr>
<tr>
<td>Navigating life transition</td>
<td>4923 (36.68)</td>
</tr>
</tbody>
</table>
Depression symptoms (PHQ\textsuperscript{b} score; n=238)

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (SD)</td>
<td>15.69 (5.91)</td>
</tr>
<tr>
<td>Median (IQR)</td>
<td>17 (13-20)</td>
</tr>
<tr>
<td>No depression (scores: 0-4), n (%)</td>
<td>18 (7.56)</td>
</tr>
<tr>
<td>Mild (score: 5-9), n (%)</td>
<td>17 (7.14)</td>
</tr>
<tr>
<td>Moderate (score: 10-14), n (%)</td>
<td>51 (21.43)</td>
</tr>
<tr>
<td>Moderately severe (score: 15-19), n (%)</td>
<td>85 (35.71)</td>
</tr>
<tr>
<td>Severe (score: 20+), n (%)</td>
<td>67 (28.15)</td>
</tr>
</tbody>
</table>

Anxiety symptoms (GAD\textsuperscript{c} score; n=791)

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (SD)</td>
<td>13.37 (5.01)</td>
</tr>
<tr>
<td>Median (IQR)</td>
<td>14 (10-17)</td>
</tr>
<tr>
<td>None to normal (score: 0-4), n (%)</td>
<td>52 (6.57)</td>
</tr>
<tr>
<td>Mild (score: 5-9), n (%)</td>
<td>125 (15.80)</td>
</tr>
<tr>
<td>Moderate (score: 10-14), n (%)</td>
<td>259 (32.74)</td>
</tr>
<tr>
<td>Severe (score: 15-21), n (%)</td>
<td>355 (44.88)</td>
</tr>
</tbody>
</table>

Overall well-being (WHO-5\textsuperscript{d} score; n=1322)

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (SD)</td>
<td>30.15 (16.06)</td>
</tr>
<tr>
<td>Median (IQR)</td>
<td>28 (20-40)</td>
</tr>
<tr>
<td>≤50, n (%)</td>
<td>1172 (88.65)</td>
</tr>
<tr>
<td>≤28, n (%)</td>
<td>747 (56.51)</td>
</tr>
</tbody>
</table>

Perceived stress (PSS\textsuperscript{e} score; n=638)

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (SD)</td>
<td>10.62 (2.56)</td>
</tr>
<tr>
<td>Median (IQR)</td>
<td>11 (9-12)</td>
</tr>
<tr>
<td>≥6, n (%)</td>
<td>623 (97.65)</td>
</tr>
</tbody>
</table>

\textsuperscript{a}LGBTQIA: lesbian, gay, bisexual, transgender, queer, intersex, asexual, and similar minority.
\textsuperscript{b}PHQ: Patient Health Questionnaire.
\textsuperscript{c}GAD: Generalized Anxiety Disorder Questionnaire.
\textsuperscript{d}WHO-5: WHO-5 Well-being Index.
\textsuperscript{e}PSS: Perceived Stress Scale.

The average age of the adolescents was 15.04 (SD 1.7) years, and they more often identified with female pronouns (7612/13,421, 56.72%) than male pronouns (1468/13,421, 10.94%), gender-neutral pronouns (1391/13,421, 10.36%), or other or decline to answer (2950/13,421, 21.98%). Onboarding topics selected by a majority of adolescents were boosting happiness (10,049/13,421, 74.88%), dealing with stressors (9337/13,421, 69.57%), managing mood (9314/13,421, 69.40%), building relationships (9000/13,421, 67.06%), and generally finding ways to cope (8025/13,421, 59.79%); 50.35% (6757/13,421) of the adolescents selected discovering your identity, and although less common, over a third selected living mindfully (5706/13,421, 42.52%) and navigating a life transition (4923/13,421, 36.68%). The most common interests endorsed by the adolescents were music (10,966/13,421, 81.71%), art (7821/13,421, 58.27%), food (7231/13,421, 53.88%), and animals (7102/13,421, 52.92%).
Table 2. Overall and specific feature engagement (N=13,421).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Values, mean (SD)</th>
<th>Values, median (IQR)</th>
<th>Values, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall app engagement</td>
<td>2.38 (2.72)</td>
<td>1 (1-3)</td>
<td>13,421 (100)</td>
</tr>
<tr>
<td>Days engaged (range 1-30)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1 (0)</td>
<td>1 (1-1)</td>
<td>6962 (51.87)</td>
</tr>
<tr>
<td>2-3</td>
<td>2.35 (0.48)</td>
<td>2 (2-3)</td>
<td>4233 (31.54)</td>
</tr>
<tr>
<td>≥4</td>
<td>6.77 (4.35)</td>
<td>5 (4-8)</td>
<td>2226 (16.59)</td>
</tr>
<tr>
<td>App sessions (range 1-1750)</td>
<td>7.94 (24.14)</td>
<td>3 (2-7)</td>
<td>13,421 (100)</td>
</tr>
<tr>
<td>Activities (range 1-776)</td>
<td>11.26 (19.81)</td>
<td>7 (4-12)</td>
<td>13,421 (100)</td>
</tr>
<tr>
<td>Specific feature engagement</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Content views (range 1-505)</td>
<td>4.59 (11.36)</td>
<td>2 (1-5)</td>
<td>12,270 (91.42)</td>
</tr>
<tr>
<td>Simple mood rating (range 1-128)</td>
<td>2.61 (3.49)</td>
<td>2 (1-3)</td>
<td>13,094 (97.56)</td>
</tr>
<tr>
<td>Interactive skills (range 1-75)</td>
<td>2.58 (3.09)</td>
<td>2 (1-3)</td>
<td>10,098 (75.24)</td>
</tr>
<tr>
<td>Interactive mood rating (range 1-80)</td>
<td>1.82 (2.57)</td>
<td>1 (1-2)</td>
<td>6677 (49.75)</td>
</tr>
<tr>
<td>Community skills (range 1-73)</td>
<td>1.75 (2.72)</td>
<td>1 (1-2)</td>
<td>1616 (12.04)</td>
</tr>
<tr>
<td>Coach session (range 1-20)</td>
<td>1.47 (1.27)</td>
<td>1 (1-1)</td>
<td>2539 (18.92)</td>
</tr>
<tr>
<td>Clinical service resource clicks (range 1-19)</td>
<td>1.40 (0.97)</td>
<td>1 (1-1)</td>
<td>2411 (17.96)</td>
</tr>
<tr>
<td>Crisis resource views (range 1-25)</td>
<td>1.52 (1.25)</td>
<td>1 (1-2)</td>
<td>2499 (18.62)</td>
</tr>
<tr>
<td>Safety plan completed (yes or no)</td>
<td>N/A</td>
<td>N/A</td>
<td>1129 (8.41)</td>
</tr>
</tbody>
</table>

Overall, 91.53% (12,285/13,421) of adolescents accessed 66,345 pieces of content (content views: mean 4.59, SD 11.35, median 2, IQR 1-5; range 1-505). Adolescents engaged most with content grounded in dialectical behavior therapy emotion regulation and distress tolerance skills (16,920/66,345, 25.5% of all content viewed), positive psychology skills (14,346/66,345, 21.62% of all content viewed), cognitive and behavioral therapy coping skills (16,920/66,345, 25.5%), and mindfulness-based self-compassion skills (8650/66,345, 13.04%). Lower engagement was found with content grounded in acceptance and commitment therapy skills (5669/66,345, 8.54%), dialectical behavioral therapy interpersonal effectiveness and social skills (5810/66,345, 8.76%), motivational interviewing skills (1693/66,345, 2.55%), behavioral activation (1091/66,345, 1.64%), and skills grounded in trauma-informed care (774/66,345, 1.17%).

Among those adolescents who engaged in each type of interactive activity, engagements were, on average, as follows: 2.61 (SD 3.49; median 2, IQR 1-3) simple mood ratings, 2.58 (SD 3.09; median 2, IQR 1-3) interactive skills, 1.82 (SD 2.57; median 1, IQR 1-2) interactive mood ratings, and 1.75 (SD 2.72; median 1, IQR 1-2) community-based skills. Considering specifically interactive skills, adolescents primarily engaged with those that used the phone’s camera to complete a distress tolerance skill (24,944/44,698, 55.81%) or a pleasurable activity (11,963/44,698, 26.76%). Considering interactive mood ratings (n=19,800 rating completed), intraclass correlation in a 2-way mixed effects model using a consistency definition showed a significant correlation among mood ratings across individuals (intraclass correlation 0.427, CI 0.42-0.44; P<.001), so frequency was tallied for all mood ratings. The most frequently identified moods were low arousal moods, including lonely (2315/19,800, 11.69%), low (2280/19,800, 11.52%), relaxed (2160/19,800, 10.91%), hurt (2074/19,800, 10.47%), bored (1947/19,800, 9.83%), and depressed (1755/19,800, 8.86%). The least endorsed moods were those with higher arousal, including pumped (368/19,800, 1.86%), furious (390/19,800, 1.97%), excited (413/19,800, 2.09%), and energetic (447/19,800, 2.26%). Other endorsed moods included chill (1681/19,800, 8.49%), insecure (1460/19,800, 7.37%), anxious (1223/19,800, 6.18%), grateful (1129/19,800, 5.7%), happy (1147/19,800, 5.79%), content (1086/19,800, 5.48%), motivated (1031/19,800, 5.21%), cheerful (957/19,800, 4.83%), rejected (943/19,800, 4.76%), frustrated (805/19,800, 4.07%), and pissed (521/19,800, 2.63%).

Among the adolescents who engaged with coaching, they averaged 1.47 (SD 1.27; median 1, IQR 1-1) sessions. The topics were coded for 1817 coaching sessions during the study period. Anxiety was the most common topic raised in coaching (649/1817, 35.72%) and was more than twice as frequent as the next most popular topic. The relationship concerns of different types were also common: romantic (304/1817, 16.73%), friend (264/1817, 14.53%), and family (187/1817, 10.29%). School-related topics (eg, workload and managing school stress) were raised in 14.42% (262/1817) of the coaching conversations. Adolescents also sought coaching on self-esteem (160/1817, 8.86%).
8.81%; depression and sadness (153/1817, 8.42%); body image (80/1817, 4.4%); issues related to lesbian, gay, bisexual, transgender, queer, intersex, asexual, and similar minority (LGBTQIA) identity (73/1817, 4.02%); anger (61/1817, 3.36%); suicidality (47/1817, 2.59%); bullying (46/1817, 2.53%); and self-harm (37/1817, 2.04%). The less common topics were related to learning new skills (35/1817, 1.93%), grief (29/1817, 1.60%), loneliness (19/1817, 1.05%), neurodiversity (15/1817, 0.83%), abuse or neglect (11/1817, 0.61%), harassment or assault (9/1817, 0.5%), racism or discrimination owing to ethnicity (2/1817, 0.11%), and substance use (2/1817, 0.11%).

The adolescents who sought out safety and clinical resources selected on average 1.52 (SD 1.25; median 1, IQR 1-2) safety resources (crisis supports and digital safety plan) and 1.35 (SD 0.90; median 1, IQR 1-1) clinical resources. Almost half (1129/2499, 45.18%) of those who engaged with the safety resources completed a digital safety plan, averaging 5.07 (SD 2.62) out of 12 reasons for living, 7.05 (SD 3.64) out of 17 crisis warning signs, 2.25 (SD 1.96) out of 8 ways to make their environments safe, and 3.69 (SD 2.28) out of 9 coping skills to use when in crisis.

Predictors of BeMe App Engagement

To examine the predictors of overall app engagement, with high versus low engagement (<7 vs >7 activities completed over 30 days) as the outcome, we first ran a logistic model including pronouns, age, and overall well-being (WHO-5 total score). The WHO-5 measure was not predictive in the model ($P=.61$) and had a lot of missing data (completed by 1322 adolescents); therefore, we reran the model with only pronouns and age as predictors (Figure 1; Table 3). Predictors were pronouns in 4 categories (she/her, he/him, they/them, and other/no response), with he/him as the reference group, and age in 4 categories, with 13-14 as the reference group (N=13,421). The findings indicated that compared with male-identified adolescents, female-identified adolescents were 32% more likely to be in the high engagement group (odds ratio [OR] 1.324, 95% CI 1.184-1.482; $P<.001$), gender-neutral adolescents were 39% more likely to be in the high engagement group (OR 1.39, 95% CI 1.199-1.61; $P=.03$), and those who did not indicate pronouns or chose other were 18% more likely to be in the high engagement group (OR 1.179, 95% CI 1.04-1.337; $P=.01$). In addition, adolescents in the youngest age group were more likely to be in the highest engagement group than the 3 older age groups (all $P<.001$).

Figure 1. Odds ratios and CIs for a logistic regression model testing the effects of pronouns and age on app engagement (total activities over 30 days; high vs low engagement).
Table 3. Logistic regression model predicting high versus low app engagement (total activities completed; N=13,421).

<table>
<thead>
<tr>
<th>Effect</th>
<th>Odds ratio (95% CI)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pronoun</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other/no response vs he/him</td>
<td>1.179 (1.04-1.337)</td>
<td>.01</td>
</tr>
<tr>
<td>She/her vs he/him</td>
<td>1.324 (1.184-1.482)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>They/them vs he/him</td>
<td>1.390 (1.199-1.61)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Age (years)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>15-16 vs 13-14</td>
<td>0.855 (0.792-0.924)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>17-18 vs 13-14</td>
<td>0.754 (0.686-0.829)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>19-20 vs 13-14</td>
<td>0.673 (0.558-0.811)</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

“Superusers,” defined as engaging with BeMe at least 2 SDs above the mean of the full sample (engaged >7 out of 30 days), were more likely to be female (351/557, 63% vs 7265/12,880, 56.4%), less likely to be male (38/557, 6.8% vs 1432/12,880, 11.12%; $\chi^2=16.1, P=.007$), and had lower PHQ-8 scores (15.04 vs 15.84; $F_{2,237}=5.08, P=.03$) compared with nonsuperusers. There were no significant differences in age, 7-item Generalized Anxiety Disorder Questionnaire, WHO-5, or 4-item Perceived Stress Scale scores according to the BeMe superuser status. BeMe superusers were more likely to engage with live coaching (306/557, 54.9% vs 2237/12,880, 17.37%; $\chi^2=491.1, P<.001$), clinical resources (267/557, 47.9% vs 2149/12,880, 16.68%; $\chi^2=353.6, P<.001$), and crisis support resources (322/557, 57.8% vs 2180/12,880, 16.93%; $\chi^2=588.9, P<.001$).

Satisfaction and Helpfulness of Content and Features

Quick pulse surveys captured thumbs up or down ratings of different content and features of BeMe that were accessed by the participants. The surveys were launched at different times throughout the study period, resulting in varying sample sizes. Among the 8468 surveys, 5362 (63.32%) rated the BeMe activities as helpful for boosting mood. Among the 6072 surveys, 4408 (72.6%) rated the BeMe activities as helpful for coping with a big feeling. Completed by fewer participants owing to strategic placement of pulse surveys to prevent survey exhaustion and preserve the user experience, 91.66% (1044/1139) of adolescents planned to use a skill they learned from BeMe when coping with a stressor; 89.8% (158/176) rated the BeMe content as helpful; 86.2% (493/572) learned something about themselves from BeMe; 85.8% (235/274) felt relaxed after using BeMe; 84.3% (369/438) gained help with self-esteem; 83.4% (586/703) felt more hopeful; and 82% (46/56) felt less alone.

Satisfaction and Helpfulness of Coaching

On average, the adolescents rated the BeMe coaching sessions 4.2 out of 5 stars (SD 1.2; n=893). Over four-fifths of the responses indicated that the sessions were helpful (747/894, 83.6%) and provided content that an adolescent would use (747/894, 83.6%; Table 4).
Table 4. Satisfaction and impact of digital activities and coaching.

<table>
<thead>
<tr>
<th>Feature type</th>
<th>Values, N</th>
<th>Yes, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Content</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Helpfulness</td>
<td>176</td>
<td>158 (89.77)</td>
</tr>
<tr>
<td>Self-efficacy</td>
<td>1139</td>
<td>1044 (91.66)</td>
</tr>
<tr>
<td>Hope</td>
<td>703</td>
<td>583 (83.36)</td>
</tr>
<tr>
<td>Self-identity</td>
<td>572</td>
<td>493 (86.19)</td>
</tr>
<tr>
<td>Self-esteem</td>
<td>438</td>
<td>369 (84.25)</td>
</tr>
<tr>
<td>Social connection</td>
<td>56</td>
<td>46 (82.14)</td>
</tr>
<tr>
<td>Relaxation</td>
<td>274</td>
<td>235 (85.77)</td>
</tr>
<tr>
<td><strong>Interactive activities</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Helpfulness</td>
<td>8468</td>
<td>5362 (63.32)</td>
</tr>
<tr>
<td>Useful in coping with a big feeling</td>
<td>6072</td>
<td>4408 (72.6)</td>
</tr>
<tr>
<td><strong>Coaching</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Helpfulness</td>
<td>894</td>
<td>747 (83.56)</td>
</tr>
<tr>
<td>Self-efficacy</td>
<td>894</td>
<td>747 (83.56)</td>
</tr>
<tr>
<td><strong>Overall rating</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 stars</td>
<td>893</td>
<td>532 (59.57)</td>
</tr>
<tr>
<td>4 stars</td>
<td>893</td>
<td>163 (18.25)</td>
</tr>
<tr>
<td>3 stars</td>
<td>893</td>
<td>84 (9.41)</td>
</tr>
<tr>
<td>2 stars</td>
<td>893</td>
<td>34 (3.81)</td>
</tr>
<tr>
<td>1 star</td>
<td>893</td>
<td>78 (8.73)</td>
</tr>
</tbody>
</table>

Predictors of Satisfaction and Helpfulness

Logistic regression models were run to examine the predictors of BeMe satisfaction and the perceived helpfulness of content and interactive activities. Modeled outcomes were yes versus no or no response on surveys of satisfaction and perceived helpfulness. An initial model with inclusion of WHO-5 Well-being Index scores was nonsignificant, and we show a second model without these scores (Table 5). The tested predictor variables were gender identity in 4 categories (she/her as the reference group), age in 4 categories (13-14 years as the reference group), and high versus low total activities (<7 vs >7 activities). The only predictor that was significant was total activities, with those completing ≥7 activities being almost 3.9 times as likely to have indicated that they were satisfied with and found help from BeMe content or an activity compared with those with low total activities (P<.001; Figure 2; Table 5).
Figure 2. Odds ratios and CIs for a logistic regression model testing the effects of pronouns, age, and app engagement (high vs low activities over 30 days) on satisfaction (positive endorsement of at least 1 survey after a piece of content or interactive activity).

Table 5. Logistic regression model predicting at least 1 positive indicator of satisfaction or impact (N=13,421).

<table>
<thead>
<tr>
<th>Effect</th>
<th>Odds ratio (95% CI)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pronoun</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other/no response vs he/him</td>
<td>1.004 (0.87-1.159)</td>
<td>.96</td>
</tr>
<tr>
<td>She/her vs he/him</td>
<td>1.066 (0.938-1.212)</td>
<td>.33</td>
</tr>
<tr>
<td>They/them vs he/him</td>
<td>1.315 (1.116-1.549)</td>
<td>.001</td>
</tr>
<tr>
<td>Age (years)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>15-16 vs 13-14</td>
<td>0.977 (0.896-1.065)</td>
<td>.59</td>
</tr>
<tr>
<td>17-18 vs 13-14</td>
<td>0.900 (0.809-1.002)</td>
<td>.06</td>
</tr>
<tr>
<td>19-20 vs 13-14</td>
<td>0.905 (0.730-1.120)</td>
<td>.36</td>
</tr>
<tr>
<td>Total activities: high vs low</td>
<td>3.903 (3.607-4.224)</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

Discussion

Principal Findings

In the first large-scale evaluation of the acceptability and utility of the BeMe app, designed by and for adolescents, >6 times as many adolescents were enrolled than initially sought for the study. In 8 weeks, >13,000 adolescents accessed the app without the enticement of any financial incentive for using the app or completing within-app surveys. The adolescents reported interest in mood boosting, stress management, help with relationships, and discovering their identity, and most participants (11,005/13,421, 82%) identified multiple areas of interest. The great response suggests the demand for multifocal and multifunctional digital mental health programs among adolescents.

Characteristic of other mental health and digital program evaluations, BeMe attracted more adolescents who identified as female than male and notably attracted a sizable proportion of adolescents identifying as gender neutral (1391/13,421, 10.36%) or another gender (671/13,421, 5%). According to the literature, adolescent girls tend to be more willing to seek mental health treatment than boys [50] and are more likely to be attracted to wellness and mental health apps [51]. BeMe also attracted and engaged younger adolescents. Early adolescence is a major transitional period physically (puberty), environmentally (eg, transition to high school), and socially.
when many new stressors arise [52] and when support may be particularly welcomed.

Across a 30-day evaluation of the BeMe app, participants’ use averaged >2 days, in over 8 sessions, engaging in >11 activities, with a great deal of variation, indicating diversity in adolescents’ needs and preferences. Notably, there was no in-app guidance toward a specific pathway; therefore, adolescents were able to gravitate toward the features that were most relevant to them. This was a conscious decision among the app’s designers and the BeMe Teen Advisory Board who worked together to create an experience that would focus on adolescent choice rather than explicit guidance. A better understanding of adolescent-guided pathways will allow for enhanced personalization over time and the ability to guide adolescents toward journeys that support their presentation (eg, clinical functioning) and their needs and preferences.

The observed level of engagement is satisfactory for a beta version of an app that does not ask or require participants to move in any particular pathway or journey through the app experience. For example, prior work has similarly found that users engage with certain app features just a couple of times, with 1 study observing that only 15.6% of unique app resources were engaged with at least once [53,54]. Another prior study of engagement with a mental health app that did not involve user prompts found that participants engaged in a total of 6 sessions on average, similar to the total of 7.94 sessions observed in this study [55].

Although the BeMe platform was initially designed to encourage exploratory self-navigation by teens (rather than a forced pathway), its developers were cautious about incorporating features in the initial design that could encourage excessive daily use, thereby avoiding overuse of the intervention. Social media platforms that also include content and live human connections (eg, messaging) have saturated the adolescent market and are being used in a way that prevents interactions with other areas of life for some teens (eg, school, in-person friend connections, and family relationships). This has likely contributed to a time-sink problem, whereby some teens report they are on social media “almost constantly” (35% in a 2022 Pew survey [16]) and that it would be difficult to give up social media (36% in the same survey). In contrast, the beta version of the BeMe app avoided some of the common features of social media platforms that promote constant use, such as algorithms designed to promote long-term content engagement [56] and social features that encourage social feedback and almost constant connections. There was an expectation that adolescents would use BeMe at variable rates, which was indeed found in this study. The findings of this study indicate that encouraging further engagement (eg, guidance toward assessment completion, personalized content pathways, and purposeful promotion of coaching sessions) could drive even further toward meaningful engagement.

A preliminary analysis of BeMe’s “superusers” confirmed active use among female adolescents and engagement in the live coaching, clinical service linkage, and crisis support features among those who used BeMe for >7 days in a month. A more detailed analysis of these users could help identify features they returned to use within the app to inform further app development, recruitment, onboarding, and impact, in line with previous work with adults [57]. A future examination of app use as it relates to changes in clinical symptoms and cognitive mediators of symptom incidence and course (eg, hope and self-esteem) will further inform targeted app development. Superusers also showed slightly lower PHQ-8 scores than those who used the app less often. Given that assessments could be completed at any time in a user’s journey, this could indicate either a positive impact of BeMe use on depression symptoms among superusers or less depression among superusers at the times they started to use the app. A more targeted journey for adolescents with depression will ensure that the experience supports them.

App engagement is greater among younger than older adolescents and among female and gender-neutral adolescents than male adolescents. BeMe’s constellation of services and support (eg, coaching) may be of greater interest to female adolescents and those who seek support for managing mood in particular. More work is needed to understand how best to reach and support male adolescents. Engagement patterns also indicate that there is potential for expanding app design, content, activities, and coaching features that resonate with older adolescents. BeMe could benefit from features that support developmental milestones of the older adolescent years (eg, graduating from high school, transitioning toward increasing independence in living situation, social interactions, work, and college).

Anxiety was the most common topic raised in coaching sessions, followed by relationships of multiple types, school, self-esteem, and depression. Developmental milestones of adolescence have, in many ways, been interrupted for this pandemic-stalled generation. Coaching may support adolescents to get back on track. The preponderance of sessions coded with the “other” topic suggests that the initial topic list should be expanded. Post hoc examination of sessions coded as other suggests that additional topics could include exploring adolescent identity or selfhood, attention or motivation, and social or conversational skills. Notably, the adolescents who engaged in the coaching sessions rated them highly, on average, 4.2 out of 5 stars. High ratings contribute to the promise of the paraprofessional model in delivering coping skill support digitally to adolescents and young adults [22].

Although a minority of the sample (1 in 10 or fewer) completed the well-being, anxiety, and depression assessments, a majority of those who self-selected to complete these measures indicated clinically concerning levels of distress, which supports the multiple offerings of BeMe, including individual counseling, safety planning, and clinical resources. BeMe can also be useful as a platform for tracking changes in anxiety and depressive symptoms over time using clinically validated measures with adolescents. Mood data from digital platforms such as BeMe can help to add nuance to the understanding of adolescent emotional experiences. Mood rating data from BeMe’s interactive mood rating feature indicate that most moods expressed while using the platform are lower arousal moods (eg, low, chill, and bored), and least endorsed moods are higher arousal moods (eg, excited and furious). This is consistent with
prior literature showing that adolescents experience low-intensity emotions (both positive and negative) more frequently than high-intensity emotions, regardless of age [58]. A future investigation could develop a more nuanced understanding of the relationships among mood rating completion, adolescent individual characteristics (eg, age and gender), and clinical functioning (eg, depression and anxiety).

The single-item response measures throughout the intervention platform provide a unique way for adolescents to share feedback and provide a pulse on satisfaction and helpfulness. The responses were very positive for cognitive precursors aimed at reducing depression and anxiety such as hopefulness, perceived helpfulness, and the ability to cope with a big feeling. The likelihood of implementing these skills is high and warrants further study.

About one-fifth of the adolescents on the BeMe platform accessed each of the live supports, including coaching sessions, clinical resources, and crisis support tools. Digital support through a platform such as BeMe may be particularly appealing to a generation that exhibits decreased stigma regarding mental health challenges, while also displaying a growing mistrust of conventional mental health assistance in comparison with previous generations [59]. Similar rates of connection to coaching and crisis support as to traditional mental health services suggest that a platform like BeMe may be able to address challenges some adolescents have with accessing traditional clinical interventions (eg, need for caregiver consent and stigma) and foster greater trust and satisfaction with accessible alternatives. Crisis support use and high completion (1129/2502, 45.12%) of digital safety plans among those who access crisis resources highlight the utility of these features for a generation that is struggling with high and increasing suicidality [60], emergency department visits for suicidal behavior [61], and suicide completions [62]. Future investigations should examine the pathways between access to clinical and crisis support services through a digital platform such as BeMe, linkage to such services, and subsequent clinical functioning.

The multiple modalities that make up BeMe’s platform were designed to support across the acuity spectrum and offer options for engagement in multiple live features that are adolescent led (eg, coaching and crisis support). The beta version allowed unlimited engagement with 24/7 live crisis support and live coaching for 14 hours per day, but this pattern might need adaption as adolescents’ use of the live service and its impact on clinical functioning are assessed over time. The dissemination of a multimodal platform such as BeMe is best supported by organizations that support health at the population level (eg, health plans) or invest in the well-being of teens and their families (eg, employers of teens’ parents). BeMe’s Teen Advisory Board and other adolescents can inform ways to best iterate upon the delivery of live features (eg, coaching) for operational efficiency and dissemination at scale.

Limitations
A study limitation is the incomplete data on measures of interest, given the self-driven nature of the BeMe app. Assessment completion was opportunistic, in that adolescents had to find the mood and well-being assessments or access content to trigger a pulse survey. The variety of information collected on participant characteristics was also limited to minimize burden in this initial evaluation of app use.

Conclusions
Overall, BeMe is a promising example of the combination of digital and live interactive support in practice. This study contributes to the growing body of work demonstrating the utility and impact of the combination of digital and live human support in digital interventions [21,63], and demonstrated acceptability and utility in a large sample of adolescents. The positive responses to BeMe’s content, activities, and coaching service are encouraging. The next stage of evaluation will measure the changes in clinical functioning and well-being associated with BeMe use over time.

Acknowledgments
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Data Availability
The data sets generated or analyzed during this study are available from the corresponding author upon reasonable request.

Authors’ Contributions
JJP, DER, and NPC designed the study and acquired funding. DER and NPC chose and designed the study assessments and the intervention content. DER and NPC led the data accrual and management. AC led institutional approvals. JJP, AC, and YW had access to the deidentified study data downloaded from Box. YW performed data analyses. JJP, MAB, and AC drafted the manuscript and incorporated feedback from the coauthors.

Conflicts of Interest
DER and NPC are employees of BeMe Health. All other authors declare no conflicts of interest related to this study.

Multimedia Appendix 1
BeMe terms of service.
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Critical Criteria and Countermeasures for Mobile Health Developers to Ensure Mobile Health Privacy and Security: Mixed Methods Study

Rita Rezaee¹,²,³ MD, PhD; Mahboobeh Khashayar⁴, MSc; Saeed Saeedinezhad¹, PhD; Mahdi Nasiri³,⁵, PhD; Sahar Zare⁶, PhD

¹Department of Health Information Technology, Shiraz University of Medical Sciences, Shiraz, Iran
²Clinical Education Research Center, Shiraz University of Medical Sciences, Shiraz, Iran
³Health Human Resources Research Center, Shiraz University of Medical Sciences, Shiraz, Iran
⁴Student Research Committee, Shiraz University of Medical Sciences, Shiraz, Iran
⁵Department of Computer Engineering and Information Technology, Shiraz University of Technology, Shiraz, Iran
⁶Health Information Management Research Center (HIMRC), Kashan University of Medical Sciences, Kashan, Iran

Corresponding Author:
Sahar Zare, PhD
Health Information Management Research Center (HIMRC)
Kashan University of Medical Sciences
5th of Qotb -e Ravandi Blvd Kashan
Kashan, 87159-73449
Iran
Phone: 98 31 55548883
Email: zare.sahar89@gmail.com

Abstract

Background: Despite the importance of the privacy and confidentiality of patients’ information, mobile health (mHealth) apps can raise the risk of violating users’ privacy and confidentiality. Research has shown that many apps provide an insecure infrastructure and that security is not a priority for developers.

Objective: This study aims to develop and validate a comprehensive tool to be considered by developers for assessing the security and privacy of mHealth apps.

Methods: A literature search was performed to identify papers on app development, and those papers reporting criteria for the security and privacy of mHealth were assessed. The criteria were extracted using content analysis and presented to experts. An expert panel was held for determining the categories and subcategories of the criteria according to meaning, repetition, and overlap; impact scores were also measured. Quantitative and qualitative methods were used for validating the criteria. The validity and reliability of the instrument were calculated to present an assessment instrument.

Results: The search strategy identified 8190 papers, of which 33 (0.4%) were deemed eligible. A total of 218 criteria were extracted based on the literature search; of these, 119 (54.6%) criteria were removed as duplicates and 10 (4.6%) were deemed irrelevant to the security or privacy of mHealth apps. The remaining 89 (40.8%) criteria were presented to the expert panel. After calculating impact scores, the content validity ratio (CVR), and the content validity index (CVI), 63 (70.8%) criteria were confirmed. The mean CVR and CVI of the instrument were 0.72 and 0.86, respectively. The criteria were grouped into 8 categories: authentication and authorization, access management, security, data storage, integrity, encryption and decryption, privacy, and privacy policy content.

Conclusions: The proposed comprehensive criteria can be used as a guide for app designers, developers, and even researchers. The criteria and the countermeasures presented in this study can be considered to improve the privacy and security of mHealth apps before releasing the apps into the market. Regulators are recommended to consider an established standard using such criteria for the accreditation process, since the available self-certification of developers is not reliable enough.

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KEYWORDS

telemedicine; mobile apps; privacy; computer security, confidentiality; mHealth; mobile health

Introduction

More than 5.19 billion people now use mobile phones, which indicates that mobile phones form an important part of daily life worldwide [1]. Mobile phone features, including mobility, instantaneous availability, and direct communication, have changed the provision of health care services. These features introduce mobile health (mHealth). Of about 2 million smartphone apps available in app stores, 318,000 are health apps [2]. According to a World Health Organization report [3], the penetration of mHealth, with promising results, in low- and middle-income countries would be even more.

mHealth has improved the patient care status through the provision of health care anytime and anywhere [4]. Even in recent years, the integration of mHealth and wireless technologies has provided clinicians with an opportunity to collect real-time data via wearable sensors [5]. Health information is deemed sensitive, and its protection is of significance. Nevertheless, smartphones are vulnerable to a wide range of security threats [6]. Moreover, electronic transmission of information has brought about concerns about its privacy and security. A national survey showed that 1 of the common reasons for people not having downloaded health apps is concern about apps gathering their data [7,8]. The privacy and confidentiality of information, as a human right, have long been considered in law and regulations. Well-known examples are the Health Insurance Portability and Accountability Act (HIPAA) rules, the General Data Protection Regulation (GDPR), and the Common Rule [9-11]. The terms “security,” “privacy” and “confidentiality” are all separate yet connected concepts that need to be addressed. The National Committee for Vital and Health Statistics [12] defines and distinguishes these concepts as follows:

Health information privacy is an individual’s right to control the acquisition, uses, or disclosures of his or her identifiable health data. Confidentiality, which is closely related, refers to the obligations of those who receive information to respect the privacy interests of those to whom the data relate. Security is altogether different. It refers to physical, technological, or administrative safeguards or tools used to protect identifiable health data from unwarranted access or disclosure.

Despite the importance of the privacy and confidentiality of patients’ information, studies report that mHealth apps may share the information with third parties, which raises the risk of violating patients’ privacy and confidentiality [13-15]. Dehling et al [16] evaluated the information security and privacy of 24,405 health-related apps and revealed that most apps request access to sensitive information. Robillard et al [17] reported that most of the apps do not include privacy policies and terms of the agreement. Moreover, it has been shown that many apps provide an insecure infrastructure and security is not a priority for the developers [18]. Similar studies emphasize assessing mHealth apps for the privacy, security, and confidentiality of information to minimize the associated risks [16,19,20].

Criteria have been proposed in previous studies for assessing mHealth apps. Benjumea et al [21] proposed a novel scale to assess the privacy policy of mHealth apps. However, the scale considers only specific items associated with the privacy policy content based on the GDPR rather than considering security and privacy in general. Another study [22] also proposed a heuristic evaluation approach to assessing the privacy of mHealth apps, but that is a time-consuming approach because heuristics require a close reading of the privacy policy. Another study proposed a security-testing method for Android mHealth apps designed based on a threat analysis, considering probable attack scenarios and vulnerabilities associated with the domain [18]. They assessed security using novel dynamic and static analysis testing methods that were expensive to perform. Benjumea et al [23] conducted a scoping review on studies exploring privacy issues in mHealth apps. Finding that most studies assess the apps based on heterogeneous criteria, Benjumea et al [23] emphasized the importance of developing a scale based on more objective criteria for evaluating privacy issues. In addition, the mHealth field faces a variety of legal and cultural differences over privacy between nations, so it needs a comprehensive tool for assessing both privacy and security issues [24]. Thus, developing a comprehensive tool assessing both privacy and security sounds necessary. This study aims to develop and validate a comprehensive tool to be considered by developers for assessing both the security and the privacy of mHealth apps targeting patients.

Methods

Study Design

This study was conducted to answer the following question: What security and privacy criteria should be considered when developing or assessing mHealth apps targeting patients based on 3 main phases: item generation, tool development, and tool evaluation? These main phases [25] were performed based on 4 steps: (1) identifying criteria associated with mHealth apps’ security/privacy according to a literature search (item generation); (2) conducting an expert panel for determining the categories and subcategories according to meaning, repetition, and overlap (tool development); (3) testing the validity of the instrument (tool evaluation); and (4) testing the reliability of the instrument (tool evaluation).

Stage 1: Literature Review

An unstructured literature search was performed to identify papers on app development, assessment, security, or privacy that reported criteria for the security and privacy of mHealth. PubMed, Scopus, Web of Science, and Cochrane were searched for English language papers published until December 15, 2021, without a time limitation. The search strategy (Multimedia Appendix 1) included a combination of 4 keywords: (“mobile
device" OR "mobile phone" OR smartphone OR "smart Phone" OR mHealth OR “mobile health”) AND (App OR apps OR application*) AND (security OR privacy OR confidentiality OR cybersecurity) AND (guideline* OR standard* OR criteria OR risk* OR assess* OR evaluat* OR measure).

The HIPAA and GDPR websites were searched for relevant criteria. After removing duplicate papers, the titles and abstracts of the studies were screened for inclusion. The full text of potentially relevant papers was investigated based on study objectives. Studies substantially focusing on security or privacy, not just mentioning them in passing, and stating clear criteria for assessing the privacy/security of mHealth apps were included. Studies evaluating the privacy or security of mHealth apps were also included to specify the criteria used for evaluation. Papers proposing a secure architecture, investigating technical solutions for mHealth apps (eg, access control, authentication approaches, encryption methods), presenting technical solutions for connecting mHealth apps to cloud computing or the internet of things devices or conducted on wearable devices without connecting to a mobile device, and discussing mobile phone access to electronic health records were excluded. Papers focusing on mHealth apps targeting users other than patients, focusing on app quality or determining functional requirements, and examining user experiences were also excluded. The criteria were extracted using content analysis.

**Stage 2: Expert Panel**

The list of primary criteria extracted through the literature search was presented to a focus group including 2 health information technology (HIT) specialists, 2 medical informatics specialists, and 1 software and IT specialist. The focus group discussion consisted of 4 major steps: designing research, collecting data, analyzing, and reporting results through a moderated interaction [26]. The experts discussed and categorized the criteria and decided over their inclusion or exclusion based on the relevancy, clarity, importance, comprehensiveness, and overlap with other included criteria, and they determined subcategories based on meaning, repetition, and overlap. This method can have a high level of validity due to the interaction among experts that confirms, reinforces, or rejects the individual respondents' contributions. The criteria extracted through the focus group discussion were used in the next stage.

**Stage 3: Testing the Validity of the Instrument**

Quantitative and qualitative methods were used for validating the instrument. To validate the instrument based on the qualitative approach, face validity was checked through face-to-face interviews by 8 HIT specialists and 5 software and IT experts. The inclusion criteria for the experts included specialists in HIT, IT, or software, with a master’s degree in science or higher, with at least 1-year work experience in software security, network security, health information security, or mobile app development. The criteria were modified based on the experts’ comments.

To validate the instrument quantitatively, the impact score was calculated for each criterion. The impact score determines inappropriate criteria. Thus, the criteria were evaluated based on a 5-point Likert scale ranging from 5 (very important) to 1 (not at all important). The impact score for each criterion was calculated as follows:

$$\text{Impact score} = \text{Frequency} \times \text{Importance}$$

Content validity was evaluated by 16 other IT (n=8, 50%) and software (n=8, 50%) experts, of whom 3 (18.8%) experts did not participate. Thus, to make sure the most essential criteria for the study objective were chosen, the content validity ratio (CVR) was measured. The CVR was calculated based on the following formula:

$$\text{CVR} = \frac{\sum \text{Frequency} \times \text{Importance}}{\sum \text{Frequency} \times \text{Importance}}$$

According to the Lawshe table, if the number of experts in the panel is 13, the minimal acceptable CVR is 0.54. In addition, to ensure the relevancy and clarity of each criterion, the content validity index (CVI) was measured. Thus, the 13 experts also completed a 4-point scale based on relevancy, clarity, and simplicity for the criteria. The CVI was calculated using the following formula:

$$\text{CVI} = \frac{\sum \text{Agreement}}{\sum \text{Experts}}$$

The criteria were included in the final assessment tool if the CVI was ≥0.79 [27,28]. If the CVI was between 0.70 and 0.79, it needed to be calculated after the criteria were revised by the experts. Criteria with a CVI of <0.70 were removed.

**Stage 4: Testing Reliability**

To assess the reliability of the final tool, the hypertensive self-care app developed in our previous study [29] was selected. The app needs to record a variety of personal information. In total, 30 experts in HIT, medical informatics, IT, and software assessed the reliability of the instrument. The instrument was distributed among these experts twice in a 2-month interval. They were asked to assess the privacy and security of the self-care app using the criteria provided in the checklist. After collecting expert opinions about the self-care app, the data were analyzed using the Cronbach $\alpha$.

**Ethical Considerations**

The research was conducted according to the principles stated by the Vice-Chancellorship for Research Affairs of Shiraz University of Medical Science and approved by the Ethics Review Board of the Vice-Chancellorship for Research Affairs of Shiraz University of Medical Science (ethical code IR.SUMS.REC.1397.500).

**Results**

**Study Selection**

The search strategy retrieved 10,092 papers, of which 1902 (18.8%) were duplicates. Of the 8190 (81.2%) remaining papers, 8072 (98.6%) were irrelevant. To retrieve the greatest number of possible relevant papers, our search strategy included smartphone or mobile devices as a synonym for mHealth ("mobile device" OR "mobile phone" OR smartphone OR "smart Phone" OR mHealth OR "mobile health"); this resulted in retrieving papers basically irrelevant to the health discipline,
in addition to those relevant to the health discipline—for example, studies associated with payment/banking/commercial apps were also retrieved in the primary result. In total, 33 (0.4%) studies were deemed eligible for inclusion in the research (Figure 1). The characteristics of the included studies [13,14,16,18-20,24,30-56] are presented in Multimedia Appendix 2.

A total of 218 criteria were extracted based on the literature search; of these, 119 (54.6%) were removed as duplicates (showing the same idea) and 10 (4.6%) were deemed irrelevant to the security or privacy of mHealth apps. The remaining 89 (40.8%) criteria were presented to the expert panel. As shown in Figure 2, 63 (70.8%) criteria were confirmed at last.

The mean CVR of the total instrument was 0.72, while the mean CVI was 0.86. Multimedia Appendix 3 shows the complete list of removed criteria in the different phases of the study.

Finally, to measure the reliability of the instrument, the experts were asked to assess the hypertensive self-care app using the instrument. When measuring the reliability of the instrument, 18 (28.6%) of the 63 criteria received the lowest and the highest score of the Likert spectrum (“not at all” and “completely”) equally. Since the variance of equal data was 0, these 18 criteria did not automatically enter for calculating the Cronbach α value. Thus, the test was performed with 45 (71.4%) criteria. The Cronbach α value was 0.89.

The 63 criteria were grouped into 8 categories: authentication and authorization (n=8, 12.7%), access management (n=6, 9.5%), security (n=13, 20.6%), data storage (n=4, 6.3%), integrity (n=2, 3.2%), encryption and decryption (n=5, 9.5%), privacy policy (n=15, 23.8%), and privacy policy content (n=10, 15.9%); see Textbox 1.

**Figure 1.** Flow diagram of study selection. EHR: electronic health record.
Figure 2. Flowchart of criteria determination. CVI: content validity index; CVR: content validity ratio.
Textbox 1. Final privacy and security assessment criteria.

1. **Authentication and authorization**
   1.1. Is there any registration/log-in available in the app?
   1.2. Does the app capture a unique username or “fixed device identifier” used as a user identifier (for both patient and health care provider)?
   1.3. Are there procedures to verify that any person or entity claiming access to electronic protected health information complies with its claim?
   1.4. Are there any ways to monitor the log and report errors?
   1.5. Are there any steps to create, change, and protect the password?
   1.6. Are the passwords complex enough (ie, of a minimum length, alphanumeric with upper- and lowercase letters and symbols)?
   1.7. Are the passwords updated periodically?
   1.8. Is the user’s account locked after a determined number of consecutive unsuccessful log-in attempts?

2. **Access management**
   2.1. Is there patient-centric access control?
   2.2. Are there measures taken to access the health information needed in an emergency?
   2.3. Is the user allowed to access personal information and to participate in treatment?
   2.4. Does the app facilitate the provision of an electronic copy of data?
   2.5. Is the app capable of cutting off or blocking a person's access at any time?
   2.6. Are users allowed to control the access level of their health information by third parties?

3. **Security**
   3.1. Does the app use secure connections (Secure Socket Layer [SSL]/Transport Layer Security [TLS])?
   3.2. Can the data be remotely controlled if the mobile phone is lost/stolen?
   3.3. Does the app use a secure platform for transmitting health data?
   3.4. Does the app protect network traffic by strong coding?
   3.5. Are default measures present to protect against, identify, and report security incidents/malware?
   3.6. Does the app use external devices?
   3.7. Does the app use random number generators?
   3.8. Are users able to change individual profiles according to the policy of the mobile health (mHealth) app?
   3.9. Does the app require interaction with the user while performing a sensitive operation or communicating with an untrusted app?
   3.10. Does the app use cookies?
   3.11. Is the security policy transparent and easy to find?
   3.12. Are there reminders for periodic system security updates?
   3.13. Has anyone been appointed to assume security responsibility?

4. **Data storage**
   4.1. Are data stored locally on the device? If no, are the users notified about using another platform for storing their data?
   4.2. Are data centers in a secure condition?
   4.3. Are data stored on the mobile phone or to the app company’s own servers?
   4.4. Are there any steps to recover lost data or any backup?

5. **Integrity**
   5.1. Are there electronic mechanisms to verify that health information is not unauthorized, altered, or destroyed (eg, check-sum verification or digital signatures)?
   5.2. Are security measures in place to prevent the unauthorized destruction or tampering of health information that is being exchanged electronically?

6. **Encryption and decryption**
   6.1. Does the app use a strong modern encryption/decryption mechanism?
   6.2. Is a proper method of encryption selected and implemented (eg, use encryption through https rather than http)?
   6.3. Are the data stored encrypted?
6.4. Are the data transmitted encrypted?
6.5. Is the username/password/keys encrypted?

7. Privacy
7.1. Is there a privacy policy on the app or a link to the full privacy policy?
7.2. Are there any restrictions on the use or disclosure of information contained in the app?
7.3. Are there restrictions on the collection of information?
7.4. Does the app have the ability to disclose information on social media by the user?
7.5. Has the principle of protecting the confidentiality of data been met?
7.6. Does the app state which regulation it complies with and which country the regulation belongs to?
7.7. Does the app ask normal permissions and provide justification for that?
7.8. Is identifiable information anonymized and de-identifiable? If anonymization is not possible, are users informed?
7.9. Have any measures been taken to notify the users of their privacy rights?
7.10. Will the user be informed of any leaks or breaches?
7.11. Does the app have the ability to manage alerts (e.g., hide them from the lock screen)?
7.12. Is the privacy policy easy to find, clear, readable, and up to date?
7.13. Are users able to manipulate or completely delete personal profiles and any data archives?
7.14. Are users informed about any security or privacy measures?
7.15. Does the app prevent disclosure of data about the location or sensor type of the user?

8. Privacy policy content
8.1. Is there a time limit for data retention?
8.2. Is the content of the contract with third parties clearly stated?
8.3. Does the app mention the collection of user data and how they are being used?
8.4. Does the privacy policy describe the purpose and the type of information collected?
8.5. Is the data ownership specified?
8.6. Are the administrative details stated (identify data controller or responsible legal entity, legal jurisdiction governing policy, jurisdictions under which transmitted data will be processed, date of policy and next review)?
8.7. Is there an explanation about the retention policy for the health information?
8.8. Does the privacy policy explain the manipulation of data by the developer or third parties?
8.9. Does the privacy policy explain the complaints procedures?
8.10. Does the privacy policy explain the procedures for changing the terms of the policy?

Discussion

Principal Findings

In this study, we developed an instrument for assessing the security and privacy of mHealth apps. The criteria proposed in this tool were classified into 8 categories: authentication and authorization, access management, security, data storage, integrity, encryption and decryption, privacy, and privacy policy. These criteria can be considered by mHealth app developers to improve the privacy and security of their apps before releasing them into the market.

Authentication and Authorization

The criteria in the tool suggest implementing rigorous authentication and authorization techniques. More time and effort should be devoted to preventing unauthorized access to personal health information. The developers are asked to provide a unique master ID and a secret key identity for users to control role-based access and verify users’ activities according to the defined identity and roles. Authentication via a fingerprint or a personal identification number is necessary for internal storage, internal cache, external storage, and databases [57]. Audit trails should be in place to track logs, protect data, and identify which user’s health data was handled and by whom. Each user should be able to create, change, and protect their passwords. The developers should make sure the passwords are strong enough and are changed periodically, because there are tools that produce $10^{14}$ guesses in an hour to find the correct password [58]. There are some strategies to be used by developers to make sure passwords are secure; these include enforcing password complexity; making passwords unviewable, even to the app administrator; and locking a user’s account after a determined number of consecutive unsuccessful log-in attempts. System-generated passwords can be strong, but they do not guarantee memorability. Using Optiwords8 passwords [59],
based on the picture superiority effect on the mobile phone keyboards, guarantees the security of passwords, while keeping them usable and memorable as a result.

Access Management

mHealth app developers need to define access controls for their team members as well as users. For those apps providing health care provider–patient communication, granting access to specific app functions should be based on predetermined and confirmed roles and attributes. Patients should be users allowed to control the access level of their health information by third parties. Greene et al [60] proposed the ShareHealth framework, which provides cryptographically enforced access to data. The framework takes advantage of combining a robust cryptographic scheme, hash chains (to control access by data time), and attribute-based encryption (to control access by data type). Rectification, deleting, or blocking of data should be facilitated for users [53].

Security

Some mHealth apps use connections for several purposes, including fetching mail, sending analytics data, or checking for updates. To protect the authenticity, confidentiality, and integrity of the connection, developers are encouraged to use an up-to-date version of the Transport Layer Security protocol and its predecessor, the Secure Socket Layer (SSL) [54]. SSL protocols provide an encrypted link that connects a server and a client and makes sure the transmitted data remain impossible to read and are kept private; however, if the coding is not strong enough, hackers would be able to interpret health data during transmission [44]. There should be a functionality of remote control of data to securely transfer, retrieve, or completely erase health information if the mobile phone is stolen/lost [35]. However, it is safer to store data on users’ own devices rather than on the app company’s servers [13]. Some apps use external devices, such as cameras, sensors, or payment apps, to improve their functionality, but this endangers users’ confidentiality through attacks, such as external-device misbonding [48]. Moreover, using cookies can jeopardize user privacy especially those used for data analysis by third parties [14]. Users should be able to manipulate their profile or delete it completely when they stop using an app [31].

Encryption and Decryption

Bhanot and Hans [61] compared various encryption algorithms based on different criteria, such as cryptography type, key management, keys number, and bit numbers used in a key. They found that elliptic-curve cryptography and blowfish encryption algorithms are the best, providing higher security levels as well as faster encryption speeds, which is required for mobile devices due to less power consumption [61]. Security measures, such as wired equivalent privacy, which is used to provide security to mobile devices, are vulnerable to hackers [62,63]. Thus, developers are required to perform a security risk analysis to determine vulnerabilities at each stage of design and implementation throughout testing and use. Arora et al [64] suggest using a “red team” for risk analysis. Red team experts are charged with hacking cyber systems in order to detect weaknesses.

Privacy

Papageorgiou et al [49] found that although many of the studied apps ask for dangerous permissions (eg, read/write external storage, access camera, location, and contacts), they do not follow well-known regulations, such as HIPAA. Developers are required to collect data as much as they need to provide their services, so they are required to provide reasons for permissions they ask for, the type of data they collect, and how the data will be used by them or third parties, including insurance companies, government institutions, or even research centers [18,38]. Third-party usage of health data can bring about privacy intrusions, such as loss of insurance coverage or higher insurance premiums [65]. Complying with regulations and which country these regulations belong to is also important because when enforcing privacy rights, the regulations may differ from the users’ own country [13]. Users’ records should be stored in incognito forms, which are anonymized and unidentifiable; if anonymization is not possible, users should be informed [40].

All mHealth apps need to provide a transparent, precise, and well-readable privacy policy statement or a link to the complete privacy policy. Procedures for refusing data sharing, consequences of not providing/sharing data, procedures for changing the terms of the policy, procedures for editing or deleting data held by developers/third parties, procedures for complaints, and procedures for handling data for vulnerable users are subsets of “user rights” a privacy policy should contain. In addition, a data retention policy, data ownership, date of the policy, and next reviews should be contained as “administrative details” of the privacy policy. Users’ access to their health information is another right. A systematic review [66] indicated that patients’ access to their health information has a positive impact. A similar study [21] proposed a 14-criteria scale for assessment of a privacy policy based on the GDPR. Although the items by proposed Benjumea et al [21] overlap our proposed criteria (some with different words but similar concepts), they include 5 items not included in our tool; 2 items are “legal basis for processing” and “legitimate interests from controller” that imply the bases for the processing determined by the GDPR. This may be similar to the criteria associated with permission/consent and how users’ data will be processed/used, which are considered in our tool in general. Another item is “transfers to non-EU countries,” which sounds similar to the “regulation the mHealth app comply with and the country (as general, only European ones) that the regulation belongs to” also considered in our tool. The fourth item is “obligation to provide personal data,” which can be considered as a subset of “user rights” [34] (existent among our criteria). As mentioned earlier, users need to be informed about the consequences of not providing their information. The last item is “existence of automated decision-making or profiling,” which is not included in our tool. It also worth to note that the criteria proposed in our study are general criteria for assessing both privacy and security classified into 8 categories. We tried to determine a comprehensive list of criteria, but we also faced a restriction to limit our criteria to general important aspects of privacy and security, because including a large number of criteria makes it difficult for assessors to consider all of them and this may result in rejection of the tool. That is why we tried to use general
concepts that cover more specific criteria (eg, user rights) or merge some criteria into a single one (eg, administrative details).

**Limitations**

In this study, a list of criteria was proposed using published papers. A limitation of this study is conducting an unstructured literature search, due to which we missed some related papers. However, to the best of our knowledge, many of the criteria included in our study overlap those that were not included. Another limitation is the large number of included criteria, which may make it difficult for assessors to consider all of them; however, we tried to limit our criteria to important ones to make them more applicable, and we also used general concepts that cover more specific criteria (eg, user rights) or merged some items into a single one (eg, administrative details). Another limitation is the difficulty in assessing some criteria—for example, app compliance with regulations may not be clearly stated in the app. It is recommended that future studies verify the proposed criteria using mobile apps. However, they should be considered in conjunction with other assessment strategies, such as risk analysis, data leakage detection, and continuous revision accordingly. Moreover, this study focused on the security and privacy challenges of mHealth apps, but there are other important challenges, such as interoperability. Thus, it is recommended that future studies combine both aspects to obtain not only a secure system but also an interoperable one, because mHealth apps communicate with a variety of sources.

**Conclusion**

With the evolution in the health field through smartphones and mHealth apps, privacy and security challenges need to be addressed. The proposed comprehensive criteria can be used as a quick guide for app designers, developers, regulators, and even researchers. The criteria and the countermeasures presented in this study can be considered to improve the privacy and security of an mHealth app before releasing it into the market. Regulators are recommended to consider an established standard using such criteria for the accreditation process, since the available self-certification of developers is not reliable enough.

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RR, MK, SS, MN, and SZ made substantial contributions to conception and design. SZ and MK made substantial contributions to data collection through a literature search. SZ and RR drafted the manuscript, and all the authors have read it to revise it critically for important intellectual content.

MN was affiliated with the Health Human Resources Research Center at Shiraz University of Medical Sciences at the time of the study and is currently affiliated with the Department of Computer Engineering and Information Technology at Shiraz University of Technology.

**Conflicts of Interest**

None declared.

Multimedia Appendix 1

This is the search strategy.
[DOCX File, 15 KB - mhealth_v11i1e39055_app1.docx ]

Multimedia Appendix 2

Characteristics of the included studies.
[DOCX File, 61 KB - mhealth_v11i1e39055_app2.docx ]

Multimedia Appendix 3

The complete list of removed criteria.
[DOCX File, 15 KB - mhealth_v11i1e39055_app3.docx ]

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Abbreviations

CVI: content validity index
CVR: content validity ratio
GDPR: General Data Protection Regulation
HIPAA: Health Insurance Portability and Accountability Act
HIT: health information technology
mHealth: mobile health

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Mobile Health Apps for Breast Cancer: Content Analysis and Quality Assessment

Seongwoo Yang¹,², MPH; Cam Nhung Bui¹, MD, PhD; Kyoungoon Park¹, MD, PhD

¹HERINGS, The Institute of Advanced Clinical & Biomedical Research, Seoul, Republic of Korea
²Department of Digital Health, Samsung Advanced Institute for Health Sciences & Technology, Sungkyunkwan University, Seoul, Republic of Korea

Corresponding Author:
Kyoungoon Park, MD, PhD
HERINGS, The Institute of Advanced Clinical & Biomedical Research
14F, 560, Eonju-ro
Gangnam-gu
Seoul, 06144
Republic of Korea
Phone: 82 269493523
Fax: 82 269493517
Email: khpark@heringsglobal.com

Abstract

Background: The number of mobile health apps is rapidly increasing. This means that consumers are faced with a bewildering array of choices, and finding the benefit of such apps may be challenging. The significant international burden of breast cancer (BC) and the potential of mobile health apps to improve medical and public health practices mean that such apps will likely be important because of their functionalities in daily life. As the app market has grown exponentially, several review studies have scrutinized cancer- or BC-related apps. However, those reviews concentrated on the availability of the apps and relied on user ratings to decide on app quality. To minimize subjectivity in quality assessment, quantitative methods to assess BC-related apps are required.

Objective: The purpose of this study is to analyze the content and quality of BC-related apps to provide useful information for end users and clinicians.

Methods: Based on a stepwise systematic approach, we analyzed apps related to BC, including those related to prevention, detection, treatment, and survivor support. We used the keywords “breast cancer” in English and Korean to identify commercially available apps in the Google Play and App Store. The apps were then independently evaluated by 2 investigators to determine their eligibility for inclusion. The content and quality of the apps were analyzed using objective frameworks and the Mobile App Rating Scale (MARS), respectively.

Results: The initial search identified 1148 apps, 69 (6%) of which were included. Most BC-related apps provided information, and some recorded patient-generated health data, provided psychological support, and assisted with medication management. The Kendall coefficient of concordance between the raters was 0.91 (P<.001). The mean MARS score (range: 1-5) of the apps was 3.31 (SD 0.67; range: 1.94-4.53). Among the 5 individual dimensions, functionality had the highest mean score (4.37, SD 0.42) followed by aesthetics (3.74, SD 1.14). Apps that only provided information on BC prevention or management of its risk factors had lower MARS scores than those that recorded medical data or patient-generated health data. Apps that were developed >2 years ago, or by individuals, had significantly lower MARS scores compared to other apps (P<.001).

Conclusions: The quality of BC-related apps was generally acceptable according to the MARS, but the gaps between the highest- and lowest-rated apps were large. In addition, apps using personalized data were of higher quality than those merely giving related information, especially after treatment in the cancer care continuum. We also found that apps that had been updated within 1 year and developed by private companies had higher MARS scores. This may imply that there are criteria for end users and clinicians to help choose the right apps for better clinical outcomes.

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KEYWORDS
app; breast cancer; quality assessment; mobile health; mHealth; digital health; digital health intervention; cancer management; tablet; prevention; survivor; peer-support

Introduction
With the increasing use of mobile apps since 2010, the number of mobile health–related (mHealth) apps has also risen [1]. According to a 2021 IQVIA report, there is a growing number of digital health care apps, with >350,000 apps related to health and fitness or medical categories available in the App Store and Google Play [2]. In 2020, a national survey in the United States found that more than half of all mobile phone users had downloaded health-related apps, and among them, two-thirds felt that such apps helped improve their health [3]. The key features of these health-related apps are maintaining a medication log, monitoring side effects, and scheduling follow-up appointments [4]. In addition, disease-specific apps may empower patients to promote self-efficacy, and self-care behavior in daily life, via information-technology services such as educational, patient-to-patient, and electronic patient-reported outcome services [5]. Therefore, maximizing the use of these advanced smartphone functions has paved the way for the delivery of diverse health care services [6]. In this respect, clinicians may want to employ useful apps to their patients and monitor their effect on patient outcomes [7]. However, to encourage health care providers to exploit them with confidence, there is a need for unbiased and scientific assessment of mHealth apps [6]. In addition, studies on mHealth have found that consumers are faced with a “bewildering array” of such apps because of the difficulty in discerning app quality, despite their beneficial functions [8].

Furthermore, since most public reviews of apps are based on individuals’ own subjective experience, more scientific and systematic assessment of mHealth apps is important [6]. Therefore, methods for the systematic search and analysis of apps have been developed [9]. Using these methods, several studies have evaluated apps concerning general cancer care [4,10], specific cancer types (eg, prostate cancer [11,12]), skin monitoring and melanoma detection [13,14], and medication compliance [15,16].

Even though breast cancer (BC) is one of the most prevalent cancers, especially in high-income countries, and is the leading cause of death in women in most low-income and many middle-income countries [17,18], morbidity and mortality can be reduced by promoting exercise, a healthy diet, adequate access to screening services, treatment, and care management [19,20]. However, a lack of information and support has prevented many women with BC from engaging in healthier behaviors during their cancer care [17,19,20]. Additionally, increased rates of early diagnosis and treatment [21] and a better prognosis and survival than other cancer types have resulted in unmet supportive-care needs for BC survivors [22,23]. In this sense, mHealth interventions can serve as promising platforms to enhance preventive and postdiagnosis behavior change with a clear goal setting and adherence to relevant theories [24]. Therefore, in terms of the international burden of BC and the potential of mHealth apps to improve medical and public health practices, the use of BC-related apps across the cancer care continuum (CCC) is important because of their functionalities in daily life [25].

According to a systematic review, in their nascent stage, BC-specific apps focused mainly on resources for BC awareness, screening, diagnosis, and treatment, so there is a lack of evidence on their utility, effectiveness, and safety [4]. Another systematic review analyzed all BC-related apps for their content and adherence to design standards outlined by the Institute of Medicine, as well as the relationships between their content, user ratings, and price [26]. The review found that mHealth apps have not met their potential for consumer engagement with evidence-based information, and BC-specific apps represented a limited spectrum on the cancer continuum [26]. Another systematic review that targeted BC survivorship and self-management pointed out that very few relevant resources were available in the apps considered [6], despite their utility in alleviating the burden and costs for BC survivors [27]. In sum, all these studies scrutinized cancer- or BC-related apps, but their focus was on mobile app availability, and they relied on user ratings to decide app quality. Therefore, to minimize subjectivity in quality assessment, quantitative methods to assess BC-related apps are required.

mHealth apps related to BC have different contents and features; therefore, the primary goal of this study was to perform a detailed evaluation of each element. In particular, patients with BC receive long-term care; they need proper information and direction outside the hospital setting through mobile apps. Therefore, the secondary goal of the study was to analyze the quality of BC-related apps to provide useful information for users and clinicians.

Methods

Overview of Mobile Apps
This stepwise systematic approach evaluated BC-related smartphone apps available on the Android and iOS platforms that had features related to cancer prevention, detection, treatment, and the provision of survivor support. We used the keywords “breast cancer” in English and Korean to identify commercially available apps in Google Play and the App Store, using accounts in both the United States and South Korea. The search was conducted on July 1, 2022, using the app search engine AppAgg, a mobile app metadata resource that was also used in a related study [28]. We recorded each app’s title, developer, final update, description, price, and website address.

Selection Criteria
This study included English and Korean BC-related apps for women who are at risk for BC across the life stages in the relevant app categories (health and fitness, medical, social, and lifestyle) that had been updated within the previous 3 years (July 2019-July 2022) and were available free of charge. We excluded apps that did not function correctly (eg, unreadable text or a
blank screen), those that merely provided lists of conditions, and those intended for medical students that used self-made flashcards. In addition, we excluded apps that were developed with specific target users in mind (e.g., those for health care professionals or children), to prompt a donation, or for trial recruitment. The eligible apps for Android and iOS were installed and alternately tested by each reviewer on a Samsung Galaxy S21 (Android version 11.0; Google LLC) and an iPhone 11 (iOS version 15.5; Apple Inc), respectively.

**Content Analysis**

The apps were independently evaluated by 2 investigators (SY and CNB). We recorded each app’s title, platform, developer, category, date of latest update, language, and description. The content and functions of the selected apps were classified using the CCC, which has been used since the mid-1970s to describe the various stages of cancer in terms of etiology, prevention, detection, diagnosis, treatment, and survivorship [29,30]. Although the CCC categories are not discrete due to their oversimplified nature, they provide useful labels based on the development of cancer biology. We adopted the coding scheme proposed by Charbonneau et al [10], which redefined the following 7 categories of cancer apps identified by Bender et al [4]: educational, fundraising, prevention, early detection, disease and treatment information, disease management, and support. By integrating these concepts with the CCC stages, we created new categories that covered the app features identified in previous studies (Multimedia Appendix 1). We assumed that the functions and content of BC-related apps would fit into these categories.

**Quality Assessment**

The Mobile App Rating Scale (MARS) was used to evaluate the quality of the selected apps. This scale is a commonly used and validated tool that evaluates the following 5 dimensions of mobile apps: engagement, functionality, aesthetics, information, and subjective quality [31,32]. The apps are scored on a 5-point scale (1=inadequate; 2=poor; 3=acceptable; 4=good; and 5=excellent). Two blinded reviewers evaluated the apps separately without sharing detailed information; the Kendall coefficient of concordance was calculated to evaluate the agreement between them [33]. The apps were evaluated based on the MARS scores (total and dimension), and the mean scores of the 2 raters were calculated. We further analyzed differences in MARS scores by content based on the CCC and the number of years since the last update. We also classified the apps by the type of developer such as individual, commercial (including private companies or for-profit organizations), or public institutions (including nongovernmental organizations, hospitals, government agencies, or universities). For multiple comparisons of the numbers of years since last updated and developer types, analysis of variance and the Tukey honestly significant difference test were performed. Statistical analyses were performed using R software (version 4.1.0; R Foundation for Statistical Computing).

**Ethical Considerations**

Since this study contains no primary data obtained from any experiment on human subjects, ethics approval was not required.

**Results**

**App Identification**

In total, 1148 apps identified through the database search were reviewed for eligibility for this study. After applying our exclusion screening criteria (eligible categories, updates, and relevance), 116 apps were downloaded and assessed in terms of content, price, language, and other criteria. Finally, 69 apps (n=41, 59% Android apps and n=28, 41% iOS apps) were included and subjected to content and quality assessment (see Figure 1 for the app-selection process and Multimedia Appendix 2 for the list of 69 BC-related apps included).
General Characteristics of the Included Apps

Of the 69 apps selected, 41 (59%) and 28 (41%) were available only on Android Google Play and the Apple App Store, respectively (Table 1), while 15 (22%) were available on both platforms. Most apps were included in the Health and Fitness category (n=48, 70%), had been updated within the previous year (n=46, 67%), were developed by a commercial organization (n=43, 62%), and were available in English (n=62, 70%).
Table 1. General characteristics of the 69 included apps.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Values, n (%)</th>
</tr>
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<tbody>
<tr>
<td><strong>Platform</strong></td>
<td></td>
</tr>
<tr>
<td>Android</td>
<td>41 (59.4)</td>
</tr>
<tr>
<td>iOS</td>
<td>28 (40.6)</td>
</tr>
<tr>
<td>Android and iOS</td>
<td>15 (21.7)</td>
</tr>
<tr>
<td><strong>Category</strong></td>
<td></td>
</tr>
<tr>
<td>Health and fitness</td>
<td>48 (69.6)</td>
</tr>
<tr>
<td>Medicine</td>
<td>15 (21.7)</td>
</tr>
<tr>
<td>Lifestyle</td>
<td>2 (2.9)</td>
</tr>
<tr>
<td>Social networking</td>
<td>4 (5.8)</td>
</tr>
<tr>
<td><strong>Updated within</strong></td>
<td></td>
</tr>
<tr>
<td>1 year</td>
<td>46 (66.7)</td>
</tr>
<tr>
<td>2 years</td>
<td>8 (11.6)</td>
</tr>
<tr>
<td>3 years</td>
<td>15 (21.7)</td>
</tr>
<tr>
<td><strong>Developer</strong></td>
<td></td>
</tr>
<tr>
<td>Individual</td>
<td>8 (11.6)</td>
</tr>
<tr>
<td>Commercial organizationa</td>
<td>43 (62.3)</td>
</tr>
<tr>
<td>Public institutionb</td>
<td>18 (26.1)</td>
</tr>
<tr>
<td><strong>Language</strong></td>
<td></td>
</tr>
<tr>
<td>English</td>
<td>62 (89.9)</td>
</tr>
<tr>
<td>Korean</td>
<td>2 (2.9)</td>
</tr>
<tr>
<td>English and Korean</td>
<td>5 (7.2)</td>
</tr>
</tbody>
</table>

*Such as private company or for-profit organization.
*Such as nongovernmental organization, hospital, government agency, or university.

Content Analysis

Table 2 shows the contents of the BC-related apps according to category and platform (Android and iOS). Their most common function was to provide information related to early detection of BC (n=34, 49%), followed by information concerning the risk factors and biological processes of BC at the prevention stage (n=28, 41%). The next most common content was information about symptoms, treatments, new advancements in BC treatment, and side effects related to BC after the treatment stage (n=27, 39%); education for lifestyle modification (n=23, 33%), and education for facts and knowledge related to BC (n=22, 32%). The apps also recorded patient-generated health data (PGHD), including tracking patients’ and survivors’ exercise, sleep, diet, and symptoms (n=19, 28%); provided psychological support (n=17, 25%); and assisted in medication management (n=16, 23%). However, content related to PGHD and medication management was more likely to be included in apps for iOS than in those for Android. The content of BC-related apps was also analyzed according to the number of years since the last update and the developer type (Multimedia Appendix 3). We found that 46 (67%) apps had been updated in the previous year, and 43 (62%) were developed by commercial organizations. Additionally, the apps that were outdated or had been developed by individuals mainly provided information or education regarding prevention or treatment. By contrast, those that had recently been updated and those that were developed by commercial organizations provided diverse content, including guidance for early detection, recording of PGHD, facilitation of medication management, and promotion of lifestyle modifications. Details of the apps’ contents are provided in Multimedia Appendix 4.
Table 2. Content analyses of the 69 breast cancer (BC)–related mobile health apps.

<table>
<thead>
<tr>
<th>Cancer control continuum and content</th>
<th>Android (n=41), n (%)</th>
<th>iOS (n=28), n (%)</th>
<th>Total (n=69), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Etiology and prevention</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Information on BC</td>
<td>19 (46.3)</td>
<td>9 (32.1)</td>
<td>28 (40.6)</td>
</tr>
<tr>
<td>Risk prediction</td>
<td>8 (19.5)</td>
<td>2 (7.1)</td>
<td>10 (14.5)</td>
</tr>
<tr>
<td>Education for prevention and risk factors for BC</td>
<td>16 (39.0)</td>
<td>6 (21.4)</td>
<td>22 (31.9)</td>
</tr>
<tr>
<td><strong>Detection</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Guidance for early detection</td>
<td>21 (51.2)</td>
<td>13 (46.4)</td>
<td>34 (49.3)</td>
</tr>
<tr>
<td>Connection to professionals</td>
<td>5 (12.2)</td>
<td>5 (17.9)</td>
<td>10 (14.5)</td>
</tr>
<tr>
<td><strong>Diagnosis and treatment</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Information on BC treatment</td>
<td>17 (41.5)</td>
<td>10 (35.7)</td>
<td>27 (39.1)</td>
</tr>
<tr>
<td>PGHD&lt;sup&gt;a&lt;/sup&gt;</td>
<td>8 (19.5)</td>
<td>11 (39.3)</td>
<td>19 (27.5)</td>
</tr>
<tr>
<td>Medical records</td>
<td>4 (9.8)</td>
<td>2 (7.1)</td>
<td>6 (8.7)</td>
</tr>
<tr>
<td>Medication management</td>
<td>7 (17.1)</td>
<td>9 (32.1)</td>
<td>16 (23.2)</td>
</tr>
<tr>
<td>Consultation by a physician</td>
<td>3 (7.3)</td>
<td>1 (3.6)</td>
<td>4 (5.8)</td>
</tr>
<tr>
<td>Tracking appointments</td>
<td>4 (9.8)</td>
<td>5 (17.9)</td>
<td>9 (13.0)</td>
</tr>
<tr>
<td>Participation in decision-making</td>
<td>5 (12.2)</td>
<td>4 (14.3)</td>
<td>9 (13.0)</td>
</tr>
<tr>
<td><strong>Survivorship</strong>                                      <strong>Information on posttreatment care and prevention of recurrence</strong></td>
<td>8 (19.5)</td>
<td>6 (21.4)</td>
<td>14 (20.3)</td>
</tr>
<tr>
<td>Education for lifestyle modification</td>
<td>15 (36.6)</td>
<td>7 (25.0)</td>
<td>23 (33.3)</td>
</tr>
<tr>
<td>Consultation with an expert</td>
<td>6 (14.6)</td>
<td>4 (14.3)</td>
<td>10 (14.5)</td>
</tr>
<tr>
<td>Psychological support</td>
<td>7 (17.1)</td>
<td>10 (35.7)</td>
<td>17 (24.6)</td>
</tr>
<tr>
<td>Community</td>
<td>7 (17.1)</td>
<td>6 (21.4)</td>
<td>13 (18.8)</td>
</tr>
<tr>
<td>Sharing information with family and caregivers</td>
<td>5 (12.2)</td>
<td>2 (7.1)</td>
<td>7 (10.1)</td>
</tr>
<tr>
<td>Fundraising</td>
<td>3 (7.3)</td>
<td>5 (17.9)</td>
<td>8 (11.6)</td>
</tr>
</tbody>
</table>

<sup>a</sup>PGHD: patient-generated health data.

Quality Assessment of the Apps
The 69 apps were evaluated by 2 raters using the MARS (Figure 2). The Kendall coefficient of concordance was 0.91 (P<.001), indicating a good agreement between the raters; disagreements between them were resolved by consensus. The mean total score (1-5) of the included apps was 3.31 (SD 0.67; range: 1.94-4.53). Among the MARS dimensions, functionality had the highest mean score (4.37, SD 0.42), followed by aesthetics (3.74, SD 1.14), information (3.53, SD 0.69), engagement (2.89, SD 0.92), and subjective quality (2.20, SD 0.79). The dimension scores of the apps varied widely, indicating large variations in app quality. The MARS scores of the included apps are presented in Multimedia Appendix 5. Of the 69 apps included, OncoPower (Android: 4.0, iOS: 4.2), Outcomes4Me Breast Cancer Care (Android: 4.4, iOS: 4.5), OWise – Breast Cancer Support (Android: 4.2, iOS: 4.1), and War On Cancer (Android: 4.0, iOS: 4.0) had the highest scores. Among the MARS dimensions, they scored especially highly in functionality and aesthetics (Multimedia Appendix 5).

The MARS scores were analyzed based on the number of years since the app was last updated and the developer type (Figure 3). Tukey test showed that the mean scores for apps that had been updated within the previous 1 (3.59, SD 0.53) or 2 (3.17, SD 0.68) years were not statistically different. However, outdated apps (ie, those that had been updated >2 years previously) had a significantly lower mean MARS score (2.54, SD 0.41) compared to the other apps (P<.001). Apps developed by individuals had a significantly lower mean MARS score (2.39, SD 0.41) than those developed by commercial organizations (3.43, SD 0.70) and public institutions (3.45, SD 0.28; P<.001).
Quality Assessment of the Apps’ Content

The quality of the content of the included apps was assessed using the MARS (Figure 4). Apps that tracked treatment records had the highest mean MARS score (T3; 4.0, SD 0.51), followed by those that facilitated consultations with experts (S3; 3.93, SD 0.38), medication management (T4; 3.91, SD 0.5), and consultations with physicians (T5; 3.85, SD 0.34). The mean MARS score was higher for apps that involved recording PGHD (T2; 3.83, SD 0.5), provided psychological support (S4; 3.81, SD 0.37), and shared information with family members or caregivers (S6; 3.77, SD 0.35) or the community (S5; 3.59, SD 0.53). Apps that only provided information on BC prevention or risk factors had significantly lower MARS scores than the other apps.
Discussion

Principal Findings

We evaluated the contents and quality of BC-related mobile apps using the MARS. We organized the CCC using the results of previous studies to establish specific definitions for the content of mobile apps for women. Our results are based on 69 BC-related mHealth apps. The most frequent content of the apps was provision of information related to early detection of BC (n=34, 49%), followed by information regarding risk factors and biological processes of BC at the prevention stage (n=28, 41%). The next most frequent content was information about symptoms, treatments, new advancements in BC treatment, and side effects related to BC after the treatment stage (n=27, 39%). Education regarding lifestyle modification (n=23, 33%), prevention and risk factors of BC (n=22, 32%), and PGHD (n=19, 28%) were employed as content in BC-related apps. A total of 46 (68%) apps had been updated in the previous year, and 43 (62%) were developed by private companies.

The mean MARS score of the included apps was 3.31 out of 5, which was higher than the “acceptable” MARS score of 3 [31]. However, there was a significant gap between the highest- and lowest-rated apps (score range: 1.94-4.53). Functionality had the highest mean score (4.37, SD 0.42) among the MARS dimensions, and outdated apps (mean 2.54, SD 0.41) and apps developed by individuals (mean 2.39, SD 0.41) had significantly lower mean MARS scores. This is in agreement with the findings of a previous review study that found the functionality and usability of apps increased over a 2-year period, but content credibility did not [34]. Therefore, users might need to use their discretion if using outdated apps.

Of the 69 mHealth apps included, OncoPower, Outcomes4Me Breast Cancer Care, Owise – Breast Cancer Support, and War On Cancer had the highest scores. These apps are available on both Google Play and the App Store, and had high scores for aesthetics, functionality, and engagement. Although OncoPower and War On Cancer do not target patients with BC and survivors exclusively, they have multiple functions that support patients with other cancer types, such as those related to nutrition and meditation. On the other hand, Outcomes4Me Breast Cancer Care and Owise – Breast Cancer Support were developed specifically for patients with BC, so these provide evidence-based treatment options and personalized resources based on individuals’ medical records to promote communication with their health care providers. The War On Cancer app was developed to promote social networking by patients with cancer and survivors, which may be useful given the importance of social support in cancer care [35-37]. The 4 highest-ranked apps focused mainly on providing personalized care after a diagnosis of BC and on treatment, a time at which patients may struggle due to physical and psychological impairments. Therefore, providing appropriate information on treatment options and lifestyle modification, facilitating medication management, providing psychological support, and tracking PGHD and medical records may ease the burden on patients.

Our results show approximately one-third (n=19, 28%) of the included apps are using individual data, such as PGHD. PGHD, including patient-reported outcomes, provide clinically relevant information obtained outside traditional care settings, and could be useful to improve outcomes and enhance patient-provider communication [38]. Some studies found that effective physician-patient communication improved patient health outcomes [39], as well as BC patients’ depression and quality of life [40]. With the increasing use of wearable devices and advancements in technology, the use of PGHD and established medical screening and surveillance strategies may enhance long-term cancer survivorship at the individual and population levels. Furthermore, these approaches can strengthen the survivor-provider relationship [41]. Despite the benefits of PGHD, there are several barriers to their use, including a lack of technical support in patients’ primary language, the reluctance of clinicians to review PGHD, a lack of access to broadband internet, and concerns related to the confidentiality of personal information [42]. Nevertheless, mobile apps that use medical records and PGHD had the highest MARS scores (4.0 and 3.83, respectively), indicating the willingness of users to use individualized health-related apps.

The large differences in MARS scores among the apps may imply a need to improve the standards used for their approval, and for quality checks at all stages of development (assessment, prototype, content, and evaluation). Some studies strived to
evaluate health-related apps by establishing a practical framework based on guidelines by the US Food and Drug Administration and the UK National Health Service [43], or by organizing published studies [44]. This framework was developed by organizing app evaluation questions from 45 previous systematic reviews and verified by the patient advisory panel. It represents the pyramid shape that begins at the bottom from background information, privacy, and security, to evidence based, ease of use, and data integration. If these kinds of evaluations were implemented effectively at the time of app approval, higher-quality apps might be released. Most BC-related apps included in this study provided information or education regarding prevention and survivorship, in line with previous studies [4,26]. However, the mean MARS score of those that provided information at any CCC stage was slightly above 3, which means acceptable but not good enough. Provision of information is important but insufficient to modify multifaceted health behaviors [45]. Additionally, patients with limited health literacy are at a distinct disadvantage during BC treatment in terms of unmet information needs [46]. Moreover, information and educational content that are not based on guidelines or evidence discourage women from consistently using mobile BC apps; this may explain the lower MARS scores on those apps that merely provided information. Furthermore, the MARS scores of apps that targeted patients after a diagnosis of BC, including those that provided survivor support, were higher than those reported previously [26]. Patients who are unconcerned regarding their health while being investigated for cancer may change their attitude toward cancer after their diagnosis [47]. Therefore, such people might search for and use the helpful tools provided by mobile apps.

Strengths and Limitations
The strengths of our study include using the MARS, an objective tool used to measure app quality. Star ratings and user reviews are also valuable for developers and potential new users because they offer a crowdsourced indicator of the effectiveness and popularity of apps [48]. However, these indicators do not accurately reflect app quality [49]. The majority of public reviews of apps rely on the personal opinions of individuals’ own experience and are thus highly subjective. Therefore, we did not record star ratings in this study. Additionally, a previous study found that MARS scores did not significantly correlate with users’ star ratings [50]. We could not confirm this in our study because of a lack of star ratings and reviews. Therefore, we employed the MARS to assess the quality of the most credible apps. Furthermore, we used these quantitative results to identify the relationship between MARS dimensions and apps’ content.

This study had several limitations. First, paid and inaccessible apps could not be downloaded because of a lack of funding and access. Such apps should be evaluated in future studies for external validity. Second, although the MARS has been widely used and validated previously, we cannot rule out subjectivity due to the nature of evaluations. However, to minimize subjectivity, we confirmed high interrater reliability between the independent raters. Lastly, qualitative measures may be needed to reflect end users’ experience.

Recommendations for Future Development
The growing numbers of BC-related mHealth apps and of studies on their usefulness allow women to select those most likely to improve their quality of life. We identified certain issues that could be addressed to improve app quality. First, the quality assessment system for the digital platform needs to be improved. Our results identified limitations in certain MARS dimensions, indicating poor app quality. Therefore, a new method should be introduced to validate the MARS that reflects differences between specific diseases and users’ experience [32]. Second, evidence-based content and functions are required. Although the mechanisms underlying the effects of mHealth apps are not known, efforts should be made toward elucidating them by developing a theory-based intervention that is administered via an mHealth app and tested in a clinical trial. Although some feasibility studies and trials have been conducted on the usefulness of PGHD [51,52], further studies of the clinical benefits of mHealth apps are required. The development of a set of core outcomes may be another option to measure their effectiveness and induce behavior change, as has been found by others [53]. Additionally, patient-centered considerations of the design and interface before the development of an app might be helpful to promote behavior change. One study suggested iterative development through a user-centered design approach involving the following 3 phases: analysis, design, and implementation to achieve less fragmented care [54]. This systematic approach could encourage patients, survivors, and health care providers to participate in the development and quality assessment of mobile apps. In sum, the mapping of app content against current BC guidelines and creating adequate evidence would help clinicians have more information about useful content and promote them to recommend using related mobile apps.

Conclusions
We systematically analyzed 69 BC-related mHealth apps, using literature-based content categories and the MARS for quality assessment. Generally, the quality of the apps was acceptable according to the MARS, but the gap between the highest- and lowest-rated apps was significant. Our findings indicate that the BC-related apps using personalized data were of higher quality than those that merely provided women with information on BC, especially after treatment in the CCC. We also found that apps that had been updated within 1 year and those developed by private companies had higher MARS scores. These findings provide specific criteria for women and clinicians to help them choose the right mobile BC apps for better clinical outcomes.

Conflicts of Interest
None declared.
Multimedia Appendix 1
Content categories for mobile apps related to cancer management.

[DOCX File, 19 KB - mhealth_v11i1e43522_app1.docx]

Multimedia Appendix 2
Full list of included breast cancer apps (n=69).

[DOCX File, 23 KB - mhealth_v11i1e43522_app2.docx]

Multimedia Appendix 3
Content analyses of the 69 breast cancer mobile apps by update year and developer.

[DOCX File, 21 KB - mhealth_v11i1e43522_app3.docx]

Multimedia Appendix 4
Details on the content of the included apps (n=69).

[DOCX File, 44 KB - mhealth_v11i1e43522_app4.docx]

Multimedia Appendix 5
Details on the results of quality assessment of the included apps (n=69).

[DOCX File, 31 KB - mhealth_v11i1e43522_app5.docx]

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Abbreviations

BC: breast cancer
CCC: cancer care continuum
MARS: Mobile App Rating Scale
mHealth: mobile health
PGHD: patient-generated health data
Menstrual Tracking Mobile App Review by Consumers and Health Care Providers: Quality Evaluations Study

Siyeon Ko¹, BSc; Jisan Lee²,³, PhD; Doyeon An¹, MPH; Hyekyung Woo¹,⁴, PhD

¹Department of Health Administration, College of Nursing & Health, Kongju National University, Gongju-Si, Chungcheongnam-do, Republic of Korea
²Department of Nursing Science, College of Life & Health Sciences, Hoseo University, Asan-si, Chungcheongnam-do, Republic of Korea
³Department of Nursing, Gangneung-Wonju National University, Wonju-si, Republic of Korea
⁴Institute of Health and Environment, Kongju National University, Gongju-si, Chungcheongnam-do, Republic of Korea

Corresponding Author:
Hyekyung Woo, PhD
Department of Health Administration
College of Nursing & Health
Kongju National University
56 Gongjudaeak-ro
Gongju-Si, Chungcheongnam-do
Republic of Korea
Phone: 82 10 3350 3486
Email: hkwoo@kongju.ac.kr

Abstract

Background: Women’s menstrual cycle is an important component of their overall health. Physiological cycles and associated symptoms can be monitored continuously and used as indicators in various fields. Menstrual apps are accessible and can be used to promote overall female health. However, no study has evaluated these apps’ functionality from both consumers’ and health care providers’ perspectives. As such, the evidence indicating whether the menstrual apps available on the market provide user satisfaction is insufficient.

Objective: This study was performed to investigate the key content and quality of menstrual apps from the perspectives of health care providers and consumers. We also analyzed the correlations between health care provider and consumer evaluation scores. On the basis of this analysis, we offer technical and policy recommendations that could increase the usability and convenience of future app.

Methods: We searched the Google Play Store and iOS App Store using the keywords “period” and “menstrual cycle” in English and Korean and identified relevant apps. An app that met the following inclusion criteria was selected as a research app: nonduplicate; with >10,000 reviews; last updated ≤180 days ago; relevant to this topic; written in Korean or English; available free of charge; and currently operational. App quality was evaluated by 6 consumers and 4 health care providers using Mobile Application Rating Scale (MARS) and user version of the Mobile Application Rating Scale (uMARS). We then analyzed the correlations among MARS scores, uMARS scores, star ratings, and the number of reviews.

Results: Of the 34 apps, 31 (91%) apps could be used to predict the menstrual cycle, and 2 (6%) apps provided information pertinent to health screening. All apps that scored highly in the MARS evaluation offer a symptom logging function and provide the user with personalized notifications. The “Bom Calendar” app had the highest MARS (4.51) and uMARS (4.23) scores. The MARS (2.22) and uMARS (4.15) scores for the “Menstrual calendar—ovulation & pregnancy calendar” app were different. In addition, there was no relationship between MARS and uMARS scores (r=0.32; P=.06).

Conclusions: We compared consumer and health care provider ratings for menstrual apps. Continuous monitoring of app quality from consumer and health care provider perspectives is necessary to guide their development and update content.

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KEYWORDS
mobile app; period; menstrual cycle; mHealth; mobile health; evaluation; women’s health; health care provider; consumer; menstrual app; digital health app; health screening; consumer satisfaction
Introduction

Background

Women’s menstrual cycles are important to their overall health [1,2] and are characterized by predictable and recurring symptoms. Continuous tracking of the menstrual cycle can aid in health management. Monitoring systems are needed to optimize menstrual health and provide easily accessible health information for women [3].

Mobile health (mHealth) apps facilitate personalized health monitoring and management [4], and menstrual apps are the most important mHealth apps for women. Such apps are typically highly accessible for most women and provide indicators relevant to various health domains [5].

Typically, menstrual apps also allow the user to log their symptoms, mood changes, and body temperature, and they visually represent statistical data via graphs and tables. Some apps offer professional-level information through communities and links, that is, they promote women’s health care by facilitating smooth communication with medical staff through information-sharing services [6]. The apps’ menstrual cycle tracking functions facilitate health care planning and management in various domains, including contraception, fertility, preparation with respect to pregnancy and ensuring adequate “menstrual supplies,” leisure activities, and travel [7].

Women use these functions for various purposes, such as tracking pregnancy, preventing pregnancy, and managing menstruation periods [8]. The functions desired by consumers depend on the intended purpose of the app. Currently, indicators to help consumers identify and select menstrual apps according to the desired functions are lacking [9]. Recently developed systems recommend apps based on consumer requirements [10,11]. Menstrual apps with various functions have been developed, and related research is being actively conducted. However, most of the existing studies are content reviews or expert evaluations [12-15]. Consumer-centered studies have also started to appear [5,16-18], but quality evaluations of menstrual apps remain scarce.

Menstrual apps are directly relevant to women’s health, so it is necessary for experts and health care providers to evaluate these apps [8]. Health care provider quality evaluations can contribute to the app development, which is important to ensure that consumers have access to high-quality apps [19]. Consumer quality evaluations provide feedback on apps, such as consumer preferences (eg, for easy-to-use content) [20,21]. Consistent use of an app is critical given the recurring nature of the menstrual cycle, but research on this topic is lacking from the developer’s standpoint. To promote sustained app use, the following app inclusion criteria have been set, based on previous studies [14,22,23]:

- The app is nonduplicate.
- It has more than 10,000 reviews.
- It has been last updated ≤180 days ago.
- It is relevant to this topic.
- The app language is Korean or English.
- The app is free to use.
- It is currently in operation.

Analysis of App Contents

To examine the apps’ main contents, we performed a pilot study of 14 representative apps. The apps’ main contents were classified as follows: menstrual cycle management, education of evaluation scores. The study’s findings could improve the utility and convenience of future mHealth apps.

Methods

App Selection

We searched for keywords related to the development and evaluation of menstrual apps commonly included in previous studies, such as “period” and “menstrual cycle” in both English and Korean. The Google Play Store and the iOS App Store were searched from April 8 to April 15, 2021. Up to 150 apps were screened for each keyword. Since then, to secure the appropriated number of apps that can be statistically analyzed, the following app inclusion criteria have been set, based on previous studies [14,22,23]:

- The app is nonduplicate.
- It has more than 10,000 reviews.
- It has been last updated ≤180 days ago.
- It is relevant to this topic.
- The app language is Korean or English.
- The app is free to use.
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Analysis of App Contents

To examine the apps’ main contents, we performed a pilot study of 14 representative apps. The apps’ main contents were classified as follows: menstrual cycle management, education of evaluation scores. The study’s findings could improve the utility and convenience of future mHealth apps.

Evaluation of App Quality

The quality of 34 menstrual apps were evaluated using Mobile Application Rating Scale (MARS) and user version of the Mobile Application Rating Scale (uMARS). The MARS was developed to evaluate mobile apps; it is a reliable tool with a high internal consistency and interrater reliability [24]. The uMARS was subsequently developed, based on the MARS, to allow consumers to evaluate the quality of mHealth apps. uMARS has excellent internal consistency [25]. Both scales comprise the following five categories: engagement, aesthetics, functionality, information, and subjective quality (Table 1). The MARS has been used to evaluate various health care–related apps, such as apps related to chronic disease, COVID-19, and physical activity, as well as apps related to allergy, hepatitis treatment support, and breast cancer [14,15,19,22,23,26,27]. The uMARS has recently been used to evaluate various types of mHealth apps, including apps pertaining to weight loss and nutrition, rheumatic diseases, and the management of ankylosing spondylitis [28-31].
Table 1. Mobile Application Rating Scale (MARS) and user version of the Mobile Application Rating Scale (uMARS) evaluation items.

<table>
<thead>
<tr>
<th>Measures</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Objective measures</strong></td>
<td></td>
</tr>
<tr>
<td>Engagement</td>
<td>• Entertainment&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>• Interest&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>• Customization&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>• Interactivity&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>• Target group&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Functionality</td>
<td>• Performance&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>• Ease of use&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>• Navigation&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>• Gestural design&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Information</td>
<td>• Accuracy of app design&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>• Goal&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>• Credibility&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>• Evidence bases&lt;sup&gt;a&lt;/sup&gt;</td>
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<tr>
<td></td>
<td>• Quality of information&lt;sup&gt;a,b&lt;/sup&gt;</td>
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<tr>
<td></td>
<td>• Quantity of information&lt;sup&gt;a,b&lt;/sup&gt;</td>
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<tr>
<td></td>
<td>• Visual information&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>• Credibility of source&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Aesthetics</td>
<td>• Layout&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>• Graphics&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>• Visual appeal&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td><strong>Subjective measures</strong></td>
<td></td>
</tr>
<tr>
<td>Subjective quality</td>
<td>• Recommendation&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>• Frequency of use&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>• Payment for expenses&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>• Star rating&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
</tbody>
</table>

<sup>a</sup>MARS evaluation items.  
<sup>b</sup>uMARS evaluation items.

A total of 6 consumers completed the uMARS between July 9 and July 22, 2021, and 4 nurses (ie, health care providers) majoring in health care and working in medical centers completed the MARS between July 21 and July 30, 2021. Each evaluator was asked to use the app for more than 10 minutes every day and the evaluation was conducted in a blind test. The apps were randomly assigned to evaluators to prevent bias related to subjectivity. Each app was cross-evaluated by at least two evaluators.

**Comparative Analysis of Consumer and Health Care Provider Data**

The MARS results represent health care providers’ perspectives, as stated above. The uMARS results, star ratings, and number of reviews were analyzed from the consumers’ perspective. After normalization, Pearson correlation was used to correlate app content, MARS and uMARS scores, star ratings, and reviews and to correlate perspectives of health care providers and consumers. We identified the top and bottom five apps based on the MARS and uMARS scores and compared app preferences between consumers and health care providers. P values <.05 were considered significant. R software (version 4.1.2; R Core Team,) was used for the analysis.

**Results**

**App Selection**

A total of 1127 menstrual apps were initially identified via the keyword search, and 34 apps (Android: n=28; iPhone: n=6) met all of the study criteria and were included in the final analysis (Figure 1).
The operating system (OS) of apps is linked with the app store, so that the app is updated simultaneously with updates of the OS [32]. Therefore, the app version and function may vary depending on the timing of the OS update. The number of reviews and star ratings differed among the apps in this study. For example, Bom Calendar had star ratings of 4.8 and 4.4 for the Android and iOS versions, respectively (23,437 and 76,258 reviews, respectively). In instances where the same apps were available for different OSs, each version was considered to be a unique app in the analysis.

**Analysis of App Contents**

Most apps (n=31, 91%) offered a menstrual cycle prediction function. Some apps (n=14, 41%) offered menstruation and fertility period notifications, while others had no specific functions (n=3, 9%). Most apps were confidential (n=29, 85%), allowed data export (n=28, 82%), and had a log-in function (n=25, 74%). However, few apps provided education or knowledge (n=10, 29%), screening-related information (n=2, 6%), or advice (n=4, 12%; Table 2).
### Table 2. App contents analysis result.

<table>
<thead>
<tr>
<th>Contents</th>
<th>App, n (%)</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>iPhone (n=6)</td>
<td>Android (n=28)</td>
<td>Total (N=34)</td>
<td></td>
</tr>
<tr>
<td><strong>Menstrual cycle management</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Symptoms (pain)</td>
<td>4 (12)</td>
<td>0 (0)</td>
<td>4 (12)</td>
<td></td>
</tr>
<tr>
<td>Additional symptom</td>
<td>18 (64)</td>
<td>6 (100)</td>
<td>24 (71)</td>
<td></td>
</tr>
<tr>
<td><strong>Ovulation management</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Calculate pregnancy probability</td>
<td>4 (14)</td>
<td>0 (0)</td>
<td>4 (12)</td>
<td></td>
</tr>
<tr>
<td>Contraception methods</td>
<td>3 (11)</td>
<td>0 (0)</td>
<td>3 (9)</td>
<td></td>
</tr>
<tr>
<td>Both</td>
<td>12 (43)</td>
<td>6 (100)</td>
<td>18 (53)</td>
<td></td>
</tr>
<tr>
<td><strong>Last update (months)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;3</td>
<td>21 (75)</td>
<td>5 (83)</td>
<td>26 (76)</td>
<td></td>
</tr>
<tr>
<td>3–6</td>
<td>7 (25)</td>
<td>1 (17)</td>
<td>8 (24)</td>
<td></td>
</tr>
<tr>
<td><strong>Function s</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Graphical chart</td>
<td>17 (61)</td>
<td>4 (67)</td>
<td>21 (62)</td>
<td></td>
</tr>
<tr>
<td>Lock</td>
<td>23 (82)</td>
<td>6 (100)</td>
<td>29 (85)</td>
<td></td>
</tr>
<tr>
<td>Advice provision</td>
<td>2 (7)</td>
<td>2 (33)</td>
<td>4 (12)</td>
<td></td>
</tr>
<tr>
<td>Data export</td>
<td>23 (82)</td>
<td>5 (83)</td>
<td>28 (82)</td>
<td></td>
</tr>
<tr>
<td>Predictions</td>
<td>25 (89)</td>
<td>6 (100)</td>
<td>31 (91)</td>
<td></td>
</tr>
<tr>
<td>Log-in</td>
<td>20 (71)</td>
<td>5 (83)</td>
<td>25 (74)</td>
<td></td>
</tr>
<tr>
<td><strong>Education or knowledge</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>General health information</td>
<td>5 (18)</td>
<td>1 (17)</td>
<td>6 (18)</td>
<td></td>
</tr>
<tr>
<td>Personalized information</td>
<td>1 (4)</td>
<td>2 (33)</td>
<td>3 (9)</td>
<td></td>
</tr>
<tr>
<td>Both</td>
<td>1 (4)</td>
<td>0 (0)</td>
<td>1 (3)</td>
<td></td>
</tr>
<tr>
<td>Health screening</td>
<td>1 (4)</td>
<td>1 (17)</td>
<td>2 (6)</td>
<td></td>
</tr>
<tr>
<td><strong>Sharing information (with health care professionals)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All information</td>
<td>4 (14)</td>
<td>3 (50)</td>
<td>7 (21)</td>
<td></td>
</tr>
<tr>
<td>Only information specified by the consumer</td>
<td>1 (4)</td>
<td>0 (0)</td>
<td>1 (3)</td>
<td></td>
</tr>
<tr>
<td><strong>Visualization</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Menstruation or ovulation</td>
<td>2 (7)</td>
<td>0 (0)</td>
<td>2 (6)</td>
<td></td>
</tr>
<tr>
<td>Menstrual cycle</td>
<td>9 (32)</td>
<td>0 (0)</td>
<td>9 (26)</td>
<td></td>
</tr>
<tr>
<td>All data</td>
<td>16 (57)</td>
<td>6 (100)</td>
<td>22 (65)</td>
<td></td>
</tr>
<tr>
<td><strong>Notifications</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Menstruation or fertility</td>
<td>2 (7)</td>
<td>0 (0)</td>
<td>2 (56)</td>
<td></td>
</tr>
<tr>
<td>Both</td>
<td>14 (50)</td>
<td>0 (0)</td>
<td>14 (41)</td>
<td></td>
</tr>
<tr>
<td>Personalized alarms</td>
<td>9 (32)</td>
<td>6 (100)</td>
<td>15 (44)</td>
<td></td>
</tr>
<tr>
<td><strong>Other features</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Community</td>
<td>4 (14)</td>
<td>2 (33)</td>
<td>6 (18)</td>
<td></td>
</tr>
<tr>
<td>Shopping</td>
<td>2 (7)</td>
<td>1 (17)</td>
<td>3 (9)</td>
<td></td>
</tr>
</tbody>
</table>

### Evaluation of App Quality

The MARS and uMARS scores of all apps were obtained through the average of the evaluator’s evaluation scores. The average MARS and uMARS scores (ie, health care provider and consumer scores, respectively) were 3.06 (SD 0.62) and 3.33 (SD 0.57), respectively. The iPhone “Bom Calendar” app had the highest score for both the MARS (4.51, SD 0.22) and uMARS (4.23, SD 0.27). The Android “Period calendar—Women’s menstrual calendar❤️” app had the second lowest score for both the MARS (2.05, SD 0.45) and uMARS (2.09, SD 0.05), despite its high star rating of 4.8. The Android
“Menstrual calendar—ovulation & pregnancy calendar” app showed contrasting scores between the MARS (2.22, SD 0.07) and uMARS (4.15, SD 0.46); it had the third highest overall uMARS score, with an engagement score of 3.86 (SD 0.49), functionality score of 4.04 (SD 0.49), aesthetics score of 4.25 (SD 0.47), information score of 4.25 (SD 0.47), and subjective quality score of 4.37 (SD 0.41). However, for the MARS, its overall score was the third lowest, with an engagement score of 2.40 (SD 0.20), functionality score of 2.50 (SD 0.50), aesthetics score of 2.00 (SD 0.00), information score of 2.58 (SD 0.42), and subjective quality score of 1.63 (SD 0.38; Table 3 and Table 4). MARS and uMARS scores of all 34 apps are presented in Multimedia Appendix 1.

Table 3. The five highest- and lowest-scoring apps (N=34) based on the user version of the Mobile Application Rating Scale (uMARS). All the values are mean (SD).

<table>
<thead>
<tr>
<th>App</th>
<th>Engagement</th>
<th>Functionality</th>
<th>Aesthetics</th>
<th>Information</th>
<th>Subjective quality</th>
<th>uMARSa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top fiveb</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Bom Calendar (iOS)</td>
<td>3.87 (0.33)</td>
<td>4.17 (0.26)</td>
<td>4.33 (0.32)</td>
<td>4.27 (0.29)</td>
<td>4.51 (0.22)</td>
<td>4.23 (0.27)</td>
</tr>
<tr>
<td>2. Pregnancy planning &amp; management (Android)</td>
<td>4.03 (0.38)</td>
<td>4.16 (0.44)</td>
<td>4.23 (0.35)</td>
<td>4.31 (0.27)</td>
<td>4.40 (0.25)</td>
<td>4.23 (0.33)</td>
</tr>
<tr>
<td>3. Menstrual calendar—ovulation &amp; pregnancy calendar (Android)</td>
<td>3.86 (0.49)</td>
<td>4.04 (0.49)</td>
<td>4.25 (0.47)</td>
<td>4.25 (0.47)</td>
<td>4.37 (0.41)</td>
<td>4.15 (0.46)</td>
</tr>
<tr>
<td>4. Flo (Android)</td>
<td>3.80 (1.01)</td>
<td>3.97 (0.78)</td>
<td>4.30 (0.51)</td>
<td>4.30 (0.51)</td>
<td>4.29 (0.49)</td>
<td>4.13 (0.66)</td>
</tr>
<tr>
<td>5. Flo (iOS)</td>
<td>3.83 (0.60)</td>
<td>4.06 (0.43)</td>
<td>4.16 (0.30)</td>
<td>4.11 (0.35)</td>
<td>4.39 (0.36)</td>
<td>4.11 (0.38)</td>
</tr>
<tr>
<td>Bottom fivec</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Maya—My Period Tracker (Android)</td>
<td>1.91 (0.34)</td>
<td>1.96 (0.39)</td>
<td>1.91 (0.54)</td>
<td>1.94 (0.75)</td>
<td>1.90 (0.72)</td>
<td>1.93 (0.54)</td>
</tr>
<tr>
<td>2. Period calendar—Women’s menstrual calendar❤ (Android)</td>
<td>1.76 (0.11)</td>
<td>2.04 (0.13)</td>
<td>2.17 (0.07)</td>
<td>2.13 (0.10)</td>
<td>2.33 (0.10)</td>
<td>2.09 (0.05)</td>
</tr>
<tr>
<td>3. Women’s menstrual calendar, menstrual &amp; ovulation day calculator, childbearing age, pregnancy planning (Android)</td>
<td>1.93 (0.38)</td>
<td>2.11 (0.53)</td>
<td>2.46 (0.47)</td>
<td>2.53 (0.37)</td>
<td>2.46 (0.51)</td>
<td>2.30 (0.44)</td>
</tr>
<tr>
<td>4. My Days—Ovulation Calendar &amp; period Tracker (Android)</td>
<td>2.30 (0.30)</td>
<td>2.50 (0.50)</td>
<td>2.70 (0.30)</td>
<td>2.74 (0.16)</td>
<td>2.90 (0.10)</td>
<td>2.63 (0.23)</td>
</tr>
<tr>
<td>5. Clover: Period &amp; Cycle Tracker (Android)</td>
<td>2.24 (1.05)</td>
<td>2.43 (1.24)</td>
<td>3.06 (1.07)</td>
<td>3.19 (1.19)</td>
<td>3.33 (1.33)</td>
<td>2.85 (1.17)</td>
</tr>
</tbody>
</table>

aAverage of uMARS scores evaluated by consumers.

bTop five apps: (1) Bom Calendar (iOS), (2) Pregnancy planning & management (Android), (3) Menstrual calendar—ovulation & pregnancy calendar (Android), (4) Flo (Android), and (5) Flo (iOS).

cBottom five apps: (1) Maya—My Period Tracker (Android); (2) Period calendar—Women’s menstrual calendar❤ (Android); (3) Women’s menstrual calendar, menstrual & ovulation day calculator, childbearing age, pregnancy planning (Android); (4) My Days—Ovulation Calendar & period Tracker (Android); and (5) Clover: Period & Cycle Tracker (Android).
Table 4. The five highest- and lowest-scoring apps (N=34) based on the Mobile Application Rating Scale (MARS).

<table>
<thead>
<tr>
<th>App and operating system</th>
<th>Engagement</th>
<th>Functionality</th>
<th>Aesthetics</th>
<th>Information</th>
<th>Subjective quality</th>
<th>MARS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Top five</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4.18 (0.63)</td>
<td>4.75 (0.25)</td>
<td>5.00 (0.00)</td>
<td>4.29 (0.11)</td>
<td>4.36 (0.25)</td>
<td>4.51 (0.14)</td>
</tr>
<tr>
<td></td>
<td>4.10 (0.10)</td>
<td>4.06 (0.21)</td>
<td>4.67 (0.33)</td>
<td>4.92 (0.08)</td>
<td>3.93 (0.24)</td>
<td>4.34 (0.15)</td>
</tr>
<tr>
<td></td>
<td>3.85 (0.46)</td>
<td>4.13 (0.63)</td>
<td>4.42 (0.43)</td>
<td>4.00 (0.33)</td>
<td>3.58 (0.58)</td>
<td>3.99 (0.48)</td>
</tr>
<tr>
<td></td>
<td>3.65 (0.75)</td>
<td>4.19 (0.57)</td>
<td>4.00 (1.00)</td>
<td>4.42 (0.58)</td>
<td>3.68 (0.07)</td>
<td>3.99 (0.59)</td>
</tr>
<tr>
<td></td>
<td>4.00 (0.00)</td>
<td>3.56 (0.37)</td>
<td>4.83 (0.17)</td>
<td>4.33 (0.35)</td>
<td>3.02 (0.61)</td>
<td>3.95 (0.29)</td>
</tr>
<tr>
<td><strong>Bottom five</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2.05 (0.65)</td>
<td>2.13 (0.63)</td>
<td>1.50 (0.50)</td>
<td>2.38 (0.71)</td>
<td>1.53 (0.53)</td>
<td>1.92 (0.60)</td>
</tr>
<tr>
<td></td>
<td>2.10 (0.71)</td>
<td>2.81 (0.48)</td>
<td>2.08 (0.60)</td>
<td>2.25 (0.25)</td>
<td>1.01 (0.26)</td>
<td>2.05 (0.45)</td>
</tr>
<tr>
<td></td>
<td>2.40 (0.20)</td>
<td>2.50 (0.50)</td>
<td>2.00 (0.00)</td>
<td>2.58 (0.42)</td>
<td>1.63 (0.38)</td>
<td>2.22 (0.07)</td>
</tr>
<tr>
<td></td>
<td>2.00 (0.20)</td>
<td>2.94 (0.57)</td>
<td>2.42 (0.43)</td>
<td>2.63 (0.14)</td>
<td>1.34 (0.09)</td>
<td>2.26 (0.15)</td>
</tr>
<tr>
<td></td>
<td>2.00 (0.00)</td>
<td>2.75 (0.25)</td>
<td>2.33 (0.33)</td>
<td>2.75 (0.08)</td>
<td>1.81 (0.56)</td>
<td>2.33 (0.01)</td>
</tr>
</tbody>
</table>

aAverage of MARS scores evaluated by health care providers.
bTop five apps: (1) Bom Calendar (iOS), (2) Pink Diary (Android), (3) Bom Calendar (Android), (4) Clue Period, Ovulation Tracker (iOS), and (5) Femometer—Fertility Tracker (Android).
cBottom five apps: (1) My Days—Ovulation Calendar & period Tracker (Android), (2) Period calendar—Women’s menstrual calendar❤ (Android), (3) Menstrual calendar—ovulation & pregnancy calendar (Android), (4) My Menstrual Diary (Android), and (5) Period Tracker (Android).

Further Comparative Analysis of Consumer and Health Care Provider Data

Table 5 shows the results of correlation analysis of the MARS and uMARS scores, star ratings, number of reviews, and app content. The number of reviews was not correlated with app content and menstrual cycle management ($r=0.53; P=.001$), and visualization ($r=0.51; P=.002$) had the highest correlation with star ratings. Among the evaluation scores, the highest correlation was found between uMARS and notification ($r=0.39; P=.02$) as well as between MARS and ovulation date management ($r=0.49; P=.003$).

Multimedia Appendix 2 shows content comparison between the top and bottom five apps in consumer and health care provider evaluation scores. Personalized alarms could be set in the top five apps. In addition, they provided a function to visualize all information through a calendar or to specify and manage ovulation days. On the contrary, in the bottom five apps did not have functions for managing or predicting the menstrual cycle.

Figure 2 shows the correlations among the MARS and uMARS scores, star ratings, and number of reviews to compare the perspective of health care providers and consumers. Figure 2 shows no correlation between MARS and uMARS scores of the health care providers and consumers ($r=0.32; P=.06$), uMARS scores and star rating ($r=0.11; P=.54$) as well as uMRAS scores and number of reviews ($r=0.07; P=.67$) also showed no significant correlations. The number of reviews and star rating ($r=0.39; P=.02$) showed a very low correlation.
Table 5. Results of correlation analysis of the Mobile Application Rating Scale (MARS) and the user version of the Mobile Application Rating Scale (uMARS) scores, star rating, number of reviews, and app content types.

<table>
<thead>
<tr>
<th>App contents</th>
<th>Health care provider and consumer perspective</th>
<th>Star rating</th>
<th>Number of reviews</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MARS</td>
<td>uMARS</td>
<td></td>
</tr>
<tr>
<td>Menstrual cycle management</td>
<td>0.39&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.18</td>
<td>0.53&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Ovulation date management</td>
<td>0.49&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.33</td>
<td>0.41&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td><strong>Functions</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Graphic chart</td>
<td>−0.06</td>
<td>−0.10</td>
<td>−0.54&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Lock</td>
<td>−0.37&lt;sup&gt;a&lt;/sup&gt;</td>
<td>−0.40&lt;sup&gt;a&lt;/sup&gt;</td>
<td>−0.32</td>
</tr>
<tr>
<td>Advice provision</td>
<td>−0.05</td>
<td>−0.31</td>
<td>−0.25</td>
</tr>
<tr>
<td>Data export</td>
<td>−0.22</td>
<td>−0.20</td>
<td>−0.53&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Prediction</td>
<td>−0.43&lt;sup&gt;a&lt;/sup&gt;</td>
<td>−0.17</td>
<td>−0.79&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Log-in</td>
<td>−0.12</td>
<td>−0.01</td>
<td>−0.47&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Educational or knowledge</td>
<td>0.23</td>
<td>0.04</td>
<td>−0.02</td>
</tr>
<tr>
<td>Health screening</td>
<td>0.25</td>
<td>0.13</td>
<td>0.12</td>
</tr>
<tr>
<td>Sharing information</td>
<td>0.16</td>
<td>0.14</td>
<td>0.04</td>
</tr>
<tr>
<td>Visualization</td>
<td>0.32</td>
<td>0.22</td>
<td>0.51&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Notification</td>
<td>0.32</td>
<td>0.39&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.24</td>
</tr>
<tr>
<td><strong>Other features</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Community</td>
<td>−0.14</td>
<td>−0.19</td>
<td>−0.16</td>
</tr>
<tr>
<td>Shopping</td>
<td>−0.35&lt;sup&gt;a&lt;/sup&gt;</td>
<td>−0.05</td>
<td>−0.14</td>
</tr>
</tbody>
</table>

<sup>a</sup><sup>P</sup><.05.  
<sup>b</sup><sup>P</sup><.01.

Figure 2. Result of the correlation analysis of the Mobile Application Rating Scale (MARS) and user version of the Mobile Application Rating Scale (uMARS) scores, star ratings, and number of reviews.

**Discussion**

**Principal Findings and Comparison With Prior Work**

Interest in mHealth apps has recently increased, and new apps are continuously being developed, including menstrual apps [33]. However, the needs of consumers and health care providers are different, and studies evaluating whether the available menstrual apps satisfy both of these groups are difficult to find. This study obtained quality evaluations of relevant apps from consumers and health care providers using the uMARS and MARS, respectively; the consistency of the evaluations of these two groups in terms of key app contents was analyzed. The health care providers valued engagement, functionality, and...
aesthetics when evaluating apps, while consumers valued aesthetics and information provision the most.

The MARS and uMARS scores were not correlated in this study. For example, the app with the third lowest MARS score had the third highest uMARS score. A significant difference was observed in app aesthetics scores between the consumers and health care providers; the scores for this attribute showed the largest group difference. Previous studies on health services have reported disparities between consumers and health care providers, and these results affect the implementation of consumer-centered services. Data from health care providers can provide a basis for high-quality apps [20], while consumer data serves as feedback on app quality [19]. To ensure high app quality and consumer satisfaction, app quality should be continuously monitored from the perspective of both health care providers and consumers. Monitoring can identify the needs of consumers and health care providers, which can in turn help in app development and update [10]. This study focused on evaluating app quality using MARS and uMARS for consistency, but could be extended to qualitative studies, including interviews, to collect in-depth answers in the future [34].

According to our findings, the uMARS (ie, consumer) scores, star ratings, and number of reviews were unrelated variables. The uMARS allows for direct assessment of mHealth apps and is a reliable measure of app quality [25]. However, reviews and star ratings are subjective indicators [24]. The currently available mHealth apps have been evaluated in a simplistic manner, such as through star ratings and reviews, even though they differ significantly with respect to content; thus, appropriate guidelines to aid app selection are lacking. By using the uMARS to guide app selection, the limitations of reviews and star ratings can be overcome such that consumers will likely select more useful apps to meet their particular needs. However, it is difficult for consumers to evaluate the quality of the apps using uMARS every time they download one. New indicators to guide app selection are needed so that consumers can make decisions based on objective evaluation results.

Most of the five apps that scored highly in the quality evaluation in this study included personalized monitoring functions. Menstrual apps are becoming increasingly popular, and apps that include self-monitoring functions and provide related information are continuously being developed [28]. Personalized monitoring can improve user well-being by encouraging them to check for signs and symptoms of health issues. Health-related information can also promote consumer health. mHealth apps that include personalized content of this nature are particularly useful for consumers [23,35]. However, only a few of the apps evaluated in this study facilitated consultations with specialists or provided information relating to women’s health. To increase the utility of apps, notifications, symptom recording functions, and the provision of knowledge should be prioritized.

mHealth apps should provide customized content for individual consumers [36]. However, the five bottom-scoring apps in this study did not meet the needs of the women who were using them. Consumers use apps to predict menstrual cycles and ovulation dates, and to monitor their general health [37]. However, most of the five bottom-scoring apps did not provide content enhancing consumer convenience, such as functions for menstrual cycle and ovulation day management, and some apps also lacked predictive functions. Such apps must be updated to include content allowing for the prediction and management of menstrual cycles based on accumulated menstrual cycle- and health-related information.

Menstrual apps collect personal information from consumers, such as name, date of birth, menstrual cycle, and medical history [38]. Personal data must be protected because it is sensitive information [12,39], but some apps do not provide locking functions, and few apps provide icon change functions for protecting personal information. Most fitness apps that record the number of steps do not consider privacy issues, and the data protection of mHealth apps related to women’s health is typically poor [39]. Therefore, regulations pertaining to app management of private data are necessary [40,41]. In fact, there are existing regulations protecting personal information, such as the European Union’s General Data Protection Regulation, but no standard regulations are enforced worldwide. mHealth apps that protect personal information tend to be favored by consumers [21]. App developers should improve data protection–related functions to protect the personal information of consumers.

The MARS and uMARS were developed specifically for evaluating mHealth apps that aim to improve consumers’ health. Meanwhile, menstrual apps were designed to help consumers keep track of their current health rather than improve it. Health apps must provide solutions customized to individual consumers [36]; reliability may be key in this respect [42]. This study’s results indicate that current health apps do not fully meet consumers’ requirements or desires with respect to content. To better identify consumer objectives and take account of them during the development of menstrual apps, a new evaluation scale is needed to evaluate menstrual apps.

Limitations

This study had several limitations. First, the results cannot be generalized to all menstrual apps because a small number of evaluators evaluated only the most popular apps. Second, the apps were selected based on App Store searches with a limited timeframe. Updates to apps may result in differences between the analyzed content and that in the future. Third, the database is not an electronic database but the App Store. The App Store’s app recommendation function may have compromised an inconsistent search accuracy.

Conclusions

In this study, consumer and health care provider ratings of menstrual apps were obtained using validated scales. Consumer preferred app had high scores of aesthetics and information, and evaluation scores differed between consumers and health care providers. The findings highlight the importance of consumer participation in menstrual app development and evaluation. This study is significant in that it is the first to compare health care providers’ and consumers’ menstrual app quality ratings. We expect our results to guide future mHealth app development and provide consumers with information on

https://mhealth.jmir.org/2023/1/e40921

Ko et al

JMIR MHEALTH AND UHEALTH

JMIR Mhealth Uhealth 2023 | vol. 11 | e40921 | p.998
menstrual app content and quality. To provide high-quality apps for consumers, continuous quality evaluation research needs to be conducted, and the perspectives of both consumers and health care providers should be taken into account.

Acknowledgments
This work was supported by a 2022 research grant from Kongju National University (KNU) and the National Research Foundation of Korea (NRF) funded by the Korean government (NRF-2020R1C1C1009679). This study was presented at the 2021 Postacademic Conference of the Korean Academy of Health Policy and Management.

JL was affiliated with the Department of Nursing Science, College of Life & Health Sciences at Hoseo University at the time of the study and is currently affiliated with the Department of Nursing at Gangneung-Wonju National University.

Conflicts of Interest
None declared.

Multimedia Appendix 1
Mobile Application Rating Scale (MARS) and user version of the Mobile Application Rating Scale (uMARS) score of all 34 apps.
[XLSX File (Microsoft Excel File), 14 KB - mhealth_v11i1e40921_app1.xlsx ]

Multimedia Appendix 2
Content comparison between the top and bottom five apps (ranked according to the consumer and health care provider evaluation scores).
[PDF File (Adobe PDF File), 74 KB - mhealth_v11i1e40921_app2.pdf ]

References


Abbreviations

MARS: Mobile Application Rating Scale
mHealth: mobile health
OS: operating system
uMARS: user version of the Mobile Application Rating Scale
**Abstract**

**Background:** Increasingly, parents use child health promotion apps to find health information. An overview of child health promotion apps for parents currently does not exist. The scope of child health topics addressed by parent apps is thus needed, including how they are evaluated.

**Objective:** This scoping review aims to describe existing reported mobile health (mHealth) parent apps of middle- to high-income countries that promote child health. The focus centers on apps developed in the last 5 years, showing how the reported apps are evaluated, and listing reported outcomes found.

**Methods:** A scoping review was conducted according to PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses for Scoping Reviews) guidelines to identify parent apps or web-based programs on child health promotion published between January 2016 and June 2021 in 5 databases: PubMed, ERIC, IEEE Xplore, Web of Science, and Google Scholar. Separate sources were sought through an expert network. Included studies were summarized and analyzed through a systematic and descriptive content analysis, including keywords, year of publication, country of origin, aims/purpose, study population/sample size, intervention type, methodology/method(s), broad topic(s), evaluation, and study outcomes.

**Results:** In total, 39 studies met the inclusion criteria from 1040 database and 60 expert-identified studies. Keywords reflected the health topics and app foci. About 64% (25/39) of included studies were published after 2019 and most stemmed from the United States, Australian, and European-based research. Studies aimed to review or evaluate apps or conducted app-based study interventions. The number of participants ranged from 7 to 1200. Quantitative and qualitative methods were used. Interventions included 28 primary studies, 6 app feasibility studies, and 5 app or literature reviews. Eight separate topics were found: parental feeding and nutrition, physical activity, maternal-child health, parent-child health, healthy environment, dental health, mental health, and sleep. Study intervention evaluations cited behavior change theories in 26 studies and evaluations were carried out with a variety of topic-specific, adapted, self-developed, or validated questionnaires and evaluation tools. To evaluate apps, user input and qualitative evaluations were often combined with surveys and frequently rated with the Mobile App Rating Scale. Outcomes reported some positive effects, while several intervention studies saw no effect at all. Effectively evaluating changes in behavior through apps, recruiting target groups, and retaining app engagement were challenges cited.

**Conclusions:** New parents are a key target group for child health apps, but evaluating child health promotion apps remains a challenge. Whether tailored to parent needs or adapted to the specific topic, apps should be rooted in a transparent theoretical groundwork. Applicable lessons for parent apps from existing research are to tailor app content, include intuitive and adaptive features, and embed well-founded parameters for long-term effect evaluation on child health promotion.

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https://mhealth.jmir.org/2023/11/e39929
KEYWORDS

scoping review; child health promotion; parents; mobile apps; health apps; digital prevention; behavior change; mHealth

Introduction

Digital health is a growing field and apps are used regularly to target health prevention. eHealth measures have steadily gained popularity and are increasingly available in the app form. For the promotion and maintenance of health, digital interventions have been examined for their ability to work as a preventive measure [1]. An increasing number of apps target parents and children for child health promotion and well-being, yet little is known about their impact. Research is conclusive that health promotion activities for child health have a long-term impact on health, whether it be mental health, physical activity, nutrition, or risk behavior prevention [2-6]. Smartphones are estimated to be owned by over 50% of the world’s population (~4.3 billion people by 2023) [7], with smartphone ownership averaging over 75% in countries with high-level economies such as the United States and the European Union [8]. Nearly all adults (96%) aged 18-29 own a smartphone in the United States [9] and in Europe on average 75% of people in this age bracket use the internet every day [10]. Current parents and the next generation of parents are seeking health information from digital sources and increasingly from apps, demonstrating the opportunity for health promotion through app use [11].

Stemming from different theoretical approaches from health psychology and fields studying social behavior [12-16], a need to evaluate the ability of illness prevention and health promotion interventions to change behaviors led to the development of behavior change techniques (BCTs) [17]. These are categories of evaluable information, termed taxonomies, that track and measure how effective health promotion interventions can be [18]. The application of such evaluative measures in digital interventions has become a well-established method to evaluate changes in behavior over the last decade [19,20]. For instance, there has been some evidence demonstrating moderate effects of health apps on physical activity and diet in pregnant women [17,21], adults [22], or children [23]. A recent meta-analysis of apps directed at health promotion and illness management described the need for stronger evidence to underscore their effects [24]. At the same time, when it comes to the promotion of health, not enough is known about how or if the use of apps has an effect on behavior change, nor to what extent the evaluation of such apps is undertaken [25], nor how this relates to the actual use of such health apps [26]. Despite the potential and opportunity for combining prevention activities into digital health apps, evaluation of behaviors to measure the effectiveness of mobile interventions is imperative to demonstrate any impact on well-being.

New parents bestow both the genetic makeup and the preliminary foundation for health to their children—from pregnancy to independent adulthood. Despite being an essential cornerstone and stakeholder of child health promotion and well-being, parents often feel unprepared for parenthood [27] and ill-informed about their child’s development [28]. There has been no review to our knowledge that assesses if and how child health promotion broadly targeted in parent-based interventions is being evaluated. In an ever-changing digital landscape with continually developed new apps, establishing what apps exist to target parenting and childhood health promotion as well as how they are evaluated is an area of interest.

A preliminary search of literature confirmed that reviews have systematically looked at the impact of apps on behavior [29], and also specific areas of health promotion have been systematically addressed for adults and children, such as nutrition or physical activity [17,30-32], literacy [33], pregnancy [32], and even general well-being [29]. However, a comprehensive compendium of apps that apply to parents for the health promotion activities in children does not exist nor are the evaluative effects of such apps clear. The need to better understand the scope of what apps exist and how they are currently evaluated provides the rationale for this review. The aim of this scoping review is therefore to address this gap by reviewing the existing studies on mobile health (mHealth) prevention apps that target parents for promoting the health of their children. The primary objective of this review is to describe existing reported mHealth parent apps of middle- to high-income countries that promote child health, with a focus on the parent apps developed in the last 5 years. To achieve the objective, this paper intends to give an overview and details on the topic areas of health promotion that parent apps cover and presents the scope of apps that are reported on (keywords, year of publication, country of origin, aims/purpose, study population and sample size, intervention type, and methods). The secondary objective of this review is to compile a list of how the reported apps are evaluated by listing and describing health measures found. The research questions that guided this review were as follows: What current parent mHealth apps exist in middle- to upper-income countries for promoting child health and how, when, and where are they reported on? What topics do they cover? How are child promotion apps for parents evaluated and what outcomes are described in terms of their effectiveness and efficacy? This scoping review aims to shed light on and give a comprehensively reported overview of existing parent apps to promote children’s health.

Methods

Design and Overview

A scoping review method was chosen as the appropriate review type to give a broad overview of the existing apps on child health available for parents because this field has not yet been comprehensively mapped and ever-emerging evidence rapidly changes. A planned 3-step search strategy study protocol was registered with the Open Science Forum [34] and used with an established scoping framework [35-37] to search for apps geared toward parents for health promotion in children. The scoping review reporting was supported throughout by the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses for Scoping Reviews) checklist [38].

https://mhealth.jmir.org/2023/11/e39929
Parental Mobile App Study Search Strategy

In a first step, from May 26, 2021 to May 28, 2021, 4 available databases were searched in 2 rounds to include the fields of health, education, and technology: PubMed, ERIC, IEEE Xplore, and Web of Science. After the first-round search with Google Scholar (Google Inc.), too many undifferentiated resources outside the inclusion were found for the search terms, and thus we decided to strategically limit the search to 2021 to find the most recent publications that may be found in the first months after publication, but before these are added to other databases.

Search terms combined the keywords “health promotion,” “parent*,” “child*,” and “app,” “eHealth” and “mHealth,” “mobile health prevention,” and “digital health” (Multimedia Appendix 1). Inclusion and exclusion were described and then tailored after the initial search with the study team (SBB, WS, IH, and GS).

In a parallel organizational step to include health expert input from May to August, 2021, the third author (IH), gathered stakeholder inputs with authors and health experts located in Germany and Europe to identify parenting studies or apps that may not have been included. This was conducted first through a LinkedIn (Microsoft Corporation) post from a well-established networking account asking for expert input(s) on apps or research projects aimed at young parents to promote the health of their children from birth and how these have been assessed or evaluated. From the expert responses, this information was followed up on to elicit more detailed information on known apps.

Eligibility and Exclusion Criteria

Apps or projects that met the inclusion criteria (Table 1) were assessed further. Study inclusion and exclusion were documented at each step (Figure 1). We aimed to include studies, evaluations, and assessments of digital apps developed toward parents for child health promotion. Studies of all types, reports, and assessments were included if they were (1) digital apps (2) used primarily by parents or expectant parents for (3) health promotion of children without a diagnosis or risk.

We included both primary studies and reviews of studies and apps. Gray literature was included as long as there was an evaluative component to the work. The apps could be web or mobile-based programs. Based on content, we allowed for a broadly range of study interest as it applied to both programs and the people these programs were applied to, including app feasibility or design, evaluation of the apps themselves, evaluation of the potential or actual effect on behaviors, or discussed evaluation strategies. For the expert input, we included studies collected from German or European digital health experts, child health experts, educational experts, or study authors. Only studies based in a middle- or high-income country and published in or after 2016 were included because we were particularly interested in the most recent apps and contexts most resembling the German context of our own research.

All studies that aimed to manage illness or high risk of illness were excluded. Exclusion was applied to any apps or programs aimed solely toward professions or children or where parents were simply gatekeepers. Additionally, studies on apps that were only used as health monitoring, tracking, product-based devices, or as information communication tools such as for text messaging/SMS transmission, videoconferencing, or telehealth were removed from review.

Table 1. Inclusion and exclusion criteria overview.

<table>
<thead>
<tr>
<th>Selection category</th>
<th>Inclusion criteria</th>
<th>Exclusion criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>Study population</td>
<td>Expectant parents, parents, and children together</td>
<td>Professionals use in work setting, primary use by children with parents only as an app gatekeeper</td>
</tr>
<tr>
<td>Health area</td>
<td>All areas of illness prevention/health promotion</td>
<td>Apps for active management of diagnosis, illness, secondary disease prevention, sexual health, those that are institution based, or those recruiting high-risk patients</td>
</tr>
<tr>
<td>App type</td>
<td>Smartphone/tablet/desktop</td>
<td>Telehealth, text messaging/SMS-based health support, videoconferencing, health product-based, app only for tracking device facilitation, virtual reality</td>
</tr>
<tr>
<td>Publication type</td>
<td>Empirical studies, reports, reviews, study synthesis, meta-analysis, theses, study protocols</td>
<td>Guidelines, handbooks, instructional manuals, user-based information, technical or specialist publications, commentary, product description</td>
</tr>
<tr>
<td>Content of interest</td>
<td>App design, reports on app functionality, evaluations of apps and study reviews, behavior change techniques reporting or evaluation, evaluation strategies, structured digital application</td>
<td>Review of app functionality, usability survey results</td>
</tr>
<tr>
<td>Countries of interest</td>
<td>All upper-middle or high-income country context [39]</td>
<td>≤Lower- to middle-income country contexts</td>
</tr>
<tr>
<td>Stakeholder input</td>
<td>Digital health experts, child health experts, educational experts, study authors (focus on Germany and Europe)</td>
<td>No restrictions applicable</td>
</tr>
<tr>
<td>Timeframe</td>
<td>≥2016 (Google Scholar &gt;2021)</td>
<td>&lt;2015</td>
</tr>
</tbody>
</table>
Study Selection

The search took place following an initial identification of studies through the databases. Then, we performed a screening of the title, abstract, and keywords for applicability according to the inclusion and exclusion criteria and studies were imported into EndNote X9 (Clarivate) [40].

In the next screening step, the first author (SBB) applied the inclusion and exclusion criteria according to study abstracts, eliminated duplicates, and added full-text PDFs of all studies fitting the inclusion criteria. All expert contributions were controlled for documentary evaluation or assessment of the apps or projects, ensuring they fit within the inclusion/exclusion criteria and removing duplication. The resulting full-text studies and corresponding research information system (RIS) files that compiled bibliographic data information were imported into the analysis management software MAXQDA (version 20; VERBI GmbH) [41].

All studies that passed the original screening were reviewed in full text, coded deductively with the bibliographic RIS content, and systematically evaluated according to the paper sections. After full-text scrutiny, studies not meeting the inclusion criteria were excluded and adjustments were discussed, justified, and made within the whole team when necessary, based on the refinement of the inclusion criteria. Additionally, scrutiny of the included bibliographies, especially topically relevant reviews, was culled for additional studies.

Summarizing the Data

The included studies summarized the key information as suggested by Peters et al [35] and this key information was analyzed through a systematic and descriptive content analysis based on Mayring and Fenzl [42] using a combined deductive and inductive approach. Deductive coding and descriptive analysis were conducted on all the included studies to compile and describe the following information: (1) keywords, (2) year of publication, (3) country of origin, (4) aims/purpose, (5) study population and sample size, (6) intervention type, (7) methodology/method(s), (8) broad topic(s), (9) evaluation, and (10) outcomes and details. Following this, key findings that related to the scoping review questions were coded inductively within the deductive descriptive categories: broad paper topics and evaluation. To verify the reliability of the coding of the study types and topics, the second author (KV) reviewed all the studies based on inductively developed definitions. Discrepancies were discussed within the team and code definitions were adjusted accordingly. A descriptive summary of how apps and behaviors were evaluated are summarized in Table 2.
<table>
<thead>
<tr>
<th>Broad paper topics and evaluation tool category</th>
<th>Evaluation tool type or name [reference]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical activity</td>
<td>• Assessment of subcategories: changes in physical activity, adult physical activity, family and social group physical activity, children’s physical activity evaluation, and tracking physical activity and real-time measurements</td>
</tr>
<tr>
<td>Moderators of physical activity</td>
<td>• Ecological Momentary Assessment (EMA); Behavioral Regulation in Exercise Questionnaire; Self-Efficacy Scale; intention to participate in physical activity and to eat healthy foods [43] • Barriers to Being Active Quiz; Self-Efficacy for Physical Activity Scale; Physical Activity Stages of Change [44]</td>
</tr>
<tr>
<td>Adult physical activity</td>
<td>• Short Questionnaire to Assess Health-Enhancing Physical Activity (SQUASH) [45] • International Physical Activity Questionnaire [43] • Stanford Brief Physical Activity Survey [44] • WHO physical activity criteria [46]</td>
</tr>
<tr>
<td>Family and social group physical activity</td>
<td>• Modified National Board of Health and Welfare’s survey [47] • Parental Support for Physical Activity Scale [48] • The Social Support and Exercise Survey [44] • Family Health Climate Scale [43] • Family physical activity goal setting [47]</td>
</tr>
<tr>
<td>Children’s physical activity evaluation</td>
<td>• Test of Gross Motor Development 2nd Edition (TGMD-2); The Burdette Outdoor Playtime Checklist [49]</td>
</tr>
<tr>
<td>Tracking physical activity</td>
<td>• Average minutes per day physical activity [47] • Accelerometers or pedometers [43,44,50] • Physical Activity Diary [43]</td>
</tr>
<tr>
<td>Body measurements for physical activity</td>
<td>• BMI or height and weight [43-45,47-50]</td>
</tr>
<tr>
<td>Parent feeding and nutrition</td>
<td>• Assessment of subcategories: food types and quality, parent feeding and food acceptance, food environment, food and body measurements, and breastfeeding</td>
</tr>
<tr>
<td>Food types and quality</td>
<td>• Youth Risk Behavior Survey questions; The Behavioral Risk Factor Surveillance System Questions [51] • The Willett Questionnaire Harvard Food Frequency; Healthy Eating Index (HEI) [45] • Healthy Kids Survey [52] • Food Frequency Questionnaire [43,45,48,53-55] • Consumption of fruit, vegetables, water, soft drinks, and snacks [48]</td>
</tr>
<tr>
<td>Parent feeding and food acceptance</td>
<td>• Infant Feeding Questionnaire [56,57] • Parent Feeding Practices Scale; Child Feeding Questionnaire (CFQ) [57] • Norwegian Mother and Child Cohort Study (MoBa) Questions; Children’s Eating Behaviour Questionnaire (CEBQ); Child Food Neophobia Scale (CFNS) [54] • Infant Food Exposure and Parental Intentions to Offer Foods [56]</td>
</tr>
<tr>
<td>Food measurements</td>
<td>• Fruit and Vegetable Intake Diary [43,53] • 24-hour dietary recall of foods and beverages [57] • Food photography and weighed food records [59,60] • Caloric counting in kilojoules [59,60]</td>
</tr>
</tbody>
</table>
Collating, Summarizing, and Reporting Results
The analysis of keywords (1) was conducted from the bibliographic RIS data according to their frequency of appearance. Presentation of the overall findings from the deductive analysis of the study information 2-7 was summarized and detailed in Multimedia Appendix 2. Within the broad topic(s), ways apps and behaviors were evaluated and study-described outcomes 8-10 and details were analyzed, and then described and summarized in an iterative, inductive process used for the included studies, including a cross-reference between topics and evaluation tools listed within the studies (Table 2).

aWHO: World Health Organization.
bzBMI: sex- and age-standardized BMI.
Reviews were included in this scoping review. For pragmatic organizational reasons, and because some of the primary source data did not fit the scope of our review objectives or fit our inclusion criteria, only the findings of the reviews themselves were included, not the primary literature that they were based on.

Results

Overview

Of the 39 studies included in this review of child health apps for parent use, most stemmed from US-, Australian-, and European-based research. A total of 8 overlapping health promotion topics that were addressed in 28 primary intervention studies, assessed in 6 app feasibility studies, and reviewed in 5 app or literature reviews were identified. The topics found in the inductive analysis were parental feeding and nutrition, physical activity, maternal-child health, parent-child health, healthy environment, dental health, mental health, and sleep. In primary intervention studies, behavior change theories were embedded in 26 studies and evaluations were carried out with a variety of topic-specific, adapted, self-developed, or validated questionnaires and evaluation tools. Methodologically, included studies were summarized and the effects, if any, of interventions were described. Reported study effects varied and used diverse tools to evaluate intervention effects. Alternatively, the feasibility of apps or health behaviors was assessed with a described combination of quantitative evaluation and survey tools along with user input. Included studies cited challenges in assessing healthy behaviors of children through parent apps, specifically in finding the appropriate way to evaluate changes in behavior through apps, recruiting target groups, and retaining app engagement.

Overall, 1040 studies from the 5 selected databases were analyzed and 60 apps and programs were gathered through the expert network. After screening for eligibility and duplication, and adding resources from reviews, 39 studies were included in total; 28 of these were found from databases, 10 were discovered by scrutinizing the bibliographies of included sources, and 1 resource was included from the expert input. An overview of study inclusion can be seen in the PRISMA-ScR flowchart (Figure 1).

Keywords

Keywords of all included studies demonstrated the following terms according to the bibliographic RIS information from the studies. The 11 most frequently used keywords listed in 9 or more included publications (with listed frequency of appearance) were humans (n=19), female (n=14), child (n=13), health promotion (n=12), male (n=12), parents (n=12), mHealth (n=11), smartphone/s (n=10), mobile apps (n=10), adult (n=9) and infant/s (n=9; Multimedia Appendix 3).

Year of Publication and Country of Origin

The included studies were published between 2016 and 2021, with two-thirds published between 2019 and 2021 and an uptick observed in 2019 (Multimedia Appendix 4). Among the upper-middle and high-income countries included, the majority came from the United States (n=15) [44,51,52,77-79], followed by Australia (n=13) [45,49,53,56,58-60,72-74,80-82] and then the European region (n=9) [43,46-48,54,55,57,83]. Included European countries with 1 study each were Belgium [48], the Netherlands [83], Portugal [57], Sweden [47], and the United Kingdom [83], with 2 studies each in Norway [54,55] and Germany [43,46]. Only 2 studies came from countries outside the global North (Singapore [66] and Iran [62]).

Aim, Sample Size, and Intervention Type

Specific aims of the studies were diverse and ranged from creating a topic overview of existing studies or apps, assessing the feasibility of developed apps, to evaluating the effectiveness of a child health promoting intervention involving app or web-based content. There were 3 types of interventions that were included in our review: 28 primary studies [43-52,54-56,58-67,70,71,78-79,82], 6 app feasibility studies [70,73-75,83,84], and 5 reviews, of which 2 were literature reviews [53,57] and the remaining 3 were app reviews [68,72,85]. In the studies, the number of participants ranged from 7 to 1200. The review of apps included between 29 and 47 apps and the review of studies included 11 studies each. Methodologically, the studies were heterogeneous in design and evaluation method. The clinical trial was the most frequent study design type for 21 studies [43-45,47-51,54-56,58-62,66,67,69,79,80] with most using the randomized controlled trial (n=15) and others with pilot, nonrandomization or experimental designs (n=6). Four of the included studies [43,47,59,69] published protocols of studies yet to be undertaken. The second most frequently undertaken type of evaluation was feasibility studies connected to the evaluation of app design features, testing, and functioning [53,70,73-75,83,84]. Quantitative and qualitative results were combined in the mixed method designs of 7 of the included primary (n=3) [63,65,70] and feasibility (n=4) [73,75,76,83] studies. A predominantly qualitative design was undertaken by 2 studies [63,84]. Of the 32 single studies, 25 individual project names were listed, of which 3 projects had 2 publications (Make Safe Happen [69,70], Swap It [59,60], and the Growing Healthy Program [56,76]) and 4 did not list a specific name [62,63,67,78]. An overview and summary of the included studies can be found in Multimedia Appendix 2.

Broad Topics

The studies included could be sorted into 8 main prevention and child health promoting topics: parental feeding and nutrition (n=19) [43,45,47,48,51-53,55-61,72-74,82,86], physical activity (n=8) [43-49,84], maternal-child health (n=6) [44,45,65,67,75,85], parent-child health (n=5) [66,68,78,79,83], healthy environment (n=3) [69-71], dental health (n=2) [62,63], mental health (n=1) [66], and sleep (n=1) [64]. A crossover of these inductively derived topics occurred in some studies and these were not mutually exclusive; if a study descriptively included more than 1 topic, then the study was included in both topics. This occurred most frequently with studies that addressed parental feeding or nutrition and physical activity: this combination of topics was found for 7 of the studies. In 2 studies physical activity was addressed in combination with maternal health. Parental feeding and nutrition addressed nutritional intake for a range of ages: starting with nutrition in pregnancy

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Blakeslee et al
feeding practices and nutrition for infants and young children, whether through breastfeeding or solid food [47,48,54-57,61,72,73,76]; or promotion of healthier school meals or family nutrition [43,51-53,59,60,74,87]. Included studies that broached physical activity were interested in either tracking the movement as part of the app-based intervention [44,45,47] or physical activity as part of obesity prevention, comprehensive child fitness, or overall family health [43,46,48-50,84]. All studies with a topical focus on maternal-child health targeted women in pregnancy. The parent-child health app studies included had an educative or informational focus on parenting and child health. Included apps promoting a healthy environment targeted home safety and accident prevention, while studies addressing dental health were concerned with caries prevention and dental hygiene. Mental health was addressed from the standpoint of overall child well-being and the sleep app studies included assessed the parent tracking of infant sleep schedules.

**Parent Mobile App Evaluation**

**Evaluation of Behavior Change in Apps**

Many of the study evaluations assessed changes in intentions, knowledge, or behavior over time. In total, 26 studies listed at least one specific behavior change theory that the study evaluation was based on: Social Cognitive Theory was mentioned in 9 studies [44,47,48,51,54,55,58,66,79] and in 1 meta-analysis [57]; Self-efficacy Theory was mentioned in 3 studies [53,65,66]; Social Determination Theory also in 3 studies [43,48,67]; and the Behavior Change Wheel in 4 studies [46,59,61,74]. Some studies also used BCTs in their interventions (n=6) [43,47,57,59,78,85]. While most studies do not explicitly name the individual BCTs (n=20), 10 of these studies used BCTs. Among studies that mentioned techniques of behavior change, the most frequently cited were the BCT taxonomy by Michie et al [88], which was cited in 2 studies [47,57], and the mHealth theory–based taxonomy for mobile apps, which was also cited in 2 studies [78,85]. Individual BCTs mentioned in the included studies were shaping knowledge, identification of self as a role model, demonstration of the behavior, self-monitoring of behavior, self-belief, prompts/cues, goal setting (behavior and outcome), identity, and social support.

To measure the potential for change in behavior, multiple questionnaires were used that cut across topics. Some questionnaires that assessed changes in behavior were self-developed [51,54,55,85] or developed out of other validated questionnaires [48,59,62]. As an essential part of most behavior change models, the most frequently used validated questionnaires in the studies assessed self-efficacy as a predictor for changes in behavior for different topics such as motherhood, nutrition, breastfeeding, and physical activity. Measures for changes in self-efficacy or knowledge before and after the intervention were described to give an outlook for the continuation of the new behavior. Listed validated questionnaires used to evaluate behavior changes were the 10-item COM-B Self-Evaluation Survey (healthy family meals) [74], Maternal Self-Efficacy Scale (a 12-item scale measuring the mother’s self-efficacy for promoting healthy eating, physical activity, and in limiting noncore foods) [50], the 14-item short form Breastfeeding Self-Efficacy Scale [58] assessing breastfeeding confidence, Self-Efficacy for Physical Activity [44], the 10-item Parenting Efficacy Scale [66], and 36-item Parenting Self-Efficacy (Tool to Measure Parenting Self-Efficacy [TOPSE]) [65]. Increasing knowledge cut across topics, ranging from a healthy environment [69,70,80], physical activity or nutrition [47,52,54,78], dental health [62,63] parenting for health [50,65], or sleep [64,78]. Despite the objective to increase health knowledge of parents, not all studies undertook explicit evaluations to measure knowledge change.

Assessment tools were mentioned and used for specific topics. An entire overview of assessment tools for evaluating data and parameters can be found in Table 2.

**Physical Activity**

Physical activity was assessed through different means: 10 studies used physical activity measures [43-50,78,84]. We identified 21 separate measures that evaluated physical activity in 3 ways: specific behaviors as they related to quantified movement (ie, accelerometer), those that predicted or moderated the physical activity undertaken (ie, self-efficacy), and measures of the outcomes of physical activity (ie, BMI or weight over time). Of these tools, 17 used validated measures to assess physical activity. Wunsch et al [43] and Choi et al [44] measured the self-efficacy of physical activity specifically. Accelerometer to track steps and physical movement were used or planned in several studies [43,44,50]. BMI calculations were investigated in 6 studies [44,45,47-50] evaluating physical activity, especially when combined with the topic of nutrition and as a secondary parameter. In studies with small children, the evaluation measurements and intervention for physical activity were frequently given by the parents or primary caregivers. For instance, in the studies by Trost and Brookes [49] and De Lepeleere et al [48], the parental support for Physical Activity Scale was used. A strong connection of studies researching the topics of nutrition and physical activity demonstrated a crossover in evaluation tools used for body measurement, such as BMI calculated from height and weight [43,45,47,48,50]. Combined nutrition and physical activity likewise evaluated parent preferences within theory-guided domains for healthy goal setting [78].

**Parent Feeding and Nutrition**

In total, 20 studies [43,45,47,48,51-61,72-74,76,78] fell into the topic of parent feeding or nutrition and had the largest number of individual assessments. Overall, we were able to identify 41 assessment tools used in the studies that fit into 1 of 6 separate evaluative purposes (see as referenced in Table 2): measuring food amounts, taking body measurements for nutrition (often also for evaluating physical activity), assessing the ways and environment in which food is consumed, evaluating the quality of food consumed, examining parent feeding and young child food acceptance, or assessing breastfeeding-specific practice. Of the 41 assessment tools and questionnaires used, the majority (n=32) were validated tools. Six tools were self-developed specifically for the study and 3 further assessments were listed in the reviews and their origin was unclear. The Child Feeding Questionnaire was found to be the most frequently used questionnaire to assess parental feeding...
practices [50,54,57]. An instrument most frequently used for evaluating nutrition was the Food Frequency Questionnaire [43,48,54,55,57,59].

**Dental Health**

Four studies evaluated parameters of dental health. In the dental study by Zolfaghari et al [62], for instance, the authors used a self-developed questionnaire to assess parent knowledge and practices that combined the self-developed questions with other validated questionnaires [89-91]. A 24-item validated questionnaire designed by Van den Branden et al [92] to measure oral health behaviors in children and the Theory of Planned Behavior determinants was used, with permission, prior to and following use of the app [63].

**Sleep**

Only 1 study [64] specifically evaluated sleep as an mHealth intervention. This specifically assessed the sleep of infants and babies with a Brief Infant Sleep Questionnaire-Revised. However, an evaluation of the sex- and age-standardized BMI (zBMI) was found in Gomes et al’s [57] review of parental feeding practices and as part of a parent information needs assessment [78].

**Mental Health**

Mental health was assessed in 3 of the included studies [44,65,66]. The Warwick-Edinburgh Mental Well-Being Scale, a validated measure, was used by Deave et al [65], using a 14-item scale of subjective mental well-being and psychological functioning. Choi et al [44] used the Center for Epidemiological Studies Depression Scale to assess the mental health.

**Parent Child Health**

A total of 8 studies [50,66-68,71,78,79,83] were found to address parent-child health interactions, including the health of families, identity, and family-based evaluations. None of the evaluation tools broadly assessed the parent-child health interactions, but rather concentrated on the specific topic of interest for the parent-child interaction. For instance, Knowlden and Sharma [79] used the most general assessment. The authors developed separate evaluations of maternal-facilitated and child-behavior constructs based on Social Cognitive Theory to evaluate the parent-child health interaction [79] with an aim to address healthy child nutrition and physical activity. Other topic-oriented parent-child health parameters were also found that focused on evaluating educative [66-68,71,83] or identity parameters [50].

**Healthy Environment**

Three studies [69,70,80] specifically evaluated healthy environment through evaluations of safety behavior and first-aid knowledge.

**Maternal Health and Parenting**

Six studies [44,45,65,67,75,85] addressed evaluations of maternal health and 7 studies [48,65,66,68,75,78,79] looked at specific parenting parameters. In 1 study [65], the parenting self-efficacy was measured with the TOPSE. The TOPSE was used to compare mothers at 3 months after birth who had downloaded the Baby Buddy app with those who had not downloaded the app, controlling for confounding factors. The postnatal mental state was measured in Shorey et al [66] with a crossover of mental health and parenting and infant bonding tools.

**App Feasibility (Quality and Usability)**

The most frequent way by which child health apps for parents were assessed was through the Mobile App Rating Scale [53,72,74], developed by Stoyanov and colleagues [93]. To further assess the feasibility and quality of parent apps, a mixed methods approach was used for further development and contextual adaptation of feedback through interviews, where mostly semistructured interviews were conducted [73-75,83,84]. Qualitative assessments of the apps used in in-person, online, and telephone [73] semistructured interviews or focus groups were analyzed by a stated inductive or thematic analysis. Whereas app development approaches guided the qualitative interview data collection [73,75], explicit stating of the qualitative theoretical approaches for the interviews themselves was notably lacking in some studies [83,84]. Braun and Clark was the most frequently cited theoretical approach [70,74,75]. Furthermore, data analytic tools for coverage, usability, and engagement were used by several studies of apps [72,74-76]. Additionally, features of apps such as push notifications, gamification, and just-in-time adaptive interventions were used or listed for apps to retain engagement [43,44,46,58,71,74].

**Parent Mobile App Outcomes**

**Reported Evaluation Outcomes Based on Topics**

The manner in which parent-based apps and interventions reported on outcomes in the primary studies was mixed. The study-reported effectiveness of an intervention was cited by many to depend on the length of the intervention, the intended intervention that was targeted, and whether an app included in-person support. Apps increasing knowledge seemed to be a particularly effective means to create a healthy environment with children [70,71] or to increase knowledge on child oral health [62]. An increase in physical activity of pregnant women was cited by 2 studies [44,50] and an 8-week app intervention was able to increase the physical activity performed by children, but this was not a significant outcome [49]. Increasing knowledge on nutrition was demonstrated in 1 study [52]; however, this intervention was coupled with in-person support classes. For nutrition outcomes, a reported increase in motivation or the consumption of fruit and vegetables in a child’s diet was reported by several studies [48,51,55] and healthier lunches saw less discretionary foods packed by parents who used an app [60]. Most improved outcomes with the interventions were not simply attributed to the use of the app alone, however. For example, a trial on dental hygiene demonstrated improvement for app users with a high level of perceived behavioral control, especially when coupled with regular dental checkups [63]. App-only outcomes demonstrated some positive effects for new parents of infants with sleep problems [64] and for improving parent bonding and self-efficacy after birth [66]. Outcomes in nutrition studies that relied on longer term growth outcomes saw little sustained or no positive effect over time with app use [54,56,61,79]. Indeed, studies on app-based interventions for baby food introduction and sustained healthy eating in early...
childhood highlighted the difficulty of achieving any sustained positive effect over time [54-56]. Across other topics, app support for partners of breastfeeding women or lifestyle advice for pregnant women resulted in no changed outcome with the apps and eHealth interventions [45,58], or even saw negative outcomes in the group receiving an app-supported intervention (ie, intervention group) to aid pregnant women decision-making [67]. This outcome supports a recommendation given in multiple interventions to use real-world interaction and support interventions in conjunction with the app [50,55,61,65,66]. Recruitment posed its own challenges. Particularly, in studies that aimed at healthier behaviors for children that were facilitated and necessitated parental support, authors employed several strategies: some recruited children but evaluated data from parents [59], some spoke of parent-child dyads [50,55,61], while others focused on the recruitment of families [51]. Some studies reported parents having higher education levels and potentially greater willingness to engage with the technology than a targeted population that would most benefit from the intervention [45,48,54,58,61,63,79].

**App Evaluations of Behavior Changes and Parent Experience**

A few studies highlighted the difficulty of customizing BCTs to their app content that combined the aims of the intervention with potential needs of parents and the ability to effectively evaluate these measures [56,65,78], a point that was discussed in additional detail in the reviews by both Gomes et al [57] and Biviji et al [85]. Particularly, the app reviews and a few studies underscored the gap of evidence-based apps with best practices among available apps for parents across health promotion topics [72,78,83]. Tracking of growth, pregnancy development, breastfeeding, dental hygiene, and diet were features that parents enjoyed, especially if these contents were tailored to the health parameters [53,63,77,83]. At the same time, features such as chat functions [53,73] or diaries [44] had mixed reviews or negative desirability by parents in the studies.

**App Content Delivery and Technical Features**

Keeping parents motivated to use the app was a challenge reported in multiple studies [45,56]. Other content delivery mechanisms, such as audio recordings (podcasts) [75] or videos [48], saw a high level of adherence in terms of the content consumption. Technical problems, interface challenges, or the inability to appropriately tailor app features were feedback highlighted by several studies [56,58,61]. The engagement with the apps by parents was described in a few studies to have the highest relevance for first-time parents [66,76] and retaining app or program engagement, particularly for the group targeted, was a challenge cited in multiple studies [46,56,61]. Features such as push notifications were seen as helpful delivery tools to maintain engagement with the app [44,58,60,61,76] and gamification was seen to have some success in achieving this goal [46,62,71]. Future designs for engaging parents reference increasingly developed “just-in-time” features to enhance practicability and interaction [43,74,76].

**Discussion**

**Principal Findings**

The 39 studies that met the inclusion criteria for this review reflected a wide range of child health topics: parental feeding and nutrition, physical activity, maternal-child health, parent-child health, healthy environment, dental health, mental health, and sleep. The 8 individual topics were concluded by an inductive analysis. Behavior change theories guided the research of 26 studies and topic-specific, adapted, self-developed, or validated questionnaires and evaluation tools were used to assess and report study outcomes. At the same time, challenges were reported in effectively evaluating changes in behavior through apps, recruiting target groups, and retaining app engagement.

An overall increase of publications on the topic may reflect the growing number of apps developed in general. The lower number of the published studies during 2020 may be an influence of the COVID-19 pandemic, a trend that we saw increase in a swift subsequent spot search in each of the included databases (see Multimedia Appendix 1). Since this review was conducted, 3 additional study results from included study protocols were published [94-96]. The demand and need for addressing child health promotion have only grown since the start of the COVID-19 pandemic [97] and digital mHealth solutions are forecasted to continue to grow [98]. The greater opportunity to digitally support child health through parents solidifies the need to make sure that parents have access to health promotion apps that are embedded in scientific evidence and best practices. Generally, the regulation of recruitment strategies was very bound to the study context and was a challenge highlighted by the studies in our findings. Varied descriptions of how potential participants were recruited and who was recruited detailed a level of complexity requiring consideration for study designs with multiple sites (homes and schools, for instance) and studied parties (children and parents).

Our findings highlighted the complexity of compiling evidence of behavior changes that are supported by apps and web-based programs for child health. When app interventions evaluated parents’ knowledge after use as a primary outcome, evaluation of the knowledge increase was easily assessed [52,62,69-71]. Evaluating the effectiveness of more complex interventions of health promotion as described in the included studies requires multiple evaluation tools and behavior-specific tailoring in order to see potential effects that may or may not continue in the long term. Prevention interventions in primary care with young children have been found to be exceptionally challenging to sustain over time, requiring complex interventions and involvement of multiple actors [99]. One additional impediment for long-term measurable changes could derive from the need for a clear theoretical underpinning and health mode within health promotion apps. With the absence of illness in the prevention setting, apps for health promotion could benefit from a health psychology theory–based development with a systematic evaluation in order to lead to substantial positive changes in behaviors [100]. The studies included in this review had varying degrees of theory embedded into the app design,
which can provide a framework for evaluation. The most frequently used framework in the included studies was the Behavior Change Taxonomy [88] and its adapted version for mobile apps [20,101], which was itself developed from an expert collaboration. Many of the included studies were not transparent in reporting the link between the theory of behaviors and the evaluation parameters assessed or app features developed. On the whole, the multipronged strategies required for developing and evaluating apps for parents exhibit methodological agility and interdisciplinary collaboration. Interventions with demonstratable effectiveness were able to do this, as was markedly evident in the included studies compiled and reviewed on the topics of maternal child health, parent feeding, and lunch box nutrition [53,57,77]. Involvement of stakeholders is an imperative first step in the development of apps. Health experts bring expertise and scientific basis to the interventions for child health promotion and such expertise can be built on to further develop and adapt apps to changing evidence and circumstances. An example of this adaptation is the Growing Healthy program, where an initial study on childhood obesity prevention starting in infancy was published [61,102] and then compared in an upscaled study with another intervention [56] and followed by parent insights and feedback that were able to be integrated back into the app development in order to make them more intuitive and adaptive to specific engagement levels and identified target groups [76]. Parent feedback demonstrates that the apps are used most when the intuitive apps and features can address their needs and questions they have about their child’s health at the point when they need answers. While parents in the included studies were not always able to imagine what theoretical features would be useful [46,78], they provided strong feedback when asked for (for instance, [53,70,74,83,84]).

Strengths and Limitations

This scoping review provides the first comprehensive overview of available mobile apps and web-based programs for use by parents aimed at the health promotion of their children. The 39 included studies were systematically categorized, provide a thorough summary of current evidence, describe some of the best practices for app development on this topic, and give a strong foundation for further research. Despite this, this review is not without limitations. Inclusion criteria for this review were purposefully phrased broadly to be as inclusive as possible for apps aimed at parents. However, the multiplicity of study types was not foreseen and may have been more succinctly described. For instance, only including primary studies may have facilitated greater clarity in study summary. This methodological choice also hindered greater comparison between the studies. This study did not include an evaluation of outcomes, a step that would be helpful in future research to evaluate measured changes in behavior or effectiveness that the parent apps had. We also purposefully only included apps and programs from middle- and upper-income countries, apps that targeted healthy children without a diagnosis, and only studies published after 2015. This limitation may have therefore excluded apps or programs in other contexts that may have had broader and more global application. A future review would benefit from a systematic evaluation of app outcomes that includes only primary studies with inclusion of middle- and lower-income countries to be more generalizable and relevant to a larger population. Despite our attempts to include potential gray literature and expert input, no unpublished app evaluations were found. Despite our best efforts to include studies from other disciplines, most apps for parents, which were aimed at the health of their children, were found and evaluated within the health field. Access to published analysis of apps with detailed information evaluation is likely a further limitation of this study, because of the assumption that most apps developed in a scientific context are motivated to publish on the development and evaluation findings. It must be recognized that apps are developed out of many contexts and future reviews would benefit from the inclusion of parent apps developed from other fields (eg, marketing, industry, governmental or nongovernmental organizations, or other interest groups). Our own attempt to bridge this gap with the addition of extending and tapping into an expert network only saw limited methodological success.

Conclusions

Existing apps and web-based programs aimed at parents to promote the health of their children cover a broad range of topics. Most aim to modify the nutrition and physical activity behavior—important for lifelong prevention of illness. New parents are a key target group for apps, whether to increase their knowledge or parental self-efficacy. Evaluating apps for child health promotion provides a special challenge and must be tailored to the needs of parents, context of the topic, and are ideally rooted in a transparent theoretical framework. Given the increasing digitalization of health and expanding focus of health policy on prevention measures, parent apps are guaranteed a role in our lives. Lessons learned can be garnered from existing research studies that tailor developed content to target group needs, include intuitive and adaptive features, and embed well-founded parameters for evaluations able to investigate long-term effects of parent apps on child health.

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Authors' Contributions

SBB was responsible for methodology, validation, formal analysis, investigation, data curation, writing, review and editing, visualization, and project administration. KV performed validation, formal analysis, writing, review and editing. IH performed investigation and data curation. WS was responsible for methodology, conceptualization, validation, formal analysis, review and editing, supervision, and project administration. GS was responsible for conceptualization, validation, resources, review and editing, supervision, funding acquisition, and project administration.

Conflicts of Interest

None to declare.

Multimedia Appendix 1
Search strategy details.
[DOCX File, 24 KB - mhealth_v11i1e39929_app1.docx ]

Multimedia Appendix 2
Detailed summary of results.
[DOCX File, 155 KB - mhealth_v11i1e39929_app2.docx ]

Multimedia Appendix 3
Research information system (RIS) keywords from all included studies (occurrence in publications ≥2).
[PNG File, 220 KB - mhealth_v11i1e39929_app3.png ]

Multimedia Appendix 4
Included scoping review publications (2016-2021).
[PNG File, 45 KB - mhealth_v11i1e39929_app4.png ]

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Abbreviations

- MARS: Mobile App Rating Scale
- mHealth: mobile health
- PES: Tool to Measure Parenting Self-Efficacy
- PRISMA-ScR: Preferred Reporting Items for Systematic Reviews and Meta-Analyses for Scoping Reviews
- RIS: research information system
- zBMI: sex- and age-standardized BMI

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Review

Stress Management Apps: Systematic Search and Multidimensional Assessment of Quality and Characteristics

Sarah Paganini1, PhD; Evelyn Meier2, MSc; Yannik Terhorst3, MSc; Ramona Wurst1, PhD; Vivien Hohberg4, MA; Dana Schultchen5, PhD; Jana Strahler1, Prof Dr; Max Wursthorn6, MSc; Harald Baumeister3, Prof Dr; Eva-Maria Messner3, PhD

1Department of Sport Psychology, Institute of Sports and Sport Science, University of Freiburg, Freiburg, Germany
2University of Education Freiburg, Freiburg, Germany
3Clinical Psychology and Psychotherapy, Ulm University, Ulm, Germany
4Department of Sport, Exercise and Health, Faculty of Medicine, University of Basel, Basel, Switzerland
5Clinical and Health Psychology, Ulm University, Ulm, Germany
6Department of Public and Nonprofit Management, University of Freiburg, Freiburg, Germany

Corresponding Author:
Sarah Paganini, PhD
Department of Sport Psychology
Institute of Sports and Sport Science
University of Freiburg
Sandfangweg 4
Freiburg, 79102
Germany
Phone: 49 76120345
Email: sarah.paganini@sport.uni-freiburg.de

Abstract

Background: Chronic stress poses risks for physical and mental well-being. Stress management interventions have been shown to be effective, and stress management apps (SMAs) might help to transfer strategies into everyday life.

Objective: This review aims to provide a comprehensive overview of the quality and characteristics of SMAs to give potential users or health professionals a guideline when searching for SMAs in common app stores.

Methods: SMAs were identified with a systematic search in the European Google Play Store and Apple App Store. SMAs were screened and checked according to the inclusion criteria. General characteristics and quality were assessed by 2 independent raters using the German Mobile Application Rating Scale (MARS-G). The MARS-G assesses quality (range 1 to 5) on the following four dimensions: (1) engagement, (2) functionality, (3) esthetics, and (4) information. In addition, the theory-based stress management strategies, evidence base, long-term availability, and common characteristics of the 5 top-rated SMAs were assessed and derived.

Results: Of 2044 identified apps, 121 SMAs were included. Frequently implemented strategies (also in the 5 top-rated SMAs) were psychoeducation, breathing, and mindfulness, as well as the use of monitoring and reminder functions. Of the 121 SMAs, 111 (91.7%) provided a privacy policy, but only 44 (36.4%) required an active confirmation of informed consent. Data sharing with third parties was disclosed in only 14.0% (17/121) of the SMAs. The average quality of the included apps was above the cutoff score of 3.5 (mean 3.59, SD 0.50). The MARS-G dimensions yielded values above this cutoff score (functionality: mean 4.14, SD 0.47; esthetics: mean 3.76, SD 0.73) and below this score (information: mean 3.42, SD 0.46; engagement: mean 3.05, SD 0.78). Most theory-based stress management strategies were regenerative stress management strategies. The evidence base for 9.1% (11/121) of the SMAs could be identified, indicating significant group differences in several variables (eg, stress or depressive symptoms) in favor of SMAs. Moreover, 38.0% (46/121) of the SMAs were no longer available after a 2-year period.

Conclusions: The moderate information quality, scarce evidence base, constraints in data privacy and security features, and high volatility of SMAs pose challenges for users, health professionals, and researchers. However, owing to the scalability of SMAs and the few but promising results regarding their effectiveness, they have a high potential to reach and help a broad audience. For a holistic stress management approach, SMAs could benefit from a broader repertoire of strategies, such as more instrumental and mental stress management strategies. The common characteristics of SMAs with top-rated quality can be used...
as guidance for potential users and health professionals, but owing to the high volatility of SMAs, enhanced evaluation frameworks are needed.

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KEYWORDS
stress management; mobile app; mHealth; mobile health; quality assessment; review; evidence base; availability

Introduction

Stress is a public health problem that poses high risks for physical and mental well-being and is increasing in industrial societies where individuals are exposed to complex demands at work and in daily life [1-5]. The results of an American survey revealed that 75% of the participants felt significantly stressed [6], and a representative sample of the German population showed a point prevalence of perceived high chronic stress of 11% [1]. There are multiple reasons for the broad impact of stress as it affects many dimensions, such as cognition (eg, negative attributional style), affect (eg, affective dysregulation, such as increase in anxiety), physiology (eg, dysregulation of the endocrine response system), and behavior (eg, harmful behavioral changes, such as smoking or physical inactivity) [3]. As a result, chronic stress causes a higher risk for various somatic diseases and mental disorders, such as gastric ulcers, migraine, hypertension, type 2 diabetes mellitus, and depression [3,5,7-11]. In addition to the substantial impact on health, work-related stress results in high costs for society, especially through productivity-related losses [12].

Due to these negative consequences, several stress management strategies have been developed and evaluated over the past decades [13,14]. Most of them refer to transactional stress models in which stress reactions are mainly determined by a subjective interpretation and the types of coping strategies employed [13-16]. Even though “stress management” is a widely and variably used term [17], Kaluza [13] proposed three categories of strategies: (1) instrumental stress management strategies with a focus on preventing and reducing stress in everyday life (eg, self-management or seeking support); (2) mental stress management strategies aiming at changing personal stress amplifiers (eg, acceptance or gratitude); and (3) regenerative stress management strategies aiming at recovery after stress exposure (eg, relaxation techniques or health behavior) [17-19]. Thereby, effective stress management seems to be characterized by a broad repertoire and a balance between instrumental, mental, and regenerative strategies [15].

Interventions use a variety of these different strategies and are often delivered in a group setting [17,18]. In particular, cognitive or behavioral-based interventions for stress management (which typically include all 3 categories of strategies) have been shown to be effective for reducing stress in different settings (eg, the occupational setting; Cohen $d=1.16$, 95% CI 0.46-1.87 [20]) and for different target groups (eg, university students; standardized mean difference=$-0.77$, 95% CI $-0.97 \text{ to } -0.57$ [21]). The same is true for mindfulness-based stress reduction in healthy individuals [22-24] (eg, Hedges $g=0.53$, 95% CI 0.41-0.64 [22]). Relaxation training (with a focus on regenerative strategies) has been shown to be effective in healthy individuals [24] and in occupational settings (Cohen $d=0.50$, 95% CI 0.31-0.69 [20]) but appears to be inferior to cognitive-behavioral interventions [20]. Implementing previously learned health-related strategies in daily life is essential for their short- and long-term health benefits [25]. Internet- and mobile-based mobile health interventions can help to integrate stress management strategies into daily routines and to overcome the barriers of face-to-face interventions, such as limited accessibility, location, time, and high costs [26,27]. As a result, the relevance of mobile phones for monitoring and delivering health interventions has increased over the last decade [27]. From 2013 to 2018, the number of downloaded health apps per year increased from 1.7 to 4.1 billion worldwide [28]. Regarding stress management apps (SMAs), about 6% of an American sample reported that they already use SMAs regularly and about 50% could imagine using them in the future [29]. An observational study showed that compared to a website, delivering a stress-management intervention via an app could offer the added benefit of more frequent use and access to more intervention content [30].

Accordingly, there is a broad and growing body of SMA research. Reviews already exist; however, they all focus on specific aspects and some might be outdated. Pre-existing SMA reviews focus on content alone [31,32], content in combination with transparency and functionality [33], efficacy [34], gamification elements [35], persuasive and behavior change strategies [36], or quality of apps, with a focus exclusively on mindfulness apps [37]. Regarding content, it was shown that mindfulness and meditation were the most commonly used strategies in the reviewed SMAs (34% to 78% of all apps included these strategies) [31,33,34], followed by breathing [31,33] or goal setting [34]. Further common strategies were personalization and self-monitoring, while social support strategies were rarely used [36]. The implementation of gamification elements is relatively scarce (on average 0.5 elements per app) [35]. Concerning the evidence base, Lau et al [34] revealed that among more than 1000 screened apps for well-being and stress management, only 2% were scientifically evaluated. The 2 studies that looked at data privacy and security features, such as privacy policy, contact information, and disclosures, revealed that only half of these criteria could be met on average [33]. In addition, most of the evaluated apps showed a lack of data privacy and security [37]. This confirms the results of other health, wellness, and medicine-related apps (eg, smoking cessation and diabetes) [38-40], showing major privacy and security risks, missing transparency, or data sharing with third parties, even when they were accredited [41].

Considering the quality of SMAs, only one of the existing reviews (which was exclusively performed for mindfulness apps and not for SMAs in general) [37] employed a valid scientific
measure, that is, the Mobile Application Rating Scale (MARS), which is an instrument for assessing app quality on multiple dimensions \cite{42,43}. This is of relevance as user star ratings and app store descriptions can be manipulated in favor of commercial interests \cite{33}.

Another challenge for users and health professionals who are seeking apps for long-term use, as well as for researchers aiming to present the most recent state of research, is the high volatility of apps \cite{44,45}. In a study considering mental health apps, only 50\% of the search results were available at the end of a 9-month period \cite{44}. Considering the excessive supply of health apps in app stores, their high update rate, and their uncertain long-term availability, as well as the current lack of transparency of app quality \cite{46}, the question arises as to which SMAs should be used and recommended.

In light of all these gaps and issues, the aim of this study was to systematically search for SMAs, to assess their quality on multiple dimensions in a scientific manner, and to give a comprehensive overview of SMAs concerning their general characteristics, theory-based stress management strategies, evidence base, and long-term availability. A further aim was to inform potential users or health professionals about common characteristics that might indicate high quality of SMAs. The following research questions were addressed:

1. What are the general characteristics of SMAs, such as descriptive information, technical aspects, strategies, and functions?
2. What is the quality of SMAs regarding multiple dimensions (ie, engagement, functionality, esthetics, and information)?
3. Which theory-based stress management strategies are used in SMAs?
4. What is the evidence base of SMAs?
5. How reliable are SMAs in terms of their long-term availability?
6. What are the common characteristics of SMAs with top-rated quality?

**Methods**

**Overview**

This study involved a systematic search and assessment of the quality and characteristics of SMAs. It was registered in the Open Science Framework (OSF) of the Center for Open Science \cite{47}.

**Search Strategy and Procedure**

The search terms were generated through a 3-step process. First, a narrative literature search was conducted to collect terms and keywords that were used in studies focusing on SMA interventions for the general population. Second, relevant search terms were identified based on interest group interviews with 3 psychotherapists and 3 potential SMA users. Third, the identified search terms from the literature search and results of the interest group interviews were merged, leading to the following search terms: “stress,” “stress management,” “stress reduction,” “stress prevention,” “stress coach,” “stress recovery,” “relaxation,” and “relaxation training.” An automated search using these search terms (in English and German language) was conducted in the European Apple App Store and Google Play Store with a search engine (web crawler). It was developed as part of the Mobile Health App Database Project \cite{48}, and it automatically extracts information, such as app name, description, and user rating, from the stores (for further details, please see \cite{49}).

Apps from both app stores were identified and listed in a central database. Duplicates were automatically removed. In the first step and based on the description in the app stores, apps were screened for the following inclusion criteria: (1) the word “stress” was included in the title or in the app store description; (2) the app was developed for adults in the general population without mental or somatic disorders; (3) the focus of the app was primarily on stress management; (4) at least two different stress management strategies were applied with the aim of including apps that potentially take a holistic approach to stress management; (5) the app could be used without further equipment, devices, or programs; (6) the app was free of cost in the basic version; and (7) the app was provided in German or English language. In the second step, the app was downloaded and rechecked for criteria 1 to 7. Apps that did not work after the download were excluded.

**Data Collection of General Characteristics and Quality Assessment**

The general characteristics and quality of each SMA were collected and rated between March and May 2020 by 2 independent raters (EM, SP, Hannah Besel, RW, or VH) with the German Mobile Application Rating Scale (MARS-G) \cite{42}. All raters had a psychology or sports science degree and completed an online training, which included the following components: (1) background information on the development of the MARS-G; (2) description of the dimensions and items; (3) application instructions; and (4) an exercise example \cite{50}. Subsequently, 3 SMAs were assessed per rater in order to compare and discuss the results and to ensure a common standard as well as high data quality. According to the standardized procedure, each rater had to test an app for at least 15 minutes. Data collection and quality assessment, including the actual average time spent per rating, have been fully documented.

**General Characteristics**

General characteristics were mainly based on the classification section of the original MARS and MARS-G \cite{42,43} and included (1) descriptive information on the app (ie, app name, URL, platform, user star rating, full version price, content-related app category, declared aims of the app, theoretical background, and certification); (2) technical aspects (eg, links to social media or type of support); (3) strategies (eg, relaxation or goal setting); and (4) functions (eg, feedback or reminder).

Owing to the high relevance of data privacy and security, the list of the MARS-G \cite{42} has been supplemented with 7 additional features (ie, passive informed consent; complex passwords; anonymization or pseudonymization; creation of an access token; automatic display of the privacy policy; permanent availability of the privacy policy; and transparency regarding...
the right of withdrawal [51,52]). The privacy policy of each included SMA was reviewed against the listed features. It was assessed whether information was provided for each feature (“yes” or “no”), but not whether it was technically and legally realized and complied with by the respective providers.

**Quality Assessment**

The multidimensional quality evaluation based on the MARS-G [42] comprised 4 subscales: user engagement (5 items: entertainment, interest, customization, interactivity, and target group), functionality (4 items: performance, ease of use, navigation, and gestural design), esthetics (3 items: layout, graphics, and visual appeal), and information quality (7 items: accuracy of app description, goals, quality of information, quantity of information, quality of visual information, credibility, and evidence base). For the interpretation, the cutoff score of 3.5 (indicating above-average quality) defined by Terhorst et al [53] was used.

Additionally, the subjective quality (4 items: expected use frequency within 1 year, willingness to pay for the app, willingness to recommend the app, and subjective star rating) and the perceived impact on the user (6 items: awareness, knowledge, attitudes, intention to change, help-seeking, and behavioral change) were assessed. All items were rated on a 5-point Likert scale (1=inadequate, 2=poor, 3=acceptable, 4=good, and 5=excellent). The MARS is a well-validated instrument [43,54]. The validation of the German version also yielded excellent internal consistency (ω=0.84, 95% CI 0.77-0.88) and high levels of interrater reliability (interclass correlation [ICC]=0.83, 95% CI 0.82-0.85 [42]).

**Theory-Based Stress Management Strategies**

To depict the variety of existing stress management strategies in more detail, we developed a list of theory-based stress management strategies [13,31]. This list contains 23 instrumental, mental, and regenerative stress management strategies (see Textbox 1). Some of the included theory-based strategies (eg, breathing, hypnosis, and mindfulness) overlapped with the strategies covered in the MARS-G. The assessment of theory-based stress management strategies was performed for each SMA by 2 independent raters.

**Textbox 1.** List of theory-based stress management strategies (adapted from Kaluza [13] and Christmann et al [31]).

<table>
<thead>
<tr>
<th>Instrumental stress management strategies</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Enhancing professional competencies (eg, learning)</td>
</tr>
<tr>
<td>- Seeking support (eg, network)</td>
</tr>
<tr>
<td>- Developing social-communicative skills (eg, self-assertion)</td>
</tr>
<tr>
<td>- Self-management</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Mental stress management strategies</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Accepting reality (also included in the German Mobile Application Rating Scale [MARS-G])</td>
</tr>
<tr>
<td>- Seeing difficulties as challenges (not as threats)</td>
</tr>
<tr>
<td>- Changing personal stress amplifiers</td>
</tr>
<tr>
<td>- Self-efficacy</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Regenerative stress management strategies</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Acupressure</td>
</tr>
<tr>
<td>- Autogenic training (the MARS-G includes the category “relaxation,” which is differentiated in more detail here)</td>
</tr>
<tr>
<td>- Biofeedback</td>
</tr>
<tr>
<td>- Breathing (also included in the MARS-G)</td>
</tr>
<tr>
<td>- Euthymic methods</td>
</tr>
<tr>
<td>- Food or nutrition</td>
</tr>
<tr>
<td>- Guided imagination or visualization</td>
</tr>
<tr>
<td>- Hypnosis or self-hypnosis (also included in the MARS-G)</td>
</tr>
<tr>
<td>- Meditation or mindfulness (also included in the MARS-G)</td>
</tr>
<tr>
<td>- Music</td>
</tr>
<tr>
<td>- Muscle relaxation (the MARS-G includes the category “relaxation,” which is differentiated in more detail here)</td>
</tr>
<tr>
<td>- Physical stress relief techniques</td>
</tr>
<tr>
<td>- Self-massage</td>
</tr>
<tr>
<td>- Sounds</td>
</tr>
<tr>
<td>- Sport (also included in the MARS-G)</td>
</tr>
</tbody>
</table>
Evidence Base of Included SMAs and Long-Term Availability

All included SMAs were unsystematically searched in a common web search engine for scholarly literature by applying the app name and screening the first pages of the results. Information on study design, app usage in weeks, sample and target groups, age, gender, measurement time points, measured variables, and main results were assessed from the studies found (with the exception of pilot studies).

In terms of long-term availability, all included SMAs were searched again in the app stores in August 2022. It was checked whether the app was still available (on the original platform), when the last update was made, and whether the basic version was still free of cost.

Characteristics of the 5 Top-Rated SMAs

Owing to the multitude of information, a concise overview of the common characteristics of the 5 top-rated SMAs (based on the MARS-G overall quality score) has been provided. This overview contains information on quality ratings, technical aspects, strategies and functions (all derived from the MARS-G), theory-based stress management strategies, evidence base, and long-term availability.

Figure 1. Flowchart according to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement 2020.

Data Analyses

To ensure consistency between raters, the ICC (2-way mixed) was calculated according to the report by Koo and Li [55]. An ICC below 0.50 is considered poor, 0.51 to 0.75 is moderate, 0.76 to 0.89 is good, and above 0.90 is excellent [56]. For all descriptive data (such as aims, background, and data security features), frequency and percentage were calculated. The mean score and standard deviation have been presented for each dimension of the MARS-G. All analyses were performed using IBM SPSS Statistics (Version 21; IBM Corp).

Results

Search Results

The web crawler identified 5650 potential SMAs (Google Play Store, n=3580; Apple App Store, n=1792). After removing duplicates, 2044 apps were screened. This screening resulted in 163 apps, of which 121 were eligible for inclusion after the download (Figure 1 [57]). On average, each SMA was used and evaluated for 30 minutes by each rater (mean 30.2, SD 4.0 minutes).
General Characteristics and Quality Rating

Descriptive Information

Of the 121 included SMAs, 68 (56.2%) were derived from the Google Play Store and 53 (43.8%) from the Apple App Store. The user star rating in the app stores could be identified for 96 (79.3%) apps. The mean user star rating was 4.27 (SD 0.56), and the number of ratings per app ranged from 1 to 126,183. Of all rated SMAs, 83 (68.6%) could be upgraded to a premium version (from 1 month [with costs between 0.99 EUR and 15.99 EUR] up to a permanent upgrade [with costs between 1.09 EUR and 449.99 EUR]; 1 EUR=1.1197 USD). Regarding content-related categories, most apps were listed under “health and fitness” (107/121, 88.4%). Further assigned categories were “lifestyle” (6/121, 5.0%), “medicine” (6/121, 5.0%), and others (3/121, 2.5%; including “learning,” “entertainment,” and “audio/music”). According to the description, all apps aimed at reducing stress (121/121, 100%). Further aims were improvement of well-being (113/121, 93.4%), reduction of anxiety (90/121, 74.4%), improvement of physical health (50/121, 41.3%), and emotion regulation (58/121, 47.9%). Some SMAs focused on the reduction of depressive symptoms (33/121, 27.3%), behavioral change (21/121, 17.4%), and entertainment (3/121, 2.5%). Moreover, 81 (66.9%) apps reported additional goals, such as relaxation, increasing motivation and focus, improvement of sleep, and concentration or self-awareness. The most often assigned theoretical background was third-wave behavioral therapy (106/121, 87.6%), followed by behavioral therapy (30/121, 24.8%) and cognitive behavioral therapy (24/121, 19.8%). Overall, more than 100 SMAs (111/121, 91.7%) were developed with a commercial background, 5 (4.1%) were developed by a nongovernmental organization, and only few SMAs were developed by a university (2/121, 1.7%) or a governmental institution (1/121, 0.8%). No SMA was certified according to the European Union Medical Device Regulation [58].

Technical Aspects

Data exchange with other users (eg, via social media) was possible in 40 (33.1%) SMAs, and an app community existed in 20 (16.5%) SMAs. SMAs were unguided (74/121, 61.2%), technically guided (70/121, 57.9%), asynchronously guided by humans (4/121, 3.3%), or synchronously guided by humans (1/121, 0.8%). All data privacy and security features are presented in Table 1. The 3 most common features were provision of privacy policy (111/121, 91.7%), provision of contact details or imprint (111/121, 91.7%), and passive informed consent (80/121, 66.1%).

Table 1. Frequency of declared data privacy and security features based on the German Mobile Application Rating Scale [42].

<table>
<thead>
<tr>
<th>Data privacy and security feature</th>
<th>Number of apps that specify this feature (N=121), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Provision of a privacy policy</td>
<td>111 (91.7)</td>
</tr>
<tr>
<td>Contact or imprint</td>
<td>111 (91.7)</td>
</tr>
<tr>
<td>Passive informed consent</td>
<td>80 (66.1)</td>
</tr>
<tr>
<td>Automatic display of the privacy policy</td>
<td>76 (62.8)</td>
</tr>
<tr>
<td>Allows password protection</td>
<td>74 (61.1)</td>
</tr>
<tr>
<td>Requires login</td>
<td>66 (54.5)</td>
</tr>
<tr>
<td>Security of data transfer</td>
<td>64 (52.9)</td>
</tr>
<tr>
<td>Permanent availability of the privacy policy</td>
<td>55 (45.5)</td>
</tr>
<tr>
<td>Active confirmation of informed consent</td>
<td>44 (36.4)</td>
</tr>
<tr>
<td>Financial background/conflict of interest</td>
<td>42 (34.7)</td>
</tr>
<tr>
<td>Transparency regarding the right of withdrawal</td>
<td>34 (28.1)</td>
</tr>
<tr>
<td>Creation of an access token</td>
<td>26 (21.5)</td>
</tr>
<tr>
<td>Complex passwords</td>
<td>25 (20.7)</td>
</tr>
<tr>
<td>Data sharing with third parties</td>
<td>17 (14.0)</td>
</tr>
<tr>
<td>Security strategies in case of device loss</td>
<td>17 (14.0)</td>
</tr>
<tr>
<td>Emergency function</td>
<td>8 (6.6)</td>
</tr>
<tr>
<td>Anonymization or pseudonymization</td>
<td>3 (2.5)</td>
</tr>
<tr>
<td>Place of storage</td>
<td>2 (1.7)</td>
</tr>
</tbody>
</table>

\[a\]A more descriptive presentation of the data can be found in Multimedia Appendix 1.

\[b\]Additional feature that has been added to the original list.
Strategies
As shown in Table 2, more than half of all 121 SMAs included the strategies breathing (95/121, 78.5%), relaxation (94/121, 77.7%), mindfulness or gratitude (91/121, 75.2%), information or education (83/121, 68.6%), and tips or advice (70/121, 57.9%).

Table 2. Frequency of the implemented strategies according to the German Mobile Application Rating Scale.a

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Number of apps that include the strategy (N=121), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Breathing</td>
<td>95 (78.5)</td>
</tr>
<tr>
<td>Relaxation</td>
<td>94 (77.7)</td>
</tr>
<tr>
<td>Mindfulness/gratitude</td>
<td>91 (75.2)</td>
</tr>
<tr>
<td>Information, education</td>
<td>83 (68.6)</td>
</tr>
<tr>
<td>Tips, advice</td>
<td>70 (57.9)</td>
</tr>
<tr>
<td>Acceptance</td>
<td>49 (40.5)</td>
</tr>
<tr>
<td>Physical exercises</td>
<td>38 (31.4)</td>
</tr>
<tr>
<td>Gamification</td>
<td>33 (27.3)</td>
</tr>
<tr>
<td>Skills, training</td>
<td>30 (24.8)</td>
</tr>
<tr>
<td>Resource orientation</td>
<td>24 (19.8)</td>
</tr>
<tr>
<td>Goal setting</td>
<td>22 (18.2)</td>
</tr>
<tr>
<td>Serious games</td>
<td>5 (4.1)</td>
</tr>
<tr>
<td>Hypnosis</td>
<td>4 (3.3)</td>
</tr>
<tr>
<td>Exposure</td>
<td>0 (0.0)</td>
</tr>
</tbody>
</table>

aA more descriptive presentation of the data can be found in Multimedia Appendix 2.

Functions
The most included function was monitoring or tracking (78/121, 64.5%), followed by reminder (76/121, 62.8%), data collection (49/121, 40.5%), feedback (48/121, 39.7%), and tailored intervention or real-time feedback (22/121, 18.2%).

Quality Rating
The agreement between raters was good (ICC=0.82, 95% CI 0.81-0.82). The mean overall quality score for the SMAs was 3.59 (SD 0.50; range 2.13-4.37), indicating acceptable to good quality exceeding the cutoff score of 3.5. The mean scores of the different dimensions were as follows: engagement, 3.05 (SD 0.78; range 1.40-4.60); functionality, 4.14 (SD 0.47; range 2.63-5.00); esthetics, 3.76 (SD 0.73; range 1.50-5.00); and information, 3.42 (SD 0.46; range 1.00-4.00). The mean score for subjective quality was 2.53 (SD 0.78; range 1.00-4.00) and that for perceived impact on the user was 2.64 (SD 0.77; range 1.25-4.25). The quality ratings of all SMAs can be found in Multimedia Appendix 3.

Theory-Based Stress Management Strategies
The most common theory-based stress management strategies were meditation or mindfulness (80/121, 66.1%), breathing (61/121, 50.4%), music (31/121, 25.6%), guided imagination or visualization (26/121, 21.5%), accepting reality (25/121, 20.7%), and enhancing professional competencies (21/121, 17.4%). In the 121 SMAs, theory-based stress management strategies were included 355 times. The most implemented strategies were regenerative stress management strategies (on average, each strategy [n=15] was mentioned 17 times and implemented 248 times, ie, 70%), followed by mental stress management strategies (on average, each strategy [n=4] was mentioned 14 times and implemented 57 times, ie, 16%) and instrumental stress management strategies (on average, each strategy [n=4] was mentioned 13 times and implemented 50 times, ie, 14%). Table 3 shows the frequencies of the investigated theory-based stress management strategies.
Table 3. Theory-based stress management strategies according to Kaluza [13] and Christmann et al [31].

<table>
<thead>
<tr>
<th>Regenerative stress management strategy</th>
<th>Number of apps that include the strategy (N=121), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meditation or mindfulness b</td>
<td>80 (66.1)</td>
</tr>
<tr>
<td>Breathing b</td>
<td>61 (50.4)</td>
</tr>
<tr>
<td>Music</td>
<td>31 (25.6)</td>
</tr>
<tr>
<td>Guided imagination or visualization</td>
<td>26 (21.5)</td>
</tr>
<tr>
<td>Sounds</td>
<td>20 (16.5)</td>
</tr>
<tr>
<td>Food and nutrition</td>
<td>8 (6.6)</td>
</tr>
<tr>
<td>Muscle relaxation</td>
<td>7 (5.8)</td>
</tr>
<tr>
<td>Sport b</td>
<td>3 (2.5)</td>
</tr>
<tr>
<td>Techniques for physical stress relief</td>
<td>3 (2.5)</td>
</tr>
<tr>
<td>Autogenic training</td>
<td>3 (2.5)</td>
</tr>
<tr>
<td>Self-massage</td>
<td>2 (1.7)</td>
</tr>
<tr>
<td>Hypnosis or self-hypnosis b</td>
<td>2 (1.7)</td>
</tr>
<tr>
<td>Euthymic methods</td>
<td>1 (0.8)</td>
</tr>
<tr>
<td>Acupressure</td>
<td>1 (0.8)</td>
</tr>
<tr>
<td>Biofeedback</td>
<td>0 (0.0)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Mental stress management strategy</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Accepting reality b</td>
<td>25 (20.7)</td>
</tr>
<tr>
<td>Seeing difficulties as challenges (not as threats)</td>
<td>17 (14.0)</td>
</tr>
<tr>
<td>Self-efficacy</td>
<td>8 (6.6)</td>
</tr>
<tr>
<td>Changing personal stress amplifiers</td>
<td>7 (5.8)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Instrumental stress management strategy</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Enhancing professional competencies</td>
<td>21 (17.4)</td>
</tr>
<tr>
<td>Self-management</td>
<td>18 (14.9)</td>
</tr>
<tr>
<td>Developing social-communicative skills</td>
<td>6 (5.0)</td>
</tr>
<tr>
<td>Seeking support</td>
<td>5 (4.1)</td>
</tr>
</tbody>
</table>

**Evidence Base and Long-Term Availability**

Scientific evaluations could be found in 11 (9.1%) of the 121 apps. Study designs varied and included randomized controlled trials (n=5), a partially randomized trial (n=1), a panel study (n=1), and pilot studies (n=3). One app was tested for its quality, and the results were summarized in a published conference paper (n=1). Target groups were university students (n=5), the general population (n=2), employed individuals (n=1), caregivers (n=1), adults with mild to moderate anxiety or depression (n=1), and nurses (n=1). Different health outcome variables were studied. In the 5 randomized controlled trials, significant group differences at postintervention in favor of the app could be found for the variables stress (n=2), self-efficacy (n=2), mindfulness (n=2), anxiety symptoms (n=4), and depression symptoms (n=4). Details of the evaluations (excluding the pilot studies and the conference paper) can be found in Multimedia Appendix 5 [59-77].

Two years after screening, 46 (38.0%) of the 121 SMAs were no longer available in the 2 app stores. Three apps did not exist anymore in English and were only available in another language (German). Nine apps were only available through other platforms that had less stringent review procedures compared with the official app stores. Among the 75 SMAs that were still accessible, 10 apps now had costs even in the basic version. Of the 121 SMAs, 46 (38.0%) had their last update in 2022 and 11 (9.1%) had not been updated since 2020.

**Characteristics of the 5 Top-Rated SMAs**

The 5 apps with the highest overall MARS-G ratings are presented in Table 4. None of these apps was developed by a public institution (such as a government or university). However, in all apps, it was emphasized that they were developed by
different experts (such as psychologists, psychotherapists, and neuroscientist), or researchers with experience in mindfulness, meditation, or coaching. Furthermore, 3 of these 5 SMAs were part of scientific studies (study design: randomized controlled trial). All apps integrated different forms of psychoeducation and information via text or audio, provided advice, and implemented breathing and mindfulness. Monitoring or tracking and reminders were also included in all apps. Additional theory-based stress management strategies were guided by imagination or visualization and music. All apps were technically guided. Moreover, 3 of the 5 apps were tailored to the users’ needs based on a screening at the beginning or provided real-time feedback. Additionally, 1 SMA included messenger coaching and a contact list with therapists in different US states. Furthermore, 3 of the 5 apps offered an app community. All apps provided a specific login area (including password), privacy policy, and contact information or imprint. Moreover, 2 of the 5 apps offered an emergency function.
Table 4. Overview of the 5 top-rated apps.

<table>
<thead>
<tr>
<th>Variable</th>
<th>App¹</th>
<th>App ²</th>
<th>App ³</th>
<th>App ⁴</th>
<th>App ⁵</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall quality (MARS-G)</td>
<td>4.36</td>
<td>4.22</td>
<td>4.21</td>
<td>4.19</td>
<td>4.16</td>
</tr>
<tr>
<td>Quality dimensions (MARS-G)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Engagement</td>
<td>4.30</td>
<td>4.10</td>
<td>3.80</td>
<td>4.00</td>
<td>4.30</td>
</tr>
<tr>
<td>Functionality</td>
<td>4.63</td>
<td>4.38</td>
<td>3.50</td>
<td>4.75</td>
<td>4.25</td>
</tr>
<tr>
<td>Esthetics</td>
<td>4.50</td>
<td>4.83</td>
<td>4.83</td>
<td>4.17</td>
<td>4.50</td>
</tr>
<tr>
<td>Information</td>
<td>4.00</td>
<td>3.57</td>
<td>3.71</td>
<td>3.86</td>
<td>3.57</td>
</tr>
<tr>
<td>Technical aspects (MARS-G)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Privacy and security features</td>
<td>10</td>
<td>10</td>
<td>8</td>
<td>10</td>
<td>8</td>
</tr>
<tr>
<td>Technical guidance</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Tailored interventions, real</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>time feedback</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>App community</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Strategies (MARS-G)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Information, education</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
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</tr>
<tr>
<td>Tips, advice</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Breathing</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Mindfulness, gratitude</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Relaxation</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Acceptance</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Functions (MARS-G)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monitoring, tracking</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Reminder</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Data collection</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Automated feedback</td>
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<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Theory-based stress management</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>strategies</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Guided imagination, visualization (RSMS)¹</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Music (RSMS)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Evidence base</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Long-term availability          |      |       |       |       |       |
| App still available after 2     | ✓    | ✓     | ✓     | ✓     | ✓     |
| years                           |      |       |       |       |       |
| Year of the last update         | 2022 | 2022  | 2022  | 2020  | 2022  |

¹App 1, Happify: bei Ärger und Stress (English translation: Happify: Anger and Stress); App 2, Sanvello: Stress & Anxiety Help; App 3, Headspace: Meditation & Schlaf (English translation: Headspace: Meditation & Sleep); App 4, go4health – gesund leben (English translation: go4health – living healthy); App 5, BamBu: Meditation & Achtsamkeit (English translation: BamBu: Meditation & Mindfulness).

²Name of this app after the second search in August 2022: “Sanvello: Anxiety and Depression.” The app may no longer meet inclusion criterion 2 (“the app was developed for adults in the general population without mental or somatic disorders”). At the time of the screening process in 2020, we listed this app as “Sanvello: Stress & Anxiety Help,” and it met the inclusion criteria.

³MARS-G: German Mobile Application Rating Scale.

⁴With the exception of “privacy and security features,” all general characteristics of the categories “technical aspects,” “strategies,” and “functions” of the MARS-G are listed, which were included in at least three of the top 5 apps.

⁵The number of statements made regarding 19 possible security features is provided.

⁶Strategies that were included in the MARS-G and also in the list of theory-based stress management strategies.
All theory-based stress management strategies (according to Kaluza [13] and Christmann et al [31]) are listed, when they were included in at least two of the top 5 apps. Theory-based stress management strategies that are already listed in the MARS-G strategies are not listed again (breathing [regenerative stress management strategy], relaxation [regenerative stress management strategy], mindfulness [regenerative stress management strategy], and acceptance [mental stress management strategy]).

RSMS: regenerative stress management strategy.

All studies were randomized controlled trials.

App 4 was still available but only in the Google Play Store and was not available anymore in the Apple App Store, where it was found in 2020.

Discussion

Principal Findings
This systematic app search and standardized multidimensional assessment aimed to evaluate the general characteristics, quality, theory-based stress management strategies, evidence base, and long-term availability of SMAs. Furthermore, characteristics that might indicate high quality were derived from the 5 top-rated SMAs.

General Characteristics
Learning and maintaining stress management strategies requires regular engagement for not only changing the stress-enhancing cognitions and emotions, but also changing behavior [14]. Most of the included SMAs support this learning process by providing information on the background of the intervention and thus about stress management, tracking progress, or the use of reminder functions. Especially, the frequent presence of reminder functions was found to be similar in previous reviews [78]. A subgroup analysis of apps for mental health problems showed a moderate effect of reminder functions in reducing stress levels [79]. However, information on background, and tracking and reminder functions have been shown to improve long-term engagement within health apps [80], which might improve effectiveness through more intense and long-term usage. Similar to the results of Lau et al [34], most SMAs in this study were oriented toward self-help as merely 5 SMAs included the possibility to communicate synchronously (1/121, 0.8%) or asynchronously (4/121, 3.3%) with practitioners. This might be subject to change in future app development as a meta-analysis showed that professional guidance within mental health apps could significantly reduce stress levels compared with unguided apps (g=0.57 vs g=0.24) [79].

Support in terms of app communities was implemented in 16.5% (20/121) of the included SMAs. This is a positive trend compared with earlier findings showing only 4% of all included mindfulness-based apps providing this kind of support [78]. Since the availability of a community has beneficial effects on user engagement [80] and social support can positively influence the stress response [81], this seems to be a desirable trend.

Even though chronic stress is a major public health problem [1,9,12], only 3 SMAs were developed by institutions in the public sector (eg, universities or health authorities) and no SMA was officially certified (eg, according to the European Union Medical Device Regulation). This, together with the finding that only 5 SMAs were evaluated in randomized controlled trials, could indicate that thoroughly developed and evaluated apps might not find their way into the most popular app stores.

This study also focused on the declaration of the privacy and safety features within each identified SMA. The high percentage of SMAs providing a privacy policy (111/121, 91.7%) is promising. However, for 63.6% (77/121) of SMAs, no active confirmation of informed consent was required, and for 71.9% (87/121) of SMAs, there was no transparency regarding the right of withdrawal of informed consent. Data sharing with third parties was disclosed in the privacy policies of 17 (14.0%) SMAs. Regarding the actual practice of data security measures, Huckvale et al [40] showed that user data of health apps (depression and smoking cessation) have been shared with third parties, even without the necessary disclosure in the privacy policy. These results might be transferable to other health apps, including SMAs. Since the lack of data security is a common reason for user dissatisfaction with health apps and leads to the app being discontinued [82], improving data security measures may lead to increased engagement.

Quality
The 121 included SMAs showed an acceptable to good overall quality (mean score 3.59, SD 0.50). The scores of the dimensions functionality and esthetics were above the cutoff value of 3.5. The scores of the dimensions engagement (mean 3.05, SD 0.78) and information (mean 3.42, SD 0.46) did not exceed this cutoff score. Overall quality was similar to that of other (mental) health apps, such as mindfulness apps (mean score 3.66, SD 0.48 [37]), physical activity apps (mean score 3.60, SD 0.59 [83]), depression apps (mean score 3.01, SD 0.56 [53]), or apps for posttraumatic stress disorder (mean score 3.36, SD 0.65 [84]). The rating below the cutoff score in the information dimension was also consistent with the findings of previous systematic reviews [33,34,37,83]. One explanation is the limited evidence base of SMAs. Only 9% of the included SMAs were scientifically evaluated. The rating below the cutoff score in the dimension engagement implies that the content and functions of SMAs might currently not be sufficient to bind the users in the long term. Implementation of diverse content or the possibility of personalization could help as these aspects are particularly relevant for the users of mental health apps [82].

Theory-Based Stress Management Strategies
The examination of 3 types of theory-based stress management strategies resulted in 2.9 strategies per app. This is similar to the results in the study by Christmann et al [31], who reported 2.8 stress management strategies per app in their content analysis. Three of the four most implemented strategies are similar to the present results: meditation or mindfulness, breathing, and music (all categorized as regenerative stress management strategies). The results showed that instrumental and mental stress management strategies, which tend to be designed for prevention, are implemented less often than regenerative stress management strategies, which tend to be used for calming down after exposure to stress [13]. Therefore, the increased implementation of instrumental and mental
strategies should be considered for a holistic approach to stress management in SMAs that seem to be relevant for effective prevention and coping with stress [13,15].

Evidence Base and Long-Term Availability
For 11 of the 121 (9.1%) SMAs, a scientific evaluation could be found. Moreover, 5 (4.1%) of the SMAs were evaluated in randomized controlled trials and 1 (0.8%) in a partially randomized controlled trial showing improvement in different outcomes such as stress, self-efficacy, mindfulness, anxiety, and depressive symptoms [59-65]. Previous reviews of mental health apps for other target groups included similar or even fewer efficacy studies [37,53,83-86]. This might be explained by the high rate of updates and the high volatility of apps [34,44,45], which could also be confirmed in this study. Of 163 apps, 13 (8.0%) became unavailable during the app rating period, and only 62.0% (75/121) of all SMAs were still available after 2 years, with most of them (64/75, 85.3%) being updated. This poses a great challenge for not only users and health professionals, but also researchers regarding the use, recommendation, and evaluation of SMAs or other health apps [44]. In addition, the trustworthiness of the information about the content and functions within app descriptions is questionable. In this study, 163 apps were included based on the information in the description. However, 24 (14.7%) apps had to be excluded after downloading because the actual content did not meet the previously described content. This confirms the findings of Coulon et al [33], who found that 33% of SMAs did not contain the content advertised in their descriptions. Potential users must check any eligible app for accuracy after overcoming the hurdles of downloading the app, installing the app, and, if required, registering an account. New evaluation frameworks are needed and do exist, but in a systematic review, it was concluded that none out of 45 evaluation frameworks for medical apps was rated as being fully suitable [87]. A different approach to deal with the fast-moving nature of apps has been proposed by a group of international and diverse stakeholders [88]. They harmonized elements of different frameworks into 5 priority levels (background info, data privacy and security, app effectiveness, user experience and adherence, and data integration) with the aim to enable informed app decision-making rather than to constantly evaluate the apps.

Overview of the Implications of the 5 Top-Rated SMAs
By presenting SMAs with top-rated MARS-G quality together with their characteristics in a comparative overview, a broad information and decision basis can be provided for researchers, health professionals, and users. The 5 top-rated SMAs showed both common characteristics and consistencies with existing evidence. Three of the 11 evidence-based apps were rated in the top 5 SMAs in terms of quality. Furthermore, some strategies, functions, and technical aspects previously shown to be effective in reducing stress or shown to improve engagement were found among the top-rated apps, such as providing psychoeducation [80], including breathing [89] and mindfulness [64], providing monitoring and tracking [80], using reminders [79], tailoring the content to the users’ needs [90,91], and providing technical guidance and a privacy policy [82]. Across all SMAs and within the 5 top-rated SMAs, there were some aspects not covered by the MARS-G (eg, theory-based stress management strategies such as guided imagination, visualization, or music). This demonstrates the value of the overview of the top-rated SMAs (eg, compared with simple app rankings), in particular when special weight is given to certain aspects or app characteristics. In addition, the joint presentation of MARS-G content and additional uncovered aspects reveals certain revision potentials of the MARS-G.

Limitations
There were some limitations. First, owing to the rapid development of the app market and the short lifespan of apps, the content and quality of the reviewed SMAs may have already changed, some SMAs may no longer be available, or new SMAs may have been launched. However, this seems to be a challenge in general for health technology evaluation [44,87], and a screenshot of the current status might help to derive implications for improving SMA quality and effectiveness, and improving the evaluation frameworks for apps in the future. Second, the search results per search term were limited to 200 results and screening was based on the titles and descriptions of the apps. It is possible that apps that met the inclusion criteria were overlooked because relevant information was not provided or the word “stress” was not present in the titles or descriptions. Furthermore, only SMAs that were free of cost or provided a free basic version were evaluated. Further evaluation of paid (full version) SMAs could show whether there is a difference in quality, declaration of data privacy and security features, or access to professional support. Third, there was only a descriptive evaluation (not a technical evaluation; eg, for data privacy issues), and no conclusions about the overall effectiveness of the included SMAs could be drawn. Fourth, the number of SMAs including “breathing” as a strategy differed in the MARS rating and in the assessment of theory-based stress management strategies. Therefore, it should be emphasized that the discriminant differentiation of the related and partially overlapping concepts or strategies of “mindfulness” and “breathing” cannot be assessed conclusively (especially considering that “breathing” can also be practiced as a concrete strategy within the context of mindfulness). However, the fact that “breathing” and “mindfulness” were listed in the top 3 strategies remains unchanged. Finally, the review and evaluation of each app took an average of 30 minutes. It is possible that specific content could not be discovered owing to the limited amount of time spent evaluating each app.

Conclusion
In this comprehensive review including a systematic search and a standardized multidimensional assessment, the overall quality of 121 SMAs was rated as acceptable to good, with a rating below the cutoff score in the dimensions of information quality and engagement. The top-rated apps included psychoeducation, breathing and mindfulness, monitoring, reminder functions, tailoring, technical guidance, and a privacy policy. However, even though most SMAs provided a privacy policy, there is still a need for better personal data protection and transparency of data processing, such as the use of a password or information about data sharing with third parties. Theory-based strategies were mostly regenerative stress management strategies. For a
holistic stress management approach, SMAs could benefit from the integration of more mental and instrumental stress management strategies. The evidence base for 11 (9.1%) of the 121 included apps showed that SMAs can reduce stress and improve further outcome variables such as self-efficacy, mindfulness, anxiety, and depressive symptoms. Moreover, SMAs have high scalability. Therefore, they have a high potential to reach and help a broad audience coping with increasing stress and demands in their work and daily living. However, the rather moderate information quality, the scarce evidence base of the included SMAs, and the fact that many SMAs changed or were unavailable after a 2-year period pose challenges for users and health professionals who are searching for high-quality apps that are effective and for long-term use. The common characteristics of SMAs with top-rated quality and evidence base of SMAs can be used as guidance for this search or even for SMA development. In addition, it is difficult for researchers to keep up to date with the latest research in this volatile field and provide potential users with helpful information. Enhanced evaluation frameworks are needed that might complement or even advance the idea of a continuous effectiveness and quality assessment to an approach that enables informed decision-making.

Acknowledgments

We want to thank Hannah Besel and Joshua Kannapin for assisting in the project. The study was self-funded (University of Freiburg). The article processing charge was partly funded by the Open Access Publication Fund of the University of Freiburg.

Data Availability

Data will be made available to researchers who provide a methodologically sound proposal, not already covered by other researchers. All requests should be directed to the corresponding author. Data requestors will need to sign a data access agreement. Provision of data is subject to data security regulations. Support depends on available resources.

Authors' Contributions

SP, EM, EMM, and HB designed the trial and initiated this study. SP, EM, RW, and VH conducted the German Mobile Application Rating Scale (MARS-G) ratings. SP supervised all MARS-G ratings. YT and DS conducted the statistical analyses. JS was involved as an expert in the field of stress research. MW was involved in the conceptualization and drafting of the manuscript and in the second assessment as part of an update in August 2022. SP wrote the first draft. All authors revised the manuscript, and read and approved the final report.

Conflicts of Interest

HB and EMM received payments for talks and workshops in the context of e-mental health. All other authors declare that they have no competing interests.

Multimedia Appendix 1

Frequency of declared data privacy and security features based on the German Mobile Application Rating Scale presented as a bar graph. The asterisk (*) indicates additional features that have been added to the original list.

[ PNG File, 22 KB - mhealth_v11i1e42415_app1.png ]

Multimedia Appendix 2

Frequency of the implemented strategies according to the German Mobile Application Rating Scale presented as a bar graph.

[ PNG File, 14 KB - mhealth_v11i1e42415_app2.png ]

Multimedia Appendix 3

Quality ratings of all included stress management apps.

[ PDF File (Adobe PDF File), 183 KB - mhealth_v11i1e42415_app3.pdf ]

Multimedia Appendix 4

Theory-based stress management strategies according to Kaluza [13] and Christmann et al [31] presented as a bar graph. Regenerative stress management strategies (RSMSs) are indicated with black, mental stress management strategies (MSMSs) are indicated with vertical lines, and instrumental stress management strategies (ISMSs) are indicated with horizontal lines. The asterisk (*) indicates theory-based stress management strategies that are also included in the German Mobile Application Rating Scale.

[ PNG File, 48 KB - mhealth_v11i1e42415_app4.png ]

Multimedia Appendix 5
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Abbreviations

ICC: interclass correlation
MARS: Mobile Application Rating Scale
MARS-G: German Mobile Application Rating Scale
SMA: stress management app
Stress Management Apps: Systematic Search and Multidimensional Assessment of Quality and Characteristics


JMIR Mhealth Uhealth 2023;11:e42415

URL: https://mhealth.jmir.org/2023/1/e42415
doi:10.2196/42415
PMID:

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Usage and Daily Attrition of a Smartphone-Based Health Behavior Intervention: Randomized Controlled Trial

Erlendur Egilsson¹, CandPsych; Ragnar Bjarnason²,³, MD, PhD; Urdur Njardvik¹, PhD

¹Department of Psychology, University of Iceland, Reykjavik, Iceland
²Department of Pediatrics, University of Iceland, Reykjavik, Iceland
³Faculty of Medicine, University of Iceland, Reykjavik, Iceland

Corresponding Author:
Erlendur Egilsson, CandPsych
Department of Psychology
University of Iceland
Saemundargata 12
Reykjavik, 102
Iceland
Phone: 354 5254240
Fax: 354 5255802
Email: erlendu@hi.is

Abstract

Background: Although most adolescents have access to smartphones, few of them use mobile health (mHealth) apps for health improvement, highlighting the apparent lack of interest in mHealth apps among adolescents. Adolescent mHealth interventions have been burdened with high attrition rates. Research on these interventions among adolescents has frequently lacked detailed time-related attrition data alongside analysis of attrition reasons through usage.

Objective: The objective was to obtain daily attrition rates among adolescents in an mHealth intervention to gain a deeper understanding of attrition patterns, including the role of motivational support, such as altruistic rewards, through analysis of app usage data.

Methods: A randomized controlled trial was conducted with 304 adolescent participants (152 boys and 152 girls) aged 13-15 years. Based on 3 participating schools, participants were randomly assigned to control, treatment as usual (TAU), and intervention groups. Measures were obtained at baseline, continuously throughout the 42-day trial period (research groups), and at the trial end. The mHealth app is called SidekickHealth and is a social health game with the following 3 main categories: nutrition, mental health, and physical health. Primary measures were attrition based on time from launch, and the type, frequency, and time of health behavior exercise usage. Outcome differences were obtained through comparison tests, while regression models and survival analyses were used for attrition measures.

Results: Attrition differed significantly between the intervention and TAU groups (44.4% vs 94.3%; $\chi^2 = 61.220; P < .001$). The mean usage duration was 6.286 days in the TAU group and 24.975 days in the intervention group. In the intervention group, male participants were active significantly longer than female participants (29.155 vs 20.433 days; $\chi^2 = 6.574; P < .001$). Participants in the intervention group completed a larger number of health exercises in all trial weeks, and a significant decrease in usage was observed from the first to second week in the TAU group ($t_{105} = 9.208; P < .001$) but not in the intervention group. There was a significant increase in health exercises in the intervention group from the fifth to sixth week ($t_{105} = 3.446; P < .001$). Such a significant increase in usage was not evident in the TAU group. The research group was significantly related to attrition time (hazard ratio 0.308, 95% CI 0.222-0.420), as well as the numbers of mental health exercises ($P < .001$) and nutrition exercises ($P < .001$).

Conclusions: Differences in attrition rates and usage between groups of adolescents were identified. Motivational support is a significant factor for lowering attrition in adolescent mHealth interventions. The results point to sensitivity periods in the completion of diverse health tasks, and emphasis on time-specific attrition, along with the type, frequency, and time of health behavior exercise usage, is likely a fruitful avenue for further research on mHealth interventions for adolescent populations, in which attrition rates remain excessive.

Trial Registration: ClinicalTrials.gov NCT05912439; https://clinicaltrials.gov/study/NCT05912439
Introduction

Throughout the past decade, ownership and access to smartphones and mobile devices have grown profoundly among adolescents and youth worldwide [1,2]. The growth has been such that smartphone ownership or access among US adolescents was 95% 4 years ago and had increased by 23% in the 4 years prior [1,2]. A similar development was observed in the majority of developed economies where adolescent smartphone access and ownership is above the 90th percentile [2]. Smartphones are so widely distributed and used that approximately 45% of adolescents spend nearly all waking hours online [3]. However, modest projections of daily usage indicate that many spend way less time online each day, though it is usually more than 4 hours [4-6].

Widespread smartphone usage in adolescent and youth populations has been extensively covered, but a more positive side to mobile usage is that a significant proportion of adolescents seek health information and clinical help online through their mobile devices, providing ample opportunities to reach at-risk adolescents with science-based methods focusing on health improvement [7-9]. Health problems (ie, mental health and lifestyle diseases) disproportionately burden lower socioeconomic status groups as well as diverse minority groups, and smartphones could become a vital tool for eliminating such disparities since smartphone access and ownership are not related to socioeconomic status, gender, or race in diverse economies [2,10,11]. The mobile health (mHealth) market is steadily becoming saturated with apps, and the yearly increase in the number of apps available has skyrocketed in recent years, with an estimated 350,000 mHealth apps currently on the market [12]. However, only 8% of adolescents seem to use health apps to improve their health, highlighting the apparent gap between easy access, extensive daily usage, and lack of interest in mHealth apps among adolescents [13].

Lack of physical activity has been labeled a global pandemic and has been reported as the fourth leading global cause of death [14]. Physical inactivity increases the risk of lifestyle diseases, such as heart disease, type 2 diabetes, and cancer, resulting in over 5 million annual global deaths [15]. Further, the estimated annual financial burden of physical inactivity is nearly USD 54 billion in health care costs around the world [16]. There seems to be a drop in physical activity in adolescence, and a large number of adolescents are under the recommended physical activity levels provided by the World Health Organization (WHO) [17-19]. Lack of sufficient physical activity tends to continue into adulthood, and research suggests that the majority of adolescents in the European Union do not even reach 30% of the recommended daily physical activity [19-21]. Further, adolescents seem to have the unhealthiest diet of all age groups, and they are particularly susceptible to weight gain [22]. Research has repeatedly revealed a significant relationship between nutritional behavior and physical activity in terms of weight management [23]. A tremendous increase in global adolescent obesity has been witnessed in the past decades, and the prevalence, for instance, has tripled since 1975 [24]. Cost-effective interventions to increase physical activity and improve nutritional behaviors in adolescent populations are therefore urgently needed.

Physical inactivity and inadequate nutritional habits are often interrelated to disabling emotional problems, and integrated strategies should include all 3 pillars to improve physical as well as mental well-being in adolescent populations. mHealth interventions targeting disabling emotional problems in adolescent populations have revealed encouraging outcomes, despite the fact that attrition rates in these interventions are generally high [11,25-30]. Varying definitions of attrition have complicated research on this topic, but attrition is defined as leaving treatment before obtaining a required level of improvement or completing intervention goals [31-33]. Research on mental mHealth interventions among adolescents has frequently lacked detailed time-related attrition data alongside accurate definitions and analysis of attrition reasons, though recent studies show promise in that regard [11,30,34]. Attrition is regularly reported at 2 distinct points of time, that is, intervention start and intervention end. A continuous measure of usage versus nonusage in mHealth interventions for adolescents while simultaneously obtaining detailed usage data to prevent or delay exact times of attrition in future interventions, would perhaps be an improved representation of attrition [35].

Increased knowledge on the actual attrition factors and patterns associated with mHealth interventions in adolescent populations is urgently needed. Obtaining a better understanding of how motivational support motivates adolescents to use mHealth apps and why adolescents maintain or lose interest in using these apps to improve their health is of vital importance. Motivational support in mHealth interventions, defined as strategies to enhance motivation and counterattrition to overcome behavior change barriers, often includes goal-setting, feedback, social support, and rewards [36,37]. Systematic reviews examining possible drivers behind usage point to group and task customization, localization, functional user support, gamification of health tasks, and immediate visual but simplified feedback on user action, while gender-related motivational support features could be contributing factors [36-38]. The timing of tailored motivational support, through just-in-time adaptive interventions, should be considered as well when implementing adolescent mHealth interventions, since time-based individualization could counter high attrition rates [35,39]. Given the magnitude of reported health problems among adolescents and lack of cost-effective health behavior interventions specifically developed for adolescent populations, the need for a better understanding of attrition reasons in adolescent mHealth interventions is large. The study aimed to (1) seek a richer understanding of continuous attrition rates for...
an mHealth intervention in an adolescent population and the effects of motivational support have on attrition rates, and (2) examine the effectiveness of the intervention with the aim to increase daily mental, nutritional, and physical health behaviors.

Methods

Participants
The study included 304 individuals (152 girls and 152 boys) aged 13 to 15 years attending 1 of 3 public schools for children and adolescents in the greater capital area of Iceland. The mean age at baseline measurement was 13.70 (SD 0.83) years. All children attending the highest 3 classes (8th to 10th classes) in the 3 participating public elementary schools in Iceland were eligible to participate (n=661; male-to-female ratio of 313:348). All children in public schools in the municipality are equipped with an iPad from 10 years of age. The exclusion criterion was the diagnosis of a severe disorder of intellectual development or a physical, developmental, or mental illness significantly restricting the ability to use mobile apps. No participant was excluded from the study based on this exclusion criterion. Research specifications and an introduction to the app were sent via email to the parents and legal caretakers of all eligible participants through school officials, along with a confirmative survey link. If the link was answered, it provided confirmation for informed consent. Adolescents with informed consent from parents or legal caretakers were invited to take part in the study through a confirmative survey link.

Ethics Approval
The study was approved by the National Bioethics Committee of Iceland (license number: VSNb2015060065/03-01).

Measurements
The amount, time, and frequency of daily health activities measured through completion of in-app exercises, quality of sleep and energy levels, self-reported stress levels, and gratitude levels were primary outcome measures. The Cronbach $\alpha$ for the current sample was .920 for all self-reported health tasks within the app.

Anxiety and depressive symptoms were assessed using the Revised Children’s Anxiety and Depression Scale (RCADS), a self-report assessment tool for children and youth. The scale involves a 4-point Likert scale, spans 47 questions, and is divided into 6 subscales (separation anxiety symptoms, general anxiety symptoms, obsessive-compulsion symptoms, social anxiety symptoms, panic symptoms, and depression symptoms). A T-score over 65 marks the clinical cutoff point. The inventory’s psychometrics have been studied with acceptable findings in both US and Icelandic pediatric populations [40,41]. The Cronbach $\alpha$ for the current sample was .958.

The General Self-Efficacy Scale (GSE), a 10-item self-report questionnaire with the total score ranging from 10 to 40, was used to measure self-efficacy levels, with a higher score indicating higher self-efficacy [42]. Acceptable psychometric properties for the questionnaire have been obtained, and it has been used globally in youth populations [43]. The Cronbach $\alpha$ for the current sample was .937.

The BEARS sleep screening algorithm was used to evaluate participants’ sleep problems. It is a sleep screening instrument for children from 2 to 18 years old, and is divided into 5 sleep domains (bedtime problems, excessive daytime sleepiness, awakenings during night, regularity and duration of sleep, and snoring) [44]. The algorithm’s psychometrics have been studied with acceptable findings in pediatric populations [45]. The Cronbach $\alpha$ for the current sample was .769.

mHealth App
The app is called SidekickHealth and has been described in the research group’s previous work [35]. SidekickHealth was initially developed through multiple focus group studies among both Icelandic elementary school students and adolescents in the obesity clinic at the Landspitali University Hospital in Iceland to incorporate the target groups’ needs and opinions. Based on results from focus group studies and design advisors, the app took the form of a social health game (Figure 1). Functionality of the app evolves around motivational support to help the user set goals and complete health tasks (gamification of tasks) in the following 3 main categories: food and drink (eg, vegetable and water intake, consumption of fruits, and avoiding sugary soda or energy drinks), physical activity (eg, body weight exercises, logged minutes of sports activity, GPS-based biking, walking, and running), and mental health exercises (eg, reducing stress, exercising gratitude, and improving sleep habits). By completing health tasks that are labeled missions and participating in friendly competitions with peers, users earn points (called “kicks”) and badges providing altruistic rewards (eg, liters of water for children in need or polio vaccines that are sent in their name to children in need through UNICEF). A visual representation of the user’s performance is provided in different categories. Keeping the app fun, entertaining, and easy to use is of integral importance and was a strong focus point throughout the developmental phases (Multimedia Appendix 1). The smartphone app operates on the Android and iOS platforms. The app’s function focuses on education and simple health behavior changes through the benefits of increased physical activity and mental health exercises, as well as a healthy diet, portion sizing, and appetite awareness training. Appetite awareness training is a behavior modification tool that has, for instance, been used in obesity treatment and encourages overweight/obese children and youth to consume food and drink in response to internal appetite cues. It has shown promise for the treatment of overweight and obese children and teenagers, and has been visually developed as an individual mission in the app’s nutrition category [46,47]. Participants in the intervention arm were randomly assigned to groups consisting of 8 individuals that collectively and individually competed in point collection through completion of in-app health tasks. In the beginning of each of the trial’s 6 weeks, the intervention group received in-app messages where a new weekly competition (both individual and group levels) with altruistic rewards was introduced. In weeks 2 to 6, altruistic rewards for the past week’s efforts were also handed out. Winners of competitions received confirmation that UNICEF had sent polio vaccines to children in need. Further, through completion of in-app health exercises, participants collected liters of water that were sent in their name to children in need through UNICEF. The total cost for the
altruistic rewards, paid for by the first author, throughout the treatment period was roughly US $68 (56 US cents per participant).

**Figure 1.** Overview of app functions and categories.

### Procedure

This study was a randomized controlled study. Group randomization was used to divide the 3 participating schools into control, treatment as usual (TAU), and intervention groups. Measures were obtained at baseline and 42 days later. Participants in both the TAU and intervention groups received an approximately 10-minute-long introduction regarding the study specifications and the app. The control group received no further contact, access to the app, or information until study-end questionnaire measures. Participants in the intervention group were randomly assigned to teams consisting of 8 individuals that collectively and individually competed in point collection through completion of in-app health tasks. Participation in the TAU and intervention groups was defined as downloading the SidekickHealth app and completing at least 3 health exercises within it. Exercise time was defined as the timestamp on completion of the exercise within any of the 3 types of exercise categories (physical activity, nutrition, and mental health) in the app. Exercise frequency referred to how often a given exercise was completed by a participant. Attrition time was defined as the timestamp of the last completed health exercise within the SidekickHealth app throughout the intervention period. The procedural difference between the TAU and intervention groups is related to motivational support. The intervention group received motivational support in the form of weekly individual and group feedback on usage, participation in friendly health task competitions, and weekly altruistic rewards for usage. Participants in the TAU group used the app individually throughout the trial period without any motivational support. A flowchart of participation is displayed in Multimedia Appendix 2.

### Statistical Analysis

The descriptive characteristics of participants along with attrition reasons are reported. Pearson correlation coefficients, independent samples t-tests, repeated measures ANOVA with adjusted alpha levels, and $\chi^2$ tests were used to measure mean differences in primary and secondary outcome measures from baseline to the trial end within and between research groups. Kaplan-Meier survival analysis plots and log-rank tests were used to assess the attrition time and possible significant differences between and within research groups [48,49]. The trial start was defined as the time of the first in-app health exercise completion, and the trial period was 6 weeks (42 days) from that moment. Attrition, or the event, was defined as the time of the participant’s last completed health exercise in the SidekickHealth app. Participant cases were evaluated as
censored when the app was still being used 42 days after the study start. Cox proportional hazard regression models with interacting covariates using research groups as clusters were used to examine attrition prediction based on usage of in-app health exercises for the time, type, and frequency of exercises, as well as sociodemographic variables (age and gender) [50]. Significance was defined as a P value <.05. Data were analyzed using IBM SPSS Statistics, Release Version 29 (IBM Corp).

**Results**

Among all invited participants with parental or caretaker consent to participate (N=451), 304 (67.41%) individuals took part in the study. Participants who did not answer questionnaires at the study end were excluded. Participant characteristics are presented in Table 1. Logged data revealed broad differences in app usage among participants as shown in Figure 2. There was a significant difference in the mean number of health exercises completed by participants, where individuals in the intervention group (mean 120.869, SD 32.434) completed on average roughly 6 times as many exercises as individuals in the TAU group (mean 18.341, SD 31.802) over the study period (t1211=-3.00; P<.001). When logged health exercises on the first day of the study period were examined, the results showed that the difference between the intervention group (mean 16.835, SD 21.820) and TAU group (mean 8.100, SD 7.237) was less extensive but still significant (t1211=-2.12; P=.04).

Forms of attrition over the 42-day study period are shown in Figure 3. Significant differences in completion rates were evident in log-rank tests between the intervention group and TAU group (χ²1=61.220; P<.001). Among participants in the TAU group, the mean survival time was 6.286 days (95% CI 4.304-8.277), while among participants in the intervention group, the mean survival time was 24.975 days (95% CI 21.452-28.518). Log-rank tests revealed significant differences in completion rates between male and female participants in the intervention group (χ²1=6.574; P<.001). In the intervention group, the mean survival time among male participants was 29.155 days (95% CI 24.519-33.812) and among female participants was 20.433 days (95% CI 15.301-25.558). Such differences were not evident in log-rank tests in the TAU group (χ²1=1.570; P=.21). Figure 4 presents Kaplan-Meier plots for gender-based attrition in the TAU and intervention groups.

There was a significant difference between groups in the average number of in-app health exercises in all weeks (Table 2). There was a significant mean drop (mean 12.347, SD 13.803) in usage in the TAU group from the first week to the second week (t105=-9.208; P<.001). Even though there was a drop in usage in the intervention group between the first and second weeks of the trial (mean 6.798, SD 37.481), the difference was not significant (t105=1.959; P=.06). There was however a significant increase (mean 22.904, SD 71.721) in the average individual in-app health exercises completed by the intervention group from the fifth week to the sixth and last week of the trial (t105=3.446; P<.001). Such a significant increase in usage was not evident in the TAU group.

No significant gender differences were found in the average weekly in-app exercise frequency within research groups (Table 3).

When exercise time was compared with the exercise category, the results revealed significant differences within both the intervention group (χ²6=2162.559; P<.001) and the TAU group (χ²6=69.372; P<.001). Differences in usage based on exercise time and exercise type are presented in Table 4 and Figure 5.

Results from the Cox proportional hazard regression models are shown in Multimedia Appendix 3. The research group that participants were assigned to (hazard ratio 0.308, 95% CI 0.222-0.420) was significantly related to attrition (P<.001), as well as the numbers of mental health exercises (P<.001) and nutrition exercises (P<.001) completed in the app by participants in both research groups. Participants in the TAU group (hazard ratio 0.387, 95% CI 0.201-0.748) who completed an in-app health exercise between day 2 and day 6 of the trial were found to be significantly more likely to finish (P=.03). Such significant differences were not found in the intervention group. Further, the numbers of health exercises completed in the app in the first week (P<.001), second week (P<.001), and last week (P<.001) of the trial were significantly related to survival rates in the TAU group. Similar significant differences were not evident in the intervention group. All types of health exercises completed in the app were also significantly related to attrition in the TAU group, although such differences were not found among intervention group members. Anxiety, depression, and self-efficacy measures between research groups are shown in Multimedia Appendix 4.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Control group (n=81)</th>
<th>TAUa group (n=106)</th>
<th>Intervention group (n=117)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years), mean (SD)</td>
<td>13.72 (0.45)</td>
<td>13.14 (0.51)</td>
<td>13.50 (0.63)</td>
</tr>
<tr>
<td>Male:female ratio</td>
<td>34:47</td>
<td>57:49</td>
<td>61:56</td>
</tr>
<tr>
<td>Disabling sleep problems, n (%)</td>
<td>32 (39.5)</td>
<td>23 (21.7)</td>
<td>38 (32.5)</td>
</tr>
<tr>
<td>Clinical anxiety symptoms, n (%)</td>
<td>18 (22.2)</td>
<td>10 (9.4)</td>
<td>14 (12.0)</td>
</tr>
<tr>
<td>Clinical depression symptoms, n (%)</td>
<td>12 (14.8)</td>
<td>7 (6.6)</td>
<td>7 (6.0)</td>
</tr>
<tr>
<td>General self-efficacy score, mean (SD)</td>
<td>17.90 (5.89)</td>
<td>16.17 (5.71)</td>
<td>18.14 (5.04)</td>
</tr>
</tbody>
</table>

aTAU: treatment as usual.
Figure 2. Mean weekly in-app exercises. TAU: treatment as usual.

Figure 3. Forms of attrition. TAU: treatment as usual.

Figure 4. Gender-based attrition in the TAU and intervention groups. TAU: treatment as usual.
Table 2. Weekly comparison of usage and attrition.

<table>
<thead>
<tr>
<th>Week</th>
<th>In-app health exercises completed, n</th>
<th>TAU&lt;sup&gt;a&lt;/sup&gt; group usage, mean (SD)</th>
<th>Intervention group usage, mean (SD)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Overall</td>
<td>Male</td>
<td>Female</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>5369</td>
<td>3531</td>
<td>1838</td>
<td>14.20 (17.34)</td>
</tr>
<tr>
<td>2</td>
<td>3265</td>
<td>2514</td>
<td>751</td>
<td>1.85 (8.71)</td>
</tr>
<tr>
<td>3</td>
<td>1016</td>
<td>548</td>
<td>468</td>
<td>0.84 (5.38)</td>
</tr>
<tr>
<td>4</td>
<td>1192</td>
<td>803</td>
<td>389</td>
<td>0.24 (1.28)</td>
</tr>
<tr>
<td>5</td>
<td>1223</td>
<td>891</td>
<td>332</td>
<td>0.00 (0.00)</td>
</tr>
<tr>
<td>6</td>
<td>4029</td>
<td>2889</td>
<td>1140</td>
<td>1.20 (6.99)</td>
</tr>
<tr>
<td>Overall</td>
<td>16,094</td>
<td>11,176</td>
<td>4918</td>
<td>18.32 (27.44)</td>
</tr>
</tbody>
</table>

<sup>a</sup>TAU: treatment as usual.

Table 3. Weekly average in-app health exercise frequency by gender.

<table>
<thead>
<tr>
<th>Week and group</th>
<th>Male, mean (SD)</th>
<th>Female, mean (SD)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Week 1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TAU&lt;sup&gt;a&lt;/sup&gt;</td>
<td>16.19 (19.36)</td>
<td>11.88 (14.50)</td>
<td>.20</td>
</tr>
<tr>
<td>Intervention</td>
<td>42.75 (97.75)</td>
<td>22.43 (20.12)</td>
<td>.13</td>
</tr>
<tr>
<td>Week 2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TAU</td>
<td>3.02 (11.71)</td>
<td>0.49 (1.56)</td>
<td>.14</td>
</tr>
<tr>
<td>Intervention</td>
<td>38.89 (72.64)</td>
<td>12.98 (23.79)</td>
<td>.13</td>
</tr>
<tr>
<td>Week 3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TAU</td>
<td>0.07 (0.42)</td>
<td>1.73 (7.84)</td>
<td>.11</td>
</tr>
<tr>
<td>Intervention</td>
<td>8.92 (22.29)</td>
<td>6.84 (30.99)</td>
<td>.68</td>
</tr>
<tr>
<td>Week 4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TAU</td>
<td>0.37 (1.70)</td>
<td>0.08 (0.45)</td>
<td>.25</td>
</tr>
<tr>
<td>Intervention</td>
<td>12.84 (30.06)</td>
<td>6.88 (26.09)</td>
<td>.35</td>
</tr>
<tr>
<td>Week 5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TAU</td>
<td>0.00 (0.00)</td>
<td>0.00 (0.00)</td>
<td>N/A&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Intervention</td>
<td>14.61 (62.43)</td>
<td>5.93 (12.73)</td>
<td>.44</td>
</tr>
<tr>
<td>Week 6</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TAU</td>
<td>1.02 (4.66)</td>
<td>1.41 (9.02)</td>
<td>.78</td>
</tr>
<tr>
<td>Intervention</td>
<td>46.41 (77.42)</td>
<td>19.13 (43.32)</td>
<td>.19</td>
</tr>
<tr>
<td>All weeks</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TAU</td>
<td>20.67 (33.60)</td>
<td>15.59 (17.85)</td>
<td>.35</td>
</tr>
<tr>
<td>Intervention</td>
<td>163.90 (271.22)</td>
<td>74.18 (109.50)</td>
<td>.08</td>
</tr>
</tbody>
</table>

<sup>a</sup>TAU: treatment as usual.
<sup>b</sup>N/A: not applicable.
Table 4. Frequency of exercise categories at different daily times.

<table>
<thead>
<tr>
<th>Group and exercise category</th>
<th>Midnight to 6 AM, n (%)</th>
<th>6 AM to noon, n (%)</th>
<th>Noon to 6 PM, n (%)</th>
<th>6 PM to midnight, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>TAU(^a) group</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Physical health</td>
<td>32 (100)</td>
<td>644 (100)</td>
<td>833 (100)</td>
<td>435 (100)</td>
</tr>
<tr>
<td>Mental health</td>
<td>1 (3.1)</td>
<td>116 (18.0)</td>
<td>210 (25.2)</td>
<td>119 (27.4)</td>
</tr>
<tr>
<td>Nutrition</td>
<td>12 (37.5)</td>
<td>329 (51.1)</td>
<td>294 (35.3)</td>
<td>130 (29.9)</td>
</tr>
<tr>
<td><strong>Intervention group</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Physical health</td>
<td>2575 (100)</td>
<td>3446 (100)</td>
<td>5113 (100)</td>
<td>3008 (100)</td>
</tr>
<tr>
<td>Mental health</td>
<td>2407 (93.5)</td>
<td>1275 (37.0)</td>
<td>2970 (58.1)</td>
<td>1576 (52.4)</td>
</tr>
<tr>
<td>Nutrition</td>
<td>90 (3.5)</td>
<td>1248 (36.2)</td>
<td>912 (17.8)</td>
<td>599 (19.9)</td>
</tr>
<tr>
<td><strong>Overall</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Physical health</td>
<td>2607 (100)</td>
<td>4090 (100)</td>
<td>5946 (100)</td>
<td>3443 (100)</td>
</tr>
<tr>
<td>Mental health</td>
<td>2408 (92.4)</td>
<td>1391 (34.0)</td>
<td>3180 (53.5)</td>
<td>1695 (49.2)</td>
</tr>
<tr>
<td>Nutrition</td>
<td>102 (3.9)</td>
<td>1577 (38.6)</td>
<td>1206 (20.3)</td>
<td>729 (21.2)</td>
</tr>
<tr>
<td><strong>Overall</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Physical health</td>
<td>97 (3.7)</td>
<td>1122 (27.4)</td>
<td>1560 (26.2)</td>
<td>1019 (29.6)</td>
</tr>
</tbody>
</table>

\(^a\)TAU: treatment as usual.

Figure 5. Time-based exercise categories in the TAU and intervention groups. TAU: treatment as usual.

**Discussion**

The focus of this study was on time-specific attrition in an adolescent mHealth intervention. We hoped to build on previous work while focusing on the type, frequency, and time of usage in order to better understand why adolescent attrition from mHealth interventions is generally as excessive as it is, with a market saturated with roughly 350,000 mHealth apps adolescents seem reluctant to engage in [12,35]. The results showed that research groups are related to time of attrition (hazard ratio 0.308, 95% CI 0.222-0.420), and attrition differed between the TAU group (94.3%) and intervention group (44.4%). Attrition was somewhat higher than in our previous study, where attrition was in the 35th percentile. The difference in attrition rates between research groups was however vast, and the only distinction in program setup was motivational support in the form of weekly feedback on individual progress through the app, friendly health task competitions at the individual and group levels, and small altruistic rewards for completion of health tasks or active participation in competitions. The app was the same, but support through program setup differed. It is interesting that the altruistic reward cost per participant was only 56 US cents but still seemed to contribute strongly to increased usage and participation.

Completion rates differed greatly between research groups as did days of active usage since the number of usage days in the intervention group was nearly 25 (95% CI 21.452-28.518) and that in the TAU group was approximately 6 (95% CI 4.304-8.277). Differences in completion rates were therefore evident between the intervention group (55.6%) and TAU group (5.7%), and gender differences in completion rates were also observed in the intervention group but not in the TAU group. Male participants (95% CI 24.519-33.812) completed in-app health tasks longer than female participants (95% CI 15.301-25.558). This gender difference was not evident in our prior research but has been observed in adult populations and should be examined in future research hoping to explain attrition factors in adolescent mHealth interventions [38]. A deeper gender-based exploration into motivational support could be a promising avenue for further research on the matter, particularly how altruistic rewards and competitive intervention features facilitate motivational support between genders.
Broad differences in the completion of health exercises were evident between groups since the intervention group completed on average roughly 6 times as many health exercises as the TAU group throughout the trial period. It is somewhat interesting that this difference was only 2-fold on the first day of the trial, suggesting that participants in the TAU group did not lack usage motivation at the beginning of the trial but were simply not supported to keep on using the app. This was more evident when average weekly health exercise frequency was examined since there was a decrease in usage between the first and second weeks among participants in the TAU group, while such a difference was not evident among participants in the intervention group. In fact, intervention group members completed on average more health exercises in all 6 weeks of the trial than their peers in the TAU group. An interesting finding is that usage increased from the fifth week of the trial to the last one among intervention group members but not among TAU group members, which is thought to be related to motivational support features as well as the altruistic reward setup at the end of the trial’s sixth week, and warrants further research.

There seemed to be different daily sensitivity periods for increased frequency of health task completion in different health categories. Adolescents in both research groups completed most of the physical activity exercises within the app from noon to 6 PM. The same applied to nutrition exercises in both groups. However, when it came to the frequency of mental health exercises, adolescents in both groups tended to do them from 6 AM to noon. Further, results from regression models indicated that the frequency of mental health exercises as well as nutrition exercises completed in the app by participants in both groups was related to delayed attrition. Physical activity exercises did not show such effects, possibly because those participants who did few exercises and were likely to drop out mainly used the physical activity category. Adolescents in the TAU group who completed an in-app health exercise between day 2 and day 6 of the trial were also found to be more likely to finish. This was not evident in the intervention group. These results imply that there are sensitivity usage periods that differ between the types of health behaviors adopted by adolescents in mHealth interventions and highlights the need for the development of just-in-time adaptive interventions in the future to hamper attrition and hopefully increase the frequency of health behavior exercises.

Taken together, the aim of this study was to examine time-specific attrition rates in an mHealth intervention for adolescents and hopefully increase our understanding of attrition in this group through a focus on the type, frequency, and time of health behavior exercise usage. Attrition between research groups was vastly different, and motivational support seems to be of vital importance to lower attrition in future mHealth interventions, specifically for adolescents in different age groups. Further research on how specific motivational support features in adolescent mHealth interventions function to lower attrition rates and how they affect usage patterns is evidently needed.

The limitations of this research include randomization factors, since randomization was between elementary schools rather than on an individual level to prevent contamination effects. Another limitation was related to the initial difference in usage between research groups. The data collection period was 6 weeks, and further research on the matter should include a prolonged research period with added randomization efforts to level usage between research groups, along with a 3-month follow-up to track usage and sustained gains from motivational support features. The generalizability of findings in adolescent mHealth studies to wider populations can be questionable, and this study is no exception (for instance, the function of altruistic reward schemes and competitive features in diverse cultural settings). The study’s foremost strength lies in added knowledge to limited research on attrition rates and patterns in adolescent mHealth interventions. Additional strong points are related to the methodological approach. Continuous data collection throughout the trial period, efforts to accurately describe time-based attrition rates through survival analysis, and use of a relatively large sample size (n=304) are regarded as strengths.

Acknowledgments
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Conflicts of Interest
EE is a minority shareholder in SidekickHealth AB and a former employee. The other authors have no conflicts to declare.

Editorial Notice
This randomized study was only retrospectively registered. The authors explained that the trial was originally registered in domestic registries through the University of Iceland and the Icelandic bioethics committee. The editor granted an exception from ICMJE rules mandating prospective registration of randomized trials because the risk of bias appears low and the study was considered formative, guiding the development of the application [or other reasons for the exception, as argued by the authors]. However, readers are advised to carefully assess the validity of any potential explicit or implicit claims related to primary outcomes or effectiveness, as retrospective registration does not prevent authors from changing their outcome measures retrospectively.

Multimedia Appendix 1
App function.
References


35. Egilsson E, Bjarnason R, Njardvik U. Usage and Weekly Attrition in a Smartphone-Based Health Behavior Intervention for Adolescents: Pilot Randomized Controlled Trial. JMIR Form Res 2021 Feb 17;5(2):e21432 [FREE Full text] [doi: 10.2196/21432]


Abbreviations

mHealth: mobile health
TAU: treatment as usual
bibliographic information, a link to the original publication on https://mhealth.jmir.org/, as well as this copyright and license information must be included.
Original Paper

Trajectories of Symptoms in Digital Interventions for Depression and Anxiety Using Routine Outcome Monitoring Data: Secondary Analysis Study

Diana Catalina Cumpanasoiu¹, PhD; Angel Enrique¹,², PhD; Jorge E Palacios¹,², MD, PhD; Daniel Duffy¹,², PhD; Scott McNamara¹, MA; Derek Richards¹,², PhD

¹SilverCloud Science, SilverCloud Health, Dublin, Ireland
²E-Mental Health Group, School of Psychology, Trinity College Dublin, Dublin, Ireland

Corresponding Author:
Diana Catalina Cumpanasoiu, PhD
SilverCloud Science
SilverCloud Health
One Stephen Street Upper
Dublin, D08 DR9P
Ireland
Phone: 353 6467031051
Email: catalina.cumpanasoiu@amwell.com

Abstract

Background: Research suggests there is heterogeneity in treatment response for internet-delivered cognitive behavioral therapy (iCBT) users, but few studies have investigated the trajectory of individual symptom change across iCBT treatment. Large patient data sets using routine outcome measures allows the investigation of treatment effects over time as well as the relationship between outcomes and platform use. Understanding trajectories of symptom change, as well as associated characteristics, may prove important for tailoring interventions or identifying patients who may not benefit from the intervention.

Objective: We aimed to identify latent trajectories of symptom change during the iCBT treatment course for depression and anxiety and to investigate the patients' characteristics and platform use for each of these classes.

Methods: This is a secondary analysis of data from a randomized controlled trial designed to examine the effectiveness of guided iCBT for anxiety and depression in the UK Improving Access to Psychological Therapies (IAPT) program. This study included patients from the intervention group (N=256) and followed a longitudinal retrospective design. As part of the IAPT’s routine outcome monitoring system, patients were prompted to complete the Patient Health Questionnaire-9 (PHQ-9) and Generalized Anxiety Disorder-7 (GAD-7) after each supporter review during the treatment period. Latent class growth analysis was used to identify the underlying trajectories of symptom change across the treatment period for both depression and anxiety. Differences in patient characteristics were then evaluated between these trajectory classes, and the presence of a time-varying relationship between platform use and trajectory classes was investigated.

Results: Five-class models were identified as optimal for both PHQ-9 and GAD-7. Around two-thirds (PHQ-9: 155/221, 70.1%; GAD-7: 156/221, 70.6%) of the sample formed various trajectories of improvement classes that differed in baseline score, the pace of symptom change, and final clinical outcome score. The remaining patients were in 2 smaller groups: one that saw minimal to no gains and another with consistently high scores across the treatment journey. Baseline severity, medication status, and program assigned were significantly associated (P<.001) with different trajectories. Although we did not find a time-varying relationship between use and trajectory classes, we found an overall effect of time on platform use, suggesting that all participants used the intervention significantly more in the first 4 weeks (P<.001).

Conclusions: Most patients benefit from treatment, and the various patterns of improvement have implications for how the iCBT intervention is delivered. Identifying predictors of nonresponse or early response might inform the level of support and monitoring required for different types of patients. Further work is necessary to explore the differences between these trajectories to understand what works best for whom and to identify early on those patients who are less likely to benefit from treatment.

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KEYWORDS
internet-delivered cognitive behavioral therapy; iCBT; depression; anxiety; trajectory of symptom change; routine outcome monitoring data

Introduction

Background
Depressive and anxiety disorders are 2 of the most common mental health difficulties, with epidemiological studies across countries suggesting that they are highly prevalent, can persist throughout lifetime, and are seriously impairing [1-4]. Cognitive behavioral therapy (CBT) is an effective psychological treatment regularly used to treat depression and anxiety symptoms [5,6]. In recent years, CBT has been adapted to an internet-delivered format (internet-delivered CBT [iCBT]) and has overcome some barriers associated with accessing traditional face-to-face psychological treatments [7,8]. Several meta-analyses have demonstrated the effectiveness of these interventions in treating depression and anxiety [9-13].

A key value in digitally delivered treatments is the ability to collect data on patient characteristics, routine outcome measures, and their engagement with the intervention. Given the volume of data collected, there is a potential new opportunity to understand treatment effects at an individual level. More than ever before, we can understand the trajectory of individual symptom changes and further explore the relationship between the use of the intervention and clinical outcomes. Understanding treatment effects over time and the relationship between use and outcomes may prove important for developing tailored interventions for different [14] patients. It may also be helpful in identifying patients who may be at risk of not responding, which can support clinical decision-making [15]. These efforts may have the potential to enhance digitally delivered treatments.

Most empirical evidence on trajectories of symptom change comes from face-to-face psychotherapy studies, which have found various classes of symptom courses, from early responders to late or delayed responders and steady or moderate responders [16,17]. Few studies have explored the evolution of symptoms during iCBT interventions. Some of them have consistently found a large group of users who show improvement and another group of users who show no or low symptom improvement [18,19]. Other studies have also found that most treatment responders experience the most clinical gains during the first weeks [20-22] and even before the treatment initiated [22]. Several of these studies also investigated the effects of individual baseline characteristics (e.g., age and sex) on class membership; however, only symptom load has been consistently associated with class membership [20,21]. Similarly, studies have examined intervention use metrics and their relationship with class membership, with inconsistent findings reported [18,20,22]. While no differences were found between classes in terms of overall use time [18,22], two studies found differences between classes in the number of assessments, modules, and sessions completed [20,22].

In terms of intervention use and its relationship with outcomes from iCBT [23], it has been proposed that higher use (i.e., better adherence or completion rate) predicts better outcomes [24]. However, other studies investigating the relationship between use metrics and outcomes have reported mixed results [25,26]. To date, many studies have been limited by their collection of outcomes at fixed time points. Evaluating use patterns in relation to continuous outcome monitoring may provide insight into how the temporal aspect of use is linked to changes in symptoms. Several studies [26,27] suggest that most use occurs at earlier stages of the intervention and that patients who improved have higher exposure levels to the intervention, especially in the first half [26]. A recent randomized controlled trial (RCT) presented an opportunity to examine the relationship between engagement and outcomes at different time points [28]. The results suggested that there was an association between use (completion rate and the frequency of items completed, but not time spent) and outcomes at 3 months but not earlier.

Objectives
Overall, the current literature on trajectories of symptom change in iCBT is at an early stage, and more research is needed to confirm whether the classes found in previous studies are also observed in diverse samples from different settings. Identifying individuals who benefit from iCBT and those at risk of not improving is key to offering tailored interventions that fit the needs of specific populations, which may ultimately lead to increased response rates. In addition, learning more about the stage of treatment at which change occurs and its association with intervention use will shed light on whether intervention use acts as a mechanism for change in these trajectories. On the basis of this, this study sought to use routine outcome monitoring (ROM) data gathered from a pragmatic RCT in a clinical service setting to (1) identify latent classes of responders and associated participant characteristics during an iCBT intervention for depression and anxiety treatment and (2) investigate the presence of a time-varying relationship between trajectories of change and intervention use.

Methods

Study Setting
This study is a secondary analysis of data collected [29] at the Berkshire Healthcare Foundation Trust, a provider within the National Health Service Improving Access to Psychological Therapies (IAPT) program. IAPT is a stepped-care model in which people with depression and anxiety are offered different intensities of treatment depending on their needs and symptom severity. At step 2, clients are recommended low-intensity CBT-based treatments, such as guided self-help, internet-delivered CBT, or group CBT, under the supervision of a psychological well-being practitioner (PWP). The PWPs are a specially trained cohort of psychology graduate students, with additional qualification in delivering low-intensity CBT. This study was conducted at step 2 of IAPT, with patients being assigned to iCBT as their preferred treatment option.

https://mhealth.jmir.org/2023/1/e41815

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(page number not for citation purposes)
Design
The original RCT where these data were collected was designed to examine the effectiveness and cost-effectiveness of the SilverCloud programs for anxiety and depression [29]. The study used a parallel-group design, in which an intervention group was compared with a waitlist control group, and the results demonstrated the effectiveness of the intervention group compared to the waitlist control after treatment, and improvements were sustained over a 12-month period [29].

Between June 28, 2017, and April 30, 2018, a total of 464 participants were invited to the original RCT; however, this study followed a longitudinal, retrospective design and included only patients from the intervention group (N=256). It captured the clinical assessments and platform use that occurred during the first 12 weeks of intervention use. While the main RCT used outcome data collected at research time points, this study used ROM data. As part of their treatment journey in IAPT, clients were prompted to complete the Patient Health Questionnaire-9 (PHQ-9) and Generalized Anxiety Disorder-7 (GAD-7) when they received a review approximately every 2 weeks. Hence, for each participant, assessments were available at baseline and at weeks 2, 4, 6, 8, 10, and 12.

Participants
The eligibility criteria for this analysis mirrored that of the main RCT; therefore, to be included in the main RCT, a participant had to be aged >18 years, to present with mild to moderate symptoms of depression or anxiety, and to consent to engage with iCBT. In addition, comorbidity with psychotic illness, current psychological treatment, previous organic mental health disorder diagnosis, substance misuse, and suicidal risk (suicide-related thoughts, ideation, or active plans) were used as exclusion criteria.

Interventions
On the basis of their symptoms and needs, clients were offered one of the following SilverCloud programs: Space from depression; Space from anxiety (different programs for specific anxiety disorders—modules for phobia, social anxiety, or generalized anxiety disorders); and Space from depression and anxiety, with the possibility of customizing treatment. Each participant had a PWP monitoring their progress and providing asynchronous reviews through the platform. The supporters monitor participants’ activities through the platform, and provide guidance and tailor feedback based on patient needs. This feedback comes in the form of regular reviews of the participants’ progress. In addition, supporters use these reviews to offer suggestions and guidance on how best to navigate the content and modules in each program to best fit an individual’s needs.

Assessments
The data collected included demographic variables (age, sex, ethnicity, and employment), clinical measures for depression (PHQ-9) and anxiety (GAD-7), and use metrics.

The PHQ-9 is a brief, self-reported measure of depression [32,33] containing 9 items on a Likert scale (from 0 to 3). The score ranges from 0 to 27, with a cutoff score of ≥10 indicating the presence of depression and higher scores reflecting more severe symptoms. This assessment is widely used in clinical and research settings, and its validity, reliability (89%), sensitivity (88%), and specificity (88%) have been confirmed [32]. The GAD-7 is a brief, self-reported measure of anxiety [34] containing 7 items on a Likert scale (from 0 to 3). The score ranges from 0 to 21, with a cutoff score of ≥8 indicating the presence of anxiety and higher scores representing more severe symptoms. Similar to the PHQ-9, this assessment is widely used, and its validity and good internal consistency have been confirmed [34].

In terms of use, several objective metrics were obtained from the SilverCloud platform. Table 1 presents a full list of all use metrics and what each measured. To assess use at different time points in the treatment journey, all metrics were computed for each 2-week period between the start of treatment and week 12.

### Table 1. Description of all usage metrics examined.

<table>
<thead>
<tr>
<th>Use metrics</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of log-ins</td>
<td>Number of log-ins for each participant adherence</td>
</tr>
<tr>
<td>Time spent</td>
<td>Length of time spent using the platform adherence</td>
</tr>
<tr>
<td>Number of reviews</td>
<td>Number of reviews each participant received from their psychological well-being practitioner engagement</td>
</tr>
<tr>
<td>Number of activities</td>
<td>Number of activities logged (eg, every time the participant used a tool or logged a journal entry)</td>
</tr>
<tr>
<td>Percentage of the program viewed</td>
<td>Percentage of new content viewed in each 2-week period engagement</td>
</tr>
</tbody>
</table>
Procedure

For the main RCT, participants were first screened and then invited to participate in the study, and the consented participants were assigned to active treatment or waitlist. Once assigned to the active treatment group, participants were offered 1 of 3 SilverCloud programs (Space from Depression, Space from Anxiety, and Space from Depression and Anxiety) based on their needs. As the participants worked through the programs, they were presented with assessments to evaluate their progress. ROM is used to trigger assessments of participants at various time intervals to provide regular measurements of their progress. These assessments correspond with predetermined research time intervals that allowed for a deeper understanding of everyone’s journey through the program. All actions taken by the participants within the platform, such as module progress, content viewed, and activities completed, were collected through SilverCloud backend data collection.

Analysis Plan

First, differences between the included and excluded participants were established using descriptive statistics (mean and SD) and independent 2-tailed t tests. To answer the first research question and identify trajectories of change, latent class growth analysis (LCGA) was used to identify latent classes. LCGA is a type of growth mixture modeling that is used to identify latent classes with different trajectories of growth. Mixture modeling approaches such as LCGA have been used more broadly in recent years because they allow the identification of underlying clusters based on unobserved heterogeneity in the data [35]. Compared with other growth modeling approaches that describe all trajectories with a single growth estimate, LCGA allows the identification of latent classes that have different characteristics (eg, intercept and slope) and assumes that all individual trajectories in a class are homogeneous [36-38]. This is done by fixing the variance of the intercept and slope within a class to 0 and allowing them to vary only across classes [37,38]. LCGA models address missing data using maximum likelihood algorithms [36,37]. To determine the optimal number of classes, models with an increasing number of classes are estimated, and different fit indices are used to compare them. There are multiple considerations taken into account when choosing the optimal model, such as the model fit indices, theoretical framework, clinical interpretation, and other criteria such as the number of participants in each class [36]. After the model is chosen, the probability of each individual to belong to one of the classes is estimated using maximum posterior probabilities and thus each individual is assigned to one of the latent classes.

LCGA is commonly conducted using statistical software, such as MPlus and SAS; however, recent efforts have made it easier to conduct such analyses in open-source R software [39]. For this analysis, the lcmm package [40] in R was used following the steps in the tutorial provided by Wardenaar [38]. A single-class growth model with a fixed intercept and slope for the subjects was initially run to test whether a linear, quadratic, or cubic model would be more appropriate for capturing the overall observed pattern of the trajectory. The coefficients of the cubic and quadratic terms had a poor model fit; therefore, a linear LCGA model was fitted. Latent class models were then constructed by increasing the number of classes from 2 to 8 to identify the optimal number of classes. Once a model was selected, 1-way ANOVAs and chi-square tests were performed to evaluate differences between classes in individual characteristics (eg, age, sex, and baseline severity).

Before investigating the relationship between use and symptom change, descriptive methods were used to explore use data, and regressions were run to understand the predictive values of different patient characteristics (eg, age and baseline severity) on each use metric. Then, to understand how different trajectories relate to use, mixed (between-factors and within-factors) ANOVAs were conducted to examine the role of time and class (PHQ and GAD) membership in use metrics. For the number of log-ins, length of use, number of reviews, number of activities, and percentage of programs viewed, five 3×5 mixed ANOVAs were conducted, with time as within-factor (3 levels: use in the first 4 weeks, 4-8 weeks, and 8-12 weeks) and class as between-factor (5 levels: the 5 trajectories identified). A total of 10 ANOVAs were run, 5 using the depression trajectories and 5 using the anxiety trajectories. All regressions and mixed ANOVAs were run using the R platform.

Data Processing

As these were ROM data, it was decided to select the assignments completed on the closest date to the time points of interest (baseline, 2 weeks, 4 weeks, 6 weeks, 8 weeks, 10 weeks, and 12 weeks). The following criteria were used to do this: (1) an interval of −6 days to +6 days from each of the time points of interest was considered, and if there were more assignments done in that period, the one on the closest date to the time point of interest was selected; (2) if in the −6 days to +6 days interval there were 2 assignments equally close to the time point (eg, 1 assignment done 4 days before the time point and 1 assignment done 4 days after the time point), the second one was selected (ie, the one after the time point); and (3) if no assignments were completed in that time interval, a check was done to see if any assignments were done on the seventh day before or after the time point. If neither of these conditions was met, no assignment was selected for that time point.

As ROM data were used for outcomes with the criteria explained earlier, there were a number of missing PHQ-9 and GAD-7 assessments at each time point (for more details regarding missing data, see Table S1 in Multimedia Appendix 1). On average, each individual had 2 missed measurements out of 7 possible. There were also no significant results (all P >.05) from the logistic regression evaluating the predictive power of age, sex, baseline PHQ score, baseline GAD score, presence of a long-term condition (LTC), psychiatric medication status, and employment status on having more (defined as 3+) or less (defined as 0-2) missing assessments.

LCGA uses the maximum likelihood algorithm to handle both participants with full and missing data [36]. Missing data patterns for outcomes were evaluated and based on the Little test. After studying the different patterns of missing data, there was no evidence to disconfirm that data were missing at random; thus, analyses proceeded under this assumption. After identifying the latent classes, the pattern of missing data in each class was evaluated, and similar proportions of missing
assessments were found in each class (Table S2 in Multimedia Appendix 1). For use, there were no missing data. Box plots were constructed to identify outliers, and the Winsorization method was applied. As use data are expected to be skewed, Winsorization was chosen over other methods (eg, truncating) to preserve all the data points and limit the influence of the extreme outliers. Several values were identified as potential outliers for the number of log-ins, length of use, and number of activities. All values determined as extreme (ie, 3 SDs or more away from the mean) were Winsorized to reduce the impact of those data points without removing them.

**Ethics Approval**

This trial was approved by the National Health Service England Research Ethics Committee (reference: 17/NW/0311). The trial was prospectively registered at Current Controlled Trials (ISRCTN91967124).

**Results**

**Overview and Sample Characteristics**

Of the 256 participants in the intervention arm, 23 were excluded because they did not have a start date, and another 12 were excluded because of having only 1 assessment (the baseline). The analyses were conducted on the remaining 221 individuals. Participants were aged 18 to 74 (mean 33, SD 12.68) years, had an overall baseline PHQ-9 score of 13.82, and had an overall baseline GAD-7 score of 12.26. Table 2 presents further descriptive information on the participants’ demographic and clinical characteristics.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age (years), mean (SD)</strong></td>
<td>32.9 (12.68)</td>
</tr>
<tr>
<td><strong>Baseline Patient Health Questionnaire-9 score, mean (SD)</strong></td>
<td>13.82 (5.36)</td>
</tr>
<tr>
<td><strong>Baseline Generalized Anxiety Disorder-7 score, mean (SD)</strong></td>
<td>12.26 (4.97)</td>
</tr>
<tr>
<td><strong>Sex, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>63 (29)</td>
</tr>
<tr>
<td>Female</td>
<td>158 (71)</td>
</tr>
<tr>
<td><strong>Religion, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>No religious group or secular</td>
<td>143 (65)</td>
</tr>
<tr>
<td>Other</td>
<td>72 (33)</td>
</tr>
<tr>
<td>N/A</td>
<td>6 (2)</td>
</tr>
<tr>
<td><strong>Sexual orientation, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Heterosexual</td>
<td>193 (87)</td>
</tr>
<tr>
<td>Other</td>
<td>20 (9)</td>
</tr>
<tr>
<td>N/A</td>
<td>8 (4)</td>
</tr>
<tr>
<td><strong>Employment, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Employed full time</td>
<td>166 (75)</td>
</tr>
<tr>
<td>Other</td>
<td>55 (25)</td>
</tr>
<tr>
<td><strong>Psychiatric medication, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Prescribed and taking</td>
<td>87 (39)</td>
</tr>
<tr>
<td>Other</td>
<td>134 (61)</td>
</tr>
<tr>
<td><strong>Long-term condition , n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>176 (80)</td>
</tr>
<tr>
<td>Yes</td>
<td>41 (19)</td>
</tr>
<tr>
<td>N/A</td>
<td>4 (1)</td>
</tr>
<tr>
<td><strong>Program assigned, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Comorbid</td>
<td>104 (47)</td>
</tr>
<tr>
<td>Depression</td>
<td>50 (23)</td>
</tr>
<tr>
<td>Anxiety</td>
<td>67 (30)</td>
</tr>
</tbody>
</table>

aN/A: not available.
The t-test and Chi-square test comparisons showed no significant differences (all $P > .05$) between the 35 excluded participants and those included in terms of baseline PHQ-9 and GAD-7 scores and demographics, such as age, sex, religion, sexual orientation, employment status, psychiatric medication status, LTCs, and type of program.

**Latent Class Growth Analysis**

Latent class models were constructed with an increasing number of classes, from 2 to 8 (Tables S3 and S4). The goodness-of-fit was assessed using Bayesian information criterion for each model to determine the optimal number of classes. In addition, the interpretability of the identified trajectories as well as their clinical meaningfulness were considered when choosing a model. On the basis of Bayesian information criterion index and theoretical considerations, the models with 5 classes were chosen for both the PHQ-9 and GAD-7.

**PHQ-9 Classes Description**

A graphical representation of the 5 classes of depression trajectories can be found in Figure 1, where the individual patient trajectories and the mean trajectory for each class are shown. The characteristics of each class are summarized in Table 3. The 5 classes were as follows: “stable high” symptoms (10/221, 4.5%), “improving high” symptoms (17/221, 7.7%), “improving moderate” symptoms (77/221, 34.8%), “stable moderate” symptoms (56/221, 25.3%), and “improving low” symptoms (61/221, 27.6%). At baseline, the mean PHQ-9 scores for classes 1 (“stable high”) and 3 (“improving high”) were similar, but the patients in class 2 had a sharp decrease in symptoms across the treatment journey, whereas those in class 1 retained consistently high scores throughout treatment throughout the 12 weeks. Patients in class 3, “improving moderate,” showed a similar but slower decrease in symptoms to class 2 (“improving high”). Class 2 was the largest class, and the 77 individuals in it started with moderate PHQ-9 scores and consistently improved across the treatment journey, reaching a mean PHQ-9 score of 6.64 (SD 3.89) at 12 weeks. The patients in class 4, “Stable moderate,” started with moderate levels of depression and had a slight decrease in scores, remaining in the moderate range at the end of the intervention. Patients in class 5, “improving low,” started with subclinical levels at baseline and slowly but consistently decreased across the treatment journey.

**Figure 1.** Trajectory classes for depression (left) and anxiety (right). GAD: Generalized Anxiety Disorder; PHQ: Patient Health Questionnaire.
### Table 3. Patient Health Questionnaire-9 (PHQ-9) class characteristics.

<table>
<thead>
<tr>
<th>PHQ class 1 (“stable high”; n=10)</th>
<th>PHQ class 2 (“improving high”; n=17)</th>
<th>PHQ class 3 (“improving moderate”; n=77)</th>
<th>PHQ class 4 (“stable moderate”; n=56)</th>
<th>PHQ class 5 (“improving low”; n=61)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participants (n=221), n (%)</td>
<td>10 (4.52)</td>
<td>17 (7.69)</td>
<td>47 (21.24)</td>
<td>56 (25.34)</td>
</tr>
<tr>
<td>Age (years), mean (SD)</td>
<td>30.1 (13.92)</td>
<td>34.47 (13.31)</td>
<td>31.31 (11.43)</td>
<td>32.38 (13.48)</td>
</tr>
<tr>
<td>Baseline PHQ-9 score, mean (SD)</td>
<td>21.6 (2.95)</td>
<td>21.41 (2.58)</td>
<td>14.12 (3.52)</td>
<td>16.05 (2.94)</td>
</tr>
<tr>
<td>Week 12 PHQ-9 score, mean (SD)</td>
<td>21.4 (2.07)</td>
<td>7.88 (3.64)</td>
<td>6.64 (3.89)</td>
<td>13.64 (3.55)</td>
</tr>
<tr>
<td>Baseline GAD-7 score, mean (SD)</td>
<td>17.4 (3.47)</td>
<td>16.65 (3.00)</td>
<td>11.96 (5.03)</td>
<td>13.55 (4.32)</td>
</tr>
<tr>
<td>Week 12 GAD-7 score, mean (SD)</td>
<td>14.2 (5.31)</td>
<td>5.75 (3.11)</td>
<td>5.56 (3.80)</td>
<td>11.42 (4.46)</td>
</tr>
<tr>
<td>Sex (male), n (%)</td>
<td>1 (10)</td>
<td>6 (35)</td>
<td>25 (32)</td>
<td>16 (29)</td>
</tr>
<tr>
<td>Employment status (employed full time), n (%)</td>
<td>6 (60)</td>
<td>14 (82)</td>
<td>60 (78)</td>
<td>36 (64)</td>
</tr>
<tr>
<td>Psychiatric medication status (prescribed and taking), n (%)</td>
<td>7 (70)</td>
<td>12 (71)</td>
<td>29 (38)</td>
<td>25 (45)</td>
</tr>
<tr>
<td>Long-term condition (no), n (%)</td>
<td>8 (80)</td>
<td>12 (71)</td>
<td>61 (79)</td>
<td>45 (80)</td>
</tr>
<tr>
<td><strong>Program type, n (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Comorbid</td>
<td>6 (60)</td>
<td>10 (59)</td>
<td>35 (45)</td>
<td>32 (57)</td>
</tr>
<tr>
<td>Depression</td>
<td>1 (10)</td>
<td>6 (35)</td>
<td>21 (27)</td>
<td>14 (25)</td>
</tr>
<tr>
<td>Anxiety</td>
<td>3 (30)</td>
<td>1 (6)</td>
<td>21 (27)</td>
<td>10 (18)</td>
</tr>
</tbody>
</table>

\[a\] GAD-7: Generalized Anxiety Disorder-7.

**GAD-7 Classes Description**

A graphical representation of the 5 classes of anxiety trajectories can be found in Figure 1 (also Figure S3 in Multimedia Appendix 1), where the individual patient trajectories and the mean trajectory for each class are shown. The characteristics of each class are summarized in Table 4. The 5 classes were as follows: “stable high” symptoms (16/221, 7.2%), “improving sharp” symptoms (36/221, 16.3%), “improving slow” symptoms (54/221, 24.4%), “stable low” symptoms (49/221, 22.2%), and “improving low” symptoms (66/221, 29.9%). Class 1 (“stable high”) was the smallest, consisting of only 16 individuals whose trajectories of change were marked by consistently high scores from the baseline to 12 weeks. Patients in class 2 (“improving sharp”) and class 3 (“improving slow”) both started with severe anxiety, but the former had a much steeper decline in symptoms across the treatment journey. Patients in class 3, “improving slow,” started with severe levels of anxiety and had a slow and consistent decrease in scores. Class 4, “stable low,” consisted of participants who started and finished with mild levels with minimal changes in symptoms. Finally, patients in class 5, “improving low,” started with mild symptoms at baseline and slowly but consistently transitioned to minimal symptoms.

One-way ANOVAs and Tukey post hoc comparisons revealed significant differences between depression classes in baseline PHQ-9 \( (F_{4,216}=23.14; P<.001) \) and GAD-7 \( (F_{4,216}=82.59; P<.001) \) scores. Chi-square tests and Bonferroni-corrected pairwise comparisons also revealed significant differences between some of the depression classes regarding medication status \( (n=221, \chi^2=18.5, P<.001) \) and the type of program \( (n=221, \chi^2=25.7, P<.001) \). Depression class 5 (“improving low”) had a significantly lower percentage (14/61, 23%) of members with “prescribed and taking” medication compared with classes 2 (12/17, 70.6% “improving high”; \( P=.003 \)) and 1 (7/10, 70.0% “stable high”; \( P=.003 \)). Class 5 was also significantly different from classes 4 (“stable moderate”; \( P=.003 \)) and 2 (“improving high”; \( P=.02 \)) in terms of program type, with a much higher percentage (32/61, 52%) of members of class 5 being in the anxiety program compared with the other 2 classes where anxiety seemed to be the least common program (17.9% in the stable moderate class, and 5.9% in the improving high class).

These results suggest that there are differences in the severity of depression and anxiety at baseline, with some of the identified PHQ and GAD classes starting with higher levels. Moreover, depression class 5 (“improving low”) seemed to distinguish itself from other depression classes by having more members in the anxiety program and a lower number of members taking medication. No other significant differences (all \( P>0.05 \)) were found between depression or anxiety classes in terms of age, sex, employment status, and the presence of LTCs.
Table 4. Generalized Anxiety Disorder-7 (GAD-7) class characteristics.

<table>
<thead>
<tr>
<th>Class</th>
<th>Patients (n=221), n (%)</th>
<th>Age (years), mean (SD)</th>
<th>Baseline PHQ-9 score, mean (SD)</th>
<th>Week 12 PHQ-9 score, mean (SD)</th>
<th>Baseline GAD-7 score, mean (SD)</th>
<th>Week 12 GAD-7 score, mean (SD)</th>
<th>Sex (male), n (%)</th>
<th>Employment status (employed full time), n (%)</th>
<th>Psychiatric medication status (prescribed and taking), n (%)</th>
<th>Long-term condition (no), n (%)</th>
<th>Program type, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GAD class 1</td>
<td>16 (7.24)</td>
<td>33.06 (13.16)</td>
<td>19.69 (4.03)</td>
<td>17.88 (2.16)</td>
<td>2.08 (1.78)</td>
<td>9 (25)</td>
<td>3 (19)</td>
<td>12 (75)</td>
<td>9 (56)</td>
<td>14 (88)</td>
<td>Comorbid 11 (69)</td>
</tr>
<tr>
<td>GAD class 2</td>
<td>36 (16.29)</td>
<td>31.22 (10.78)</td>
<td>15.08 (5.47)</td>
<td>15.28 (3.22)</td>
<td>13 (36)</td>
<td>28 (52)</td>
<td>15 (42)</td>
<td>28 (78)</td>
<td>13 (36)</td>
<td>31 (86)</td>
<td>Depression 1 (6)</td>
</tr>
<tr>
<td>GAD class 3</td>
<td>54 (24.43)</td>
<td>31.46 (12.48)</td>
<td>16.65 (4.65)</td>
<td>16.31 (2.85)</td>
<td>40 (74)</td>
<td>28 (52)</td>
<td>11 (14)</td>
<td>39 (72)</td>
<td>28 (52)</td>
<td>40 (74)</td>
<td>Anxiety 4 (25)</td>
</tr>
<tr>
<td>GAD class 4</td>
<td>49 (22.17)</td>
<td>30.86 (11.57)</td>
<td>12.43 (3.94)</td>
<td>9.41 (2.91)</td>
<td>38 (78)</td>
<td>17 (35)</td>
<td>12 (27)</td>
<td>37 (76)</td>
<td>17 (35)</td>
<td>53 (80)</td>
<td></td>
</tr>
<tr>
<td>GAD class 5</td>
<td>66 (29.86)</td>
<td>36.47 (13.74)</td>
<td>10.42 (5.92)</td>
<td>10.97 (3.54)</td>
<td>7 (18)</td>
<td>9 (18)</td>
<td>9 (18)</td>
<td>50 (76)</td>
<td>20 (30)</td>
<td>53 (80)</td>
<td></td>
</tr>
</tbody>
</table>

Platform Use

Overall, participants spent an average of 312 minutes on the platform, logged in approximately 18 times, viewed 57% of the total program, completed 150 activities, and received 4.26 reviews from their supporters (Table 5 provides descriptive information on platform use). It is noteworthy that there is large variability in all these use metrics, indicating considerable individual differences.

The results of the regressions indicate that age was a significant predictor of the number of log-ins ($\beta=0.13; P<0.04$), length of time spent on the internet ($\beta=166.62; P<0.03$), and number of reviews ($\beta=-0.02; P=0.009$), whereas the presence of an LTC was a significant predictor of the number of activities ($\beta=-43.5; P=0.02$), and the type of program was a significant predictor of the percentage of programs viewed ($\beta=0.07; P<0.001$). Overall, older people had a higher number of log-ins and spent more time on the platform but fewer reviews. The evaluation of box plots and descriptive summaries further showed that patients with an LTC had a higher number of activities compared with those without an LTC, and patients in the comorbid program had a smaller percentage of programs viewed compared with those in the depression or anxiety programs. No other baseline characteristics or demographic variables were found to be significant predictors of use (all $P>0.05$).

Table 5. Platform use.

<table>
<thead>
<tr>
<th>Use metric</th>
<th>Values, mean (SD)</th>
<th>Values, median (range)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of log-ins (Winsorized)</td>
<td>17.67 (11.13)</td>
<td>15 (1-70)</td>
</tr>
<tr>
<td>Length of use (Winsorized; minutes)</td>
<td>312.16 (228.83)</td>
<td>274.92 (2.47-1376.55)</td>
</tr>
<tr>
<td>Number of reviews</td>
<td>4.26 (1.63)</td>
<td>5 (0-8)</td>
</tr>
<tr>
<td>Number of activities (Winsorized)</td>
<td>150.48 (108.47)</td>
<td>126 (0-646)</td>
</tr>
<tr>
<td>Percentage of program viewed</td>
<td>0.57 (0.25)</td>
<td>0.58 (0.01-1)</td>
</tr>
</tbody>
</table>

Relationship Between Outcomes and Use

Mixed ANOVAs were conducted to identify the effect of depressive symptom trajectory and time on use. There were no significant interactions of time by trajectory (all $P>0.05$). For all 5 use metrics: the number of log-ins ($F_{2,432}=53.37; P<0.001$), length of use ($F_{2,432}=70.51; P<0.001$), number of reviews ($F_{2,432}=28.13; P<0.001$), number of activities ($F_{2,432}=56.20; P<0.001$), and percentage of program viewed ($F_{2,432}=86.34; P<0.001$), the ANOVAs revealed a significant effect of time. Paired $t$ tests with $P$-adjusted Bonferroni post hoc analyses indicated that there were significant differences between all time points for all 5 use metrics (all $P<0.001$), with most use occurring in the first 4 weeks, followed by weeks 4 to 8, and the least use occurring in the last 4 weeks (8-12). A detailed set of comparisons has been included as supplementary material.
for anyone who wants to delve deeper into the data (Tables S5 and S6 in Multimedia Appendix 1).

Mixed ANOVAs similar to the ones mentioned earlier were conducted to explore the effect of anxiety trajectory and time on usage. The Mauchly test demonstrated that the sphericity assumption had been violated, so Greenhouse-Geisser corrections were applied. There were significant interaction effects of time by trajectory for the number of log-ins ($F_{8,432}=1.99; \ P=.045$) and number of activities ($F_{8,432}=1.98; \ P=.047$); however, these effects were no longer significant after applying Greenhouse-Geisser corrections ($P>.05$). Interaction effects were not statistically significant for other use metrics (all $P>.05$). For the number of logins ($F_{2,432}=65.43; \ P<.001$), length of use ($F_{2,432}=91.46; \ P<.001$), number of reviews ($F_{2,432}=30.57; \ P<.001$), number of activities ($F_{2,432}=85.62; \ P<.001$), and percentage of programs viewed ($F_{2,432}=121.85; \ P<.001$), the ANOVAs revealed a significant effect of time. For all use metrics where a main effect of time was observed in the ANOVA, paired t tests with $P$-adjusted Bonferroni post hoc analyses indicated that there were significant differences between all time points (all $P<.001$), with most use occurring in the first 4 weeks, followed by 8 weeks, and the least at 12 weeks. Moreover, in the graphs for both depression and anxiety (Figure 2), it can be observed that there is substantial variability in use between the PHQ and GAD classes, where most of the variability between classes seems to occur in the early stages of treatment (first 4 weeks), and the differences between classes in the other 2 periods (weeks 4-8 and weeks 8-12) are less obvious. In addition, even after the Winsorization of the use metrics, the graphs allow us to see a high number of outliers.

Figure 2. Differences in usage between trajectory classes at different time points. GAD: Generalized Anxiety Disorder; PHQ: Patient Health Questionnaire.
Discussion

Principal Findings

This study aimed to identify different trajectories of symptom change across supported iCBT treatment for depression and anxiety using continuous outcomes data from patients treated in a mental health service setting. In addition, this study aimed to explore the relationship between the identified trajectories and use data. Overall, we found high heterogeneity in treatment response, with 5 latent classes emerging from data for both depression and anxiety. Across the 5 classes for depression and anxiety, we identified 3 improving classes and 2 classes that showed little to no change in symptoms. Across all classes, we also found an effect of time, with most use occurring in the first 4 weeks.

Understanding the different types of responses to an intervention as well as factors that may influence those responses could help improve the quality and delivery of iCBT interventions. This study found that approximately 70% of the sample improved across treatments; however, these individuals experienced different trajectories of change based on 3 characteristics: their baseline score, the pace of the improvement, and their posttreatment symptom scores. Some of the improver classes identified in this study are consistent with other iCBT studies that found individuals who started with moderate or moderate-severe scores and progressed toward recovery at a steady, moderate pace [19-22] and individuals who started with milder baseline symptoms and improved at a slower pace [20,21]. However, in general, our results showed steady improvements across improver classes instead of the early improvement classes observed in iCBT research [22]. These differences could be partially attributed to the nature of the ROM assessments linked to supporter reviews, as opposed to fixed time points. Of importance, we also found a class with severe anxiety (anxiety class 3) who, despite showing steady improvements, were still within the clinical definition of anxiety after treatment. Patients showing these trajectories could benefit from extending treatment or even adding high-intensity clinical interventions, such as face-to-face therapy, to support continued improvement that could help them achieve recovery [41].

It is perhaps even more important to understand the class characteristics of the individuals that see smaller to no gains so that in future, we could identify them early on, monitor their trajectory of symptoms, and make any necessary treatment decisions earlier to maximize treatment benefits. In particular, the 2 classes of nonresponders that start in the moderate severity range and see limited improvements (depression class 4 and anxiety class 4) could be ripe candidates for monitoring more closely symptom change trajectories and perhaps identify symptom change thresholds, whereby, from week to week, if thresholds are not met for symptom change, it could result in treatment decisions being made. Although some prior iCBT studies [19,22] have identified a class of limited to no improvement akin to depression class 4 and anxiety class 4 mentioned earlier, the nonresponder severe class found here has not been reported in other studies, perhaps because not many studies have included baseline scores on the severe end. It is possible that individuals in this severe nonresponder class need more support or to be stepped up in their care or that the interventions are unsuitable because they are primarily developed for mild to moderate ranges of symptom presentation. Therefore, the early identification of patients with high symptoms at baseline and an unchanged trajectory of symptom change early in treatment may also support better clinical decision-making.

It is also worth mentioning that we did not find a deterioration class similar to others [22], which could be a result of the intervention used here, or because of differences in the sample and methods used. In our primary RCT, where the current sample data originated, among 8-week measure completers, 5.2% (10/194) of participants in the intervention arm deteriorated (ie, increases in PHQ-9 score ≥6 or GAD-7 score ≥4) [42], which is in line with a recent individual patient data meta-analysis [43] that suggested only 5.8% of individuals in the intervention groups showed deterioration. Therefore, individuals with deteriorating trajectories in the current sample could be too few to create a subgroup of their own and may be mixed across the nonimproving classes.

A better understanding of the attributes of the classes identified has implications for tailoring, intervention delivery, and the early identification of individuals who are not on an improving path. We found no significant associations between the classes and baseline sociodemographic variables (ie, age, sex, employment status, and LTC), which is consistent with some studies [18,21], although other studies found that female individuals were more likely to be in the high-severity class [20]. Overall, the small classes with high interpersonal variability may have made it more difficult to identify differences between the groups, but future work could investigate other moderators related to clinical variables instead of demographic variables.

The results did not show a time-varying relationship between use and the various trajectories of change, indicating that the effect of platform use did not result in immediate clinical gains. This is consistent with findings from a study by Zeng et al [28], who only found this association by the end of treatment and therefore calls into question the potential role of use as a mechanism of change in iCBT. Studies with large observational samples should be conducted to detect these effects because the association between use and outcomes is more consistently found in large samples with aggregated data [12,24], whereas small-scale studies lead to more inconsistent findings [25,26]. However, we did find a consistent effect of time on the overall use of the intervention across classes and outcomes, suggesting that all participants used the intervention significantly more in the first 4 weeks. This is an important finding, as it replicates work from our group from a previous RCT [26], and the finding is consistent with other published literature [26,27,44]. Attention could be given to help maximize patients’ use of the intervention early in treatment. This can be achieved through frontloading key content or by increasing the schedule of support and guidance in the first 4 weeks.

The predictors of use were also investigated to better understand overall platform use. Age was a significant predictor for some
of the use metrics, with older clients logging in more frequently and for longer periods, which is consistent with previous findings [27,45,46]. The content of the intervention may be better suited for older clients or older clients may need or have more time to read the material [45,46]. Alternatively, there may be a need to tailor the content in terms of cognitive load, delivery mode, and time commitment across different age groups.

Limitations

A limitation of this study is the observational nature of this substudy, with no manipulation of the variables related to use, which makes it impossible to establish causal relationships between use metrics and outcomes. Moreover, using routine continuous outcome data compared with regular time point assignments comes with challenges, such as many missing questionnaires or complex data processing required to retrieve the relevant assignments. The small size of some of the classes presents another limitation, and future studies may benefit from larger sample sizes that could allow the detection of smaller effects and could provide an opportunity to apply other methods (eg, growth mixture modeling) to allow for both between- and within-class variability. Another limitation was the lack of access to baseline clinical information, which could have been useful for investigating differences between classes. For instance, variables that have been previously linked to treatment response include previous episodes of depression and anxiety [47], previous treatment or medication [48], client expectations [49], and treatment credibility [48,50]. Moreover, some of these clinical variables could be comorbidities and have a significant effect on the clusters found here. Further work is necessary to investigate and understand the role of these other clinical characteristics on the classes identified here.

Conclusions

This study identified 5 distinct classes of symptom trajectories for depression and anxiety over the course of iCBT treatment. The results showed that although iCBT works for the majority, the way improvement occurs varies, which may have implications for how iCBT is delivered. The absence of effects on the time-varying relationship between platform use and trajectories calls into question the role of use as a mechanism for change. Other contextual information and larger sample sizes may need to be presented to explore these effects better. Further work is necessary to better understand these patterns of change, as well as factors impacting them as insights gained, which may be useful in tailoring treatments for different patient groups and in identifying and monitoring patient groups to enable earlier and enhanced treatment decisions.

Acknowledgments

The authors would like to thank the staff at Berkshire National Health Service Foundation Trust for providing assistance that allowed us to successfully complete the execution of the original study, which is the basis of this secondary analysis.

Conflicts of Interest

DCC, AE, JEP, DD, SM, and DR are employees of SilverCloud Health. DR is a shareholder in Amwell, a company that SilverCloud Health has been a subsidiary of since 2021. SM was an employee at Amwell while this work was in progress.

Multimedia Appendix 1

Supplementary tables and figures with additional analysis information.

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Abbreviations

- **CBT**: cognitive behavioral therapy
- **GAD-7**: Generalized Anxiety Disorder-7
- **IAPT**: Improving Access to Psychological Therapies
- **iCBT**: internet-delivered cognitive behavioral therapy
- **LCGA**: latent class growth analysis
- **LTC**: long-term condition
- **PHQ-9**: Patient Health Questionnaire-9
- **PWP**: psychological well-being practitioner
- **RCT**: randomized controlled trial
- **ROM**: routine outcome monitoring

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Longer-Term Effects of Cardiac Telerehabilitation on Patients With Coronary Artery Disease: Systematic Review and Meta-Analysis

Wen Zhong¹²*, BSc; Rui Liu¹²*, BSc; Hongxin Cheng¹², MD; Lin Xu¹², BSc; Lu Wang¹², MD; Chengqi He¹², MD, PhD; Quan Wei¹², MD, PhD

¹Department of Rehabilitation Medicine and Institute of Rehabilitation Medicine, West China Hospital, Sichuan University, Chengdu, Sichuan, China
²Key Laboratory of Rehabilitation Medicine in Sichuan Province, Chengdu, Sichuan, China
*these authors contributed equally

Corresponding Author:
Quan Wei, MD, PhD
Department of Rehabilitation Medicine and Institute of Rehabilitation Medicine
West China Hospital
Sichuan University
No 37 Guoxue Alley
Wuhou District, Sichuan Province
Chengdu, Sichuan, 610041
China
Phone: 86 2885422847
Fax: 86 2828423819
Email: weiquan@scu.edu.cn

Abstract

Background: Cardiac telerehabilitation offers a flexible and accessible model for patients with coronary artery disease (CAD), effectively transforming the traditional cardiac rehabilitation (CR) approach.

Objective: This systematic review and meta-analysis aimed to evaluate the long-term effectiveness of cardiac telerehabilitation.

Methods: We searched randomized controlled trials (RCTs) in 7 electronic databases: PubMed, Web of Science, EMBASE, the Cochrane Central Register of Controlled Trials, ClinicalTrials.gov, the China National Knowledge Infrastructure, and WANFANG. The primary outcome focused on cardiopulmonary fitness. For secondary outcomes, we examined cardiovascular risk factors (blood pressure, BMI, and serum lipids), psychological scales of depression and anxiety, quality of life (QoL), cardiac telerehabilitation adherence, and adverse events.

Results: In total, 10 RCTs fulfilled the predefined criteria, which were reviewed in our meta-analysis. The results showed that after cardiac telerehabilitation, there was a significant difference in the improvement in long-term peak oxygen uptake compared to center-based CR (mean difference [MD] 1.61, 95% CI 0.38-2.85, P=.01), particularly after 6-month rehabilitation training (MD 1.87, 95% CI 0.34-3.39, P=.02). The pooled effect size of the meta-analysis indicated that there were no significant differences in the reduction in cardiovascular risk factor control. There was also no practical demonstration of anxiety scores or depression scores. However, cardiac telerehabilitation demonstrated an improvement in the long-term QoL of patients (MD 0.92, 95% CI 0.06-1.78, P=.04). In addition, the study reported a high completion rate (80%) for cardiac telerehabilitation interventions. The incidence of adverse events was also low during long-term follow-up.

Conclusions: Cardiac telerehabilitation proves to be more effective in improving cardiopulmonary fitness and QoL during the long-term follow-up for patients with CAD. Our study highlights monitoring-enabled and patient-centered telerehabilitation programs, which play a vital role in the recovery and development of CAD and in the long-term prognosis of patients.

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KEYWORDS
cardiac telerehabilitation; coronary artery disease; CAD; cardiac rehabilitation; CR; long-term effect; meta-analysis
Introduction

Cardiovascular diseases (CVDs) are the leading cause of a large proportion of deaths worldwide, accounting for approximately 1/3 of all deaths [1]. The global burden of CVDs is rising, increasing from 271 million in 1990 to 523 million in 2019, and the total number of cases of CVDs have almost doubled, especially coronary artery disease (CAD) [2]. CAD occurs mainly due to the progression of atherosclerosis of coronary arteries to narrowing or occlusion, leading to blood flow limitation, which causes cardiomyocyte or myocardial necrosis [3]. Population growth and aging are the main drivers, and the prevention and control of CVDs face significant challenges.

Cardiac rehabilitation (CR) is a complex, multidisciplinary intervention aimed at comprehensive rehabilitation assessment of the patient’s condition to meet the needs of patients with CVD, preventing disease recurrence and further progression. CR involves various components, such as exercise training, drug counseling, diet, nutrition, psychological regulation, and risk factor management [4]. To better serve patients with CAD, this multidisciplinary treatment method can be combined with well-validated strategies to assess physical function and risk factors in order to personalize treatment strategies [5]. Studies have shown that CR can reduce the risk of recurrent heart attacks by 47%, heart disease mortality by 36%, and all-cause mortality by 26% [6]. Furthermore, secondary prevention recommendations emphasize CR’s importance in patients with CAD, which has been recognized as comprehensive medical monitoring to reduce CAD mortality, morbidity, disability, and high expense [7,8]. Although participation in CR is a class IA recommendation for CAD [9], rates of referral and usage remain low [8]. Aragam et al [10] demonstrated that approximately >40% of patients are not referred for CR after percutaneous coronary intervention (PCI) by the time of hospital discharge. Participation enrollment in CR ranges from only 20% to 30% in the United States [8]. Low participation and adherence to CR programs may be attributed to multifactorial conditions, such as comorbidities, living farther from medical organizations, high medical costs, and time commitment [11,12].

To alleviate these barriers and improve the uptake rates of CR, cardiac telerehabilitation, a targeted approach, is used to effectively shift the traditional rehabilitation mode to a high-value overall strategy. Telerehabilitation is defined as a telemedicine platform, including telediagnosis, teletreatment, and remote monitoring [13]. These technologies are conducive to the joint participation of doctors and patients and medical departments in patients’ health management work. For patients with CVD, doctors can monitor the patients’ vital signs and cardiac telerehabilitation progress through a remote monitoring system and adjust the CR treatment plan according to the patients’ condition. Cardiac telerehabilitation uses internet information technology to allow patients to receive rehabilitation treatment at home or in other nonhospital settings regardless of time and geographical restrictions. This can motivate and help supervise patients, improving patient compliance. These factors have promoted the popularity of cardiac telerehabilitation, and the comprehensive promotion of telemedicine construction and development is gradually focusing on this aspect. Most patients eligible for cardiac telerehabilitation have a low rate of adverse events during exercise training if previously adequately evaluated. A review by Stefanakis et al [14], which included 5 studies on adverse event rates in home telerehabilitation, estimated the incidence of adverse events in the sample to be 1 in 23,823 patient-hours of exercise.

As a more accessible and flexible model of CR, cardiac telerehabilitation has been developed based on new communication technologies and advanced telemedical devices, such as smartphones, web-based apps, wearable sensors, and virtual reality [15]. This is supported by recent meta-analyses [16,17] that have shown that cardiac telerehabilitation as an alternative rehabilitation delivery model achieves an equivalent effect on physical exercise capacity, behavior change, reduction in risk factors, and improvement in the quality of life (QoL) of patients with CAD compared to the traditional rehabilitation model. At present, in addition to the traditional outpatient rehabilitation model, the main approaches to the CR model include home-based CR and cardiac telerehabilitation. Both cardiac telerehabilitation and home-based CR refer to rehabilitation in a nonhospital setting and have their advantages. Telerehabilitation is delivered and implemented through telemedical equipment, while home-based CR refers to rehabilitation carried out in the patient’s home. Both approaches can serve as important supplements or alternatives to traditional in-hospital rehabilitation models. However, the main difference between the 2 approaches is that home-based CR patients rely on outpatient or community follow-up guidance, take subjective initiatives at home for rehabilitation, and lack uninterrupted supervision and guidance from doctors; cardiac telerehabilitation makes up for these disadvantages of home-based CR. Therefore, the control of patients participating in telerehabilitation is strict. In a 2019 joint statement, the American Association of Cardiovascular and Pulmonary Rehabilitation (AACVPR), the American Heart Association (AHA), and the American College of Cardiology (ACC) [5] suggested that cardiac telerehabilitation could be a reasonable alternative for patients with clinically stable, low-to-moderate-risk CVD. However, high-risk patients, such as patients with unstable angina, CVD with heart failure or symptomatic arrhythmias, and other hemodynamic instabilities, usually require careful evaluation, outpatient CR under supervision, and reassessment for stabilization during the convalescent phase before participating in cardiac telerehabilitation.

Cardiac telerehabilitation has been found to be effective, as evidenced by improvements in the condition of patients with CVD. Still, current telerehabilitation studies have aimed to assess whether telerehabilitation affects short-term (about 3-month follow-up) or medium-term (about 6-month follow-up) effectiveness [18-20]. There are limited data describing the long-term (more than 1-year follow-up) effects of telerehabilitation. A self-regulation lifestyle program [21] reported that motivation for lifestyle changes tends to diminish. At the same time, patients with CAD feel healed, which influences long-term beneficial changes in lifestyle and risk factors. Hence, evaluating the long-term effectiveness of telerehabilitation has practical significance for implementing CR. Considering the well-established association between
telerehabilitation and the potential beneficial effects in CAD, in this study, we hypothesized that cardiac telerehabilitation could maintain the results for longer-term consequences.

**Methods**

**Study Design**
This meta-analysis was performed according to the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) statement.

**Ethical Considerations**
All analyses were based on previously published studies, so no ethical approval or patient consent was needed.

**Literature Search**
A literature search was performed to identify relevant studies in the following 7 electronic databases: PubMed, Web of Science, EMBASE, the Cochrane Central Register of Controlled Trials (CENTRAL), ClinicalTrials.gov, the China National Knowledge Infrastructure (CNKI), and WANFANG.

The search proceedings used the following different keywords without a time or language limit: (coronary artery disease or left main coronary artery disease or coronary arteriosclerosis) AND (telerehabilitation or tele-rehabilitation or tele rehabilitation or remote rehabilitation or virtual rehabilitation or telemedicine or mobile health or telehealth or eHealth or internet or online or web or sensor or wearable or smartphone or App or WeChat or QQ). Multimedia Appendix 1 provides the complete search strategy. To retrieve a comprehensive list of eligible papers, we manually screened reference lists, relevant conference lists, and even gray literature.

**Inclusion and Exclusion Criteria**
We defined and applied explicit inclusion criteria to select eligible studies for this meta-analysis as follows:

- **Population:** adults (≥18 years old) diagnosed with CVD (stable angina pectoris, acute coronary syndrome, myocardial infarction, or postcoronary revascularization, such as PCI or coronary artery bypass grafting [CABG]).
- **Intervention:** We focused on telerehabilitation as an emerging model of rehabilitation service delivery based on smartphones, wearable monitoring portable devices, virtual reality, or other internet interventions. Modern telecommunications technology combined with rehabilitation is designed to complete functional exercise training sessions, achieve self-management, and improve physical function. Patients are available at home with remote monitoring and remote health care consultation.
- **Comparison:** A control group was randomly assigned to usual-care or center-based CR.
- **Outcomes:** The primary outcome focused on cardiopulmonary function assessed with the peak oxygen uptake (peak VO₂) using the cardiopulmonary exercise test (CPET). For secondary outcomes, we focused on changes in cardiovascular risk factors, psychological scales of depression and anxiety, QoL, cardiac telerehabilitation adherence, and adverse events.
- **Study design:** Randomized controlled trials (RCTs) that compared the cardiac telerehabilitation group with the control group and evaluated the longer-term effects during least 12 months’ follow-up were included in the review.

We also set the following exclusion criteria: (1) patients with severe heart failure with New York Heart Association (NYHA) functional class III or IV, malignant cardiomyopathy, valvular disease, heart failure; (2) papers with an unreasonable literature research design, non-RCTs, nonhuman or animal studies, or a follow-up time of <12 months; (3) repeated publication; (4) unavailable full text, incomplete information and data, or an inability to extract and compare data; and (5) conference papers, abstracts, reviews, letters to the editor, and case reports.

**Selection of Studies**
Potentially relevant papers meeting the abovementioned search strategy were imported into the EndNote X9.2 tool (Clarivate). Initially, 2 reviewers each independently screened the titles and abstracts of all studies on the finalized list. Next, they conducted full-text screening according to the inclusion and exclusion criteria to determine the final eligibility. During the overall flow of the process, if there were any different views, a third reviewer provided an opinion and resolved the disagreement via consensus.

**Data Extraction**
Two authors collaborated on the final decision of data extraction, which was summarized in Microsoft Word 2019 and Microsoft Excel 2019: (1) study design (eg, first author, year of publication, country, study design, follow-up time), (2) participants (eg, sample size, sex, age, diagnosis), (3) intervention (eg, telerehabilitation group vs control group), (4) change in our protocol-specified outcomes, and (5) risk of bias. Although relevant details were insufficiently reported in the included studies, we contacted the authors via email for further information.

**Risk-of-Bias and Quality Assessment of Studies**
We evaluated each study’s eligibility using the Cochrane risk-of-bias tool [22] to assess the risk of all types of bias (selection bias, performance bias, attrition bias, reporting bias, and other sources of bias). Furthermore, we also used the Physiotherapy Evidence Database (PEDro) scale [23] to perform a quality assessment of the studies included. The PEDro scale comprises 11 items that correspond to a maximum of 10 points, except for item 1. A study with a PEDro score of 9-10 points is considered excellent, a score of 6-8 points is considered good, and a score of ≤5 is considered poor (low level of quality). The quality of the studies was independently assessed by 2 authors, and any dissent was settled through discussion or via consultation with a third reviewer.

**Statistical Analysis**
Data analysis and synthesis were performed using Cochrane Review Manager (RevMan) version 5.2 for Windows. Although all RCTs follow the principle of randomization and most baseline characteristics have no significant difference, we calculated the change from initial to final follow-up treatment difference values with a correlation coefficient of 0.5 [24] to
obtain a more accurate comparison of changes in the outcomes. For continuous data, we presented the outcomes using the mean difference (MD) with 95% CIs, and \( P < .05 \) was considered statistically significant. If studies used different units or measurement scales, we used the standardized mean difference (SMD) with 95% CIs. As a basis for assessing heterogeneity, an inconsistency of \( I^2 \) test values of more than 50% was considered indicative of substantially high heterogeneity. If we observed statistical heterogeneity with a threshold of >50%, random-effect models were used; otherwise, fixed-effect models were applied. In addition, if this threshold was exceeded, we performed a leave-one-out sensitivity analysis to ascertain whether our findings were driven by a single study, and checked the potential reasons for heterogeneity.

**Results**

**Search and Study Selection**

A comprehensive overview of the study screening and selection process is presented using a PRISMA 2020 flow diagram in **Figure 1**. The diagram provides a visual representation of the selection process, while the exclusion and inclusion reasons are explained in detail later. A total of 3007 citations were identified, and 1433 (47.7%) duplicates were excluded. Of the remaining 1574 (52.3%) papers that underwent title and abstract screening, 256 (16.3%) were found to be potentially relevant to the research topic. For further assessment, full-text screening was performed, and 10 (3.9%) RCTs fulfilled the predefined criteria and were incorporated into our systematic review and meta-analysis. Importantly, a significant number of intervention-related RCTs were excluded from the analysis due to having a follow-up period of less than 12 months.

**Figure 1.** The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram for the selection of studies. CENTRAL: Central Register of Controlled Trials; CNKI: China National Knowledge Infrastructure.

### Study Characteristics

Descriptive characteristics of the 10 studies [25-34] were captured and are summarized in Multimedia Appendix 2, including study design, main follow-up time, population, intervention, control setting, and measured outcomes. Of these 10 studies, 9 (90%) [26-34] were designed as 2-arm prospective RCTs with a parallel design, and the remaining study [25] was a 3-arm RCT. In addition, 2 (20%) studies each were performed in the Netherlands [30,33], China [28,34], Canada [31,32], and Belgium [25,29] and 1 (10%) each in the Czech Republic [26] and Spain [27]. In total, 1417 participants completed the RCTs, with 709 (50%; n=123, 17.3%, women and n=586, 82.7%, men) participants in the intervention group and 708 (50%; n=119, 16.8%, women and n=589, 83.2%, men) participants in the control group. The mean age of the intervention and control...
groups at baseline was 59.1 (SD 9.5) years and 59.9 (SD 9.8) years, respectively ($P=.16$).

**Intervention Programs**

In our systematic review, CR involved multiple components, mainly focusing on exercise intervention, risk factor management, medical evaluation, reasonable dietary combinations, and psychosocial counseling [35]. In the papers included, these telemonitoring and telerehabilitation-delivered CR interventions were implemented using different remote application equipment, as summarized in Multimedia Appendix 2. Depending on how a network (the internet) is accessed and the devices used, there are different design options available for the presentation of cardiac telerehabilitation. For example, Kraal et al [30] and Snoek et al [33] used wearable monitoring devices to enable real-time monitoring of patients’ personalized exercise training. Avila et al [25], Batalik et al [26], Frederix et al [29], Kraal et al [30], and Snoek et al [33] focused mainly on exercise-based cardiac telerehabilitation, with a predominantly moderate exercise intensity, a training heart rate equivalent to 70%-80% of the heart rate reserve, and individualized control through electronic monitoring. Among them, only Snoek et al [33] used an exercise intensity not only above the first ventilation threshold but also in the moderate exercise intensity range, approximately equal to 70%-80% of the heart rate reserve. When constructing personalized exercise sessions, the purpose of exercise also needs to be considered, and different exercise methods can have different health benefits. We included studies that mainly aimed to enhance cardiorespiratory fitness, choosing walking, jogging, and cycling, while Blasco et al [27], Reid et al [32], and Wang et al [34] performed some aerobic exercises in a home environment according to their preferences. However, Batalik et al [26], Kraal et al [30], Snoek et al [33], and particularly Frederix et al [29] and Dorje et al [28] recorded patients’ walking to assess their exercise condition. In addition to enhancing cardiorespiratory function, it is also vitally essential to increase muscle strength and endurance, and most of the exercises involved in these studies are aerobic exercises. Only Avila et al [25] used strength exercises, such as arm ergometry and rowing, but did not report whether strength training, such as weightlifting, sit-ups, and push-ups, was used. However, there was a lack of exercise to improve flexibility and body coordination. In 5 (50%) studies, Blasco et al [27], Dorje et al [28], Lear et al [31], Reid et al [32], and Wang et al [34], the focus was on structured comprehensive CR, including risk factor management for CVD, emotional management, dietary management, and medication management, and the studies also involved the core component of exercise coaching. Although these studies did not have detailed exercise prescriptions, using social platforms, such as WeChat, to provide more comprehensive CR, with motivational feedback about progress, can lead to better effects.

Moreover, Avila et al [25], Frederix et al [29], and Reid et al [32] supervised home exercises and uploaded web-based reports to motivate patients to improve adherence and self-management enthusiasm. Batalik et al [26], Blasco et al [27], Dorje et al [28], Lear et al [31], and Wang et al [34], mainly used educational videos or electronic pamphlets supported by WeChat and other apps, which enabled medical staff to communicate online with patients. Patients could carry out remote health consultations to improve their QoL and control cardiac risk factors.

**Risk of Bias**

All the 10 (100%) studies analyzed in this review using the PEDro scale had acceptable methodological quality (score ≥6); see Table 1. The results of the risk-of-bias assessment for the included studies are graphically displayed in Figure 2. We first used the Cochrane risk-of-bias tool, including selection, performance, attrition, and reporting biases. The 10 studies described specific randomization methods, 9 (90%) [25,26,28-34] reported allocation concealment, while 1 (10%) [27] had no allocation concealment. All studies had no subject blinding, and most studies had no therapist blinding due to regular supervision and timely feedback in the rehabilitation environments. Moreover, 8 (80%) studies had no reporting bias, 2 (20%) were unclear, and all studies had no clear descriptions of other biases.
Table 1. The PEDro\textsuperscript{a} scale to assess the included RCTs\textsuperscript{b} methodological quality.

<table>
<thead>
<tr>
<th>Quality metric</th>
<th>Author</th>
<th>Eligibility criteria\textsuperscript{c}</th>
<th>Random allocation</th>
<th>Concealed allocation</th>
<th>Baseline comparability</th>
<th>Blinded subjects</th>
<th>Blinded therapists</th>
<th>Blinded assessors</th>
<th>Adequate follow-up</th>
<th>Intention-to-treat analysis</th>
<th>Between-group comparisons</th>
<th>Point estimates and variability</th>
<th>Total score</th>
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</table>

\textsuperscript{a}PEDro: Physiotherapy Evidence Database.

\textsuperscript{b}RCT: randomized controlled trial.

\textsuperscript{c}Eligibility criteria did not contribute to the total score.

\textsuperscript{d}1=yes (reported in the study).

\textsuperscript{e}0=no (not met).
Assessment of Outcomes

Cardiorespiratory Fitness

We included 10 studies on people with CVD that evaluated long-impact cardiac telerehabilitation interventions. 5 (50%) of the 10 RCTs reported peak VO₂, and a total of 421 participants who had at least 12 months of follow-up were included in the analysis. To exclude the effect of the type of control group intervention, stratified based on center-based CR or usual care, on outcomes, subgroup analyses of the 5 studies were performed, of which the control group of only 1 (20%) study, by Snoke et al [33], received usual care. Therefore, the combined meta-results of the analyses of the remaining 4 (80%) studies showed that real-time monitored exercise-based cardiac telerehabilitation significantly improves long-term peak VO₂ compared to center-based CR (MD 1.61, 95% CI 0.38-2.85, \( P=0.01 \)), as shown in Figure 3A. Subgroup analyses were also performed for patients considering the different effects of intervention durations in exercise protocols. As shown in Figure 3B, peak VO₂ improvement in the intervention group was significantly greater than that in the control group after 6-month telerehabilitation training (MD 1.87, 95% CI 0.34-3.39, \( P=0.02 \)), but there was no significant difference after 3-month telerehabilitation training.
Figure 3. Pooled MD between cardiac telerehabilitation and control groups in terms of peak VO2 in long-term follow-up, divided into (A) cardiac telerehabilitation vs center-based CR or usual care and (B) a 3- or 6-month telerehabilitation program in the intervention group. CR: cardiac rehabilitation; MD: mean difference; peak VO2: peak oxygen uptake.

<table>
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<tr>
<th>Study or Subgroup</th>
<th>Tele-CR</th>
<th>Center</th>
<th>Mean</th>
<th>SD</th>
<th>Total</th>
<th>Mean</th>
<th>SD</th>
<th>Total</th>
<th>Weight</th>
<th>Mean Difference</th>
<th>IV, Fixed</th>
<th>95% CI</th>
<th>Mean Difference</th>
<th>IV, Fixed</th>
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<td>26</td>
<td>-0.9</td>
<td>6.9</td>
<td>29</td>
<td>12.1%</td>
<td>1.30</td>
<td>[2.24, 4.84]</td>
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<td>23</td>
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<td>-3</td>
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<td>64</td>
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<td><strong>Total (95% CI)</strong></td>
<td>148</td>
<td>155</td>
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<td>100.0%</td>
<td>1.61</td>
<td>[0.38, 2.85]</td>
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Heterogeneity: Chi² = 3.18, df = 3 (P = .36); I² = 6%  
Test for overall effect: Z = 2.57 (P = .01)

<table>
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<tr>
<th>Study or Subgroup</th>
<th>Tele-CR</th>
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<th>Mean</th>
<th>SD</th>
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<th>Mean</th>
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<td>58</td>
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<td>100.0%</td>
<td>0.60</td>
<td>[-1.62, 2.82]</td>
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</table>

Heterogeneity: Not applicable  
Test for overall effect: Z = 0.53 (P = .80)

Cardiovascular Risk Factors

In our study, cardiovascular risk factors mainly included the BMI, blood pressure, and lipid profile. Of the 10 studies, 6 (60%) [26,27,30,31,33,34] reported the BMI after long-term follow-up, showing no significant difference between cardiac telerehabilitation and center-based CR (MD –0.10, 95% CI –1.56 to 1.36, P=.89; I²=0%) or between cardiac telerehabilitation and usual care (MD –0.60, 95% CI –0.57 to 0.70, P=.85; I²=0%); see Figure 4A. In terms of blood pressure, there was no significant difference in systolic blood pressure (MD –1.58, 95% CI –3.34 to 1.99, P=.52; I²=0%; Figure 4B) and diastolic blood pressure (MD –1.12, 95% CI –2.71 to 0.47, P=0.17; I²=0%; Figure 4C) compared to the usual-care combined effect size. Only 4 (40%) studies [28,29,31,33] included the blood lipid index as an outcome measure, of which 3 (75%) studies [28,31,33] used usual care for the control group, and only Frederix et al [29] used center-based CR. Therefore, to maintain the consistency of the control group and reduce bias, the 3 (75%) studies [28,31,33] were finally included to analyze the improvement in blood lipids. The results showed that there was no more significance than the usual-care group in improving total cholesterol (TC; MD –0.14, 95% CI –0.52 to 0.24, P=.47; I²=73%; Figure 4D), low-density lipoprotein cholesterol (LDL-C; MD –0.13, 95% CI –0.45 to 0.20, P=.44; I²=74%; Figure 4E), high-density lipoprotein cholesterol (HDL-C; MD 0.00, 95% CI –0.05 to 0.05, P=.99; I²=0%; Figure 4F), and triglycerides (TGs; MD –0.16, 95% CI –0.40 to 0.07, P=.18; I²=70%; Figure 4G).
Figure 4. Pooled MD between the cardiac telerehabilitation and control groups in terms of (A) BMI, (B) systolic blood pressure, (C) diastolic blood pressure, (D) total cholesterol (TC), (E) low-density lipoprotein cholesterol (LDL-C), (F) high-density lipoprotein cholesterol (HDL-C), and (G) triglycerides (TGs) in long-term follow-up. CR: cardiac rehabilitation; MD: mean difference.

Depression and Anxiety

Of the 10 studies included, 2 (20%) [30,33] applied fixed-effect meta-analysis and showed no significant long-term improvement in anxiety scores (MD 0.15, 95% CI –0.71 to 1.02, P=.73, I²=0%; Figure 5A) or depression scores (MD –0.43, 95% CI –1.23 to 0.38, P=.30; I²=0%; Figure 5B).
Quality of Life

Due to the different scales used to measure QoL, we used the SMD as a practical measure. The MacNew Heart Disease Health-related Quality of Life (MacNew) questionnaire was used to explore the effects of cardiac telerehabilitation on QoL in people with CVD in 3 (30%) of the 10 studies included [30,32,33], and 1 (10%) study [29] used the HeartQoL questionnaire. However, the combined results showed high heterogeneity ($\Gamma^2=95\%$; Figure 6), and $\Gamma^2$ still fluctuated between 70% and 95% after sensitivity analysis, so the random-effect model was used for analysis. The results showed that cardiac telerehabilitation could improve the long-term QoL of patients with CVD (MD 0.92, 95% CI 0.06-1.78, $P=.04$).

Adherence to the Telerehabilitation Program

Completion rates for cardiac telerehabilitation were reported in 8 (80%) of the 10 studies (MD 0.80, 95% CI 0.64-0.95; Figure 7) [25-28,31-34], with high heterogeneity ($\Gamma^2=98\%$) based on our pooled meta-analysis.
**Adverse Events**

Of the 10 studies, in 4 (40%) [26,31-33], 13% of patients reported all-cause adverse events (MD 0.13, 95% CI 0.00-0.25; see Figure 8).

**Discussion**

**Principal Findings**

Compared to center-based CR, cardiac telerehabilitation was effective in improving cardiorespiratory fitness and exercise capacity in patients with CAD, particularly in terms of peak VO\(_2\) during long-term follow-up. However, technology-based cardiac telerehabilitation had no long-term benefits in terms of risk factor management. Based on the RCTs included, we also found that telehealth interventions do not result in significant improvements in depression and anxiety scores in the long term. Nevertheless, there was evidence of improved long-term QoL with cardiac telerehabilitation. Our study also revealed positive adherence to cardiac telerehabilitation interventions, and the incidence of adverse events during long-term follow-up was low.

Cardiorespiratory fitness is a crucial determinant of CR and a strong predictor of all-cause mortality and cardiovascular mortality [36]. The peak VO\(_2\) in CPET is 1 of the most critical and gold-standard indicators of cardiorespiratory fitness in patients with CVD, representing the maximum oxygen intake by the human body per unit body weight (mL/kg/minute). Peak VO\(_2\) reflects cardiopulmonary function in transporting oxygen and carbon dioxide around the body [37], the maximum aerobic metabolic capacity [38], and the skeletal muscles’ ability to absorb and use oxygen [39]. Our study confirms that compared to center-based CR training, cardiac telerehabilitation can significantly improve long-term peak VO\(_2\) in patients. Furthermore, we found that the duration of exercise training has a positive impact on the improvement in peak VO\(_2\). There is debate over whether ambulatory cardiac telerehabilitation is superior to traditional in-hospital or center-based CR, and this has also been widely discussed in recent years. Our primary finding, consistent with previous studies and related reviews [40-42], showed that exercise-based cardiac telerehabilitation with remote monitoring is equivalent or superior to center-based CR in terms of exercise capacity in cardiac disease. This can help patients overcome barriers such as transportation limitations and conflicts with work schedules, thereby expanding the implementation of rehabilitation programs for a wider range of patients. However, it is worth noting that these previous studies have primarily focused on short- or medium-term follow-up, and there is a lack of long-term evaluation. Therefore, our results further support the notion that compared to center-based CR, cardiac telerehabilitation can better sustain patients’ cardiorespiratory endurance over an extended period. Our finding is consistent with a retrospective study performed by Ramadi et al [43], who provided evidence that an extensive multidisciplinary and structured CR program retains the improvement in exercise capacity until 1-year follow-up. Interestingly, Aamot et al [44] and Smith et al [45] indicated that the monitoring strategy in CR enables the therapist to help patients sustain long-term exercise adherence so that peak VO\(_2\) significantly increases compared to baseline values. To strengthen our results, we also focused on other variables of CPET. Unexpectedly, we did not observe a significant difference. For example, only 2 RCTs [25,46] reported oxygen consumption at the anaerobic threshold (VO\(_2\) AT, mL/kg/minute) and showed that the improvement in VO\(_2\) AT does not persist for long. These indicators, especially VO\(_2\) AT, have a strong correlation with the clinical symptoms of patients with CVD [47], so further studies can evaluate whether cardiac telerehabilitation protocols can improve long-term clinical outcomes in order to strengthen the evidence that cardiac telerehabilitation can maintain cardiopulmonary fitness levels and exercise capacity.

Although our study and previous studies have shown that cardiac telerehabilitation shows significant long-term effectiveness in increasing peak VO\(_2\), the current intervention methods for cardiac telerehabilitation show considerable variability in their design. For example, in the 10 studies included in this review, Avila et al [25], Batalik et al [26], Kraal et al [30], and Snoek et al [33] used heart rate monitors, such as heart rate belts and sports bracelets, to detect exercise intensity and record health data in order to promptly synchronize patients’ exercise status. Blasco et al [27], Frederix et al [29], Lear et al [31], and Reid et al [32] used self-health management systems, such as smartphones or computers, to transmit patients’ blood sugar levels, blood pressure, smoking status, and other daily life conditions to the online platform to manage CVD risk factors; Frederix et al [29] also used activity trackers to monitor patients’ exercise. Furthermore, with continuous software and hardware optimization, Dorjie et al [28] and Wang et al [34] used social software, such as the WeChat group mode, for education, management, and follow-up, as well as emotional and nutrition...
management. Although remote methods of intervention vary, at the core, they are the same; that is, using various types of remote equipment, they mobilize the subjective initiative of patients for rehabilitation, under the effective communication of medical care, for them to implement rehabilitation treatments, such as exercise prescription, drug prescription, psychological prescription, and risk factor management. Therefore, future remote CR content and the operation process will be more standardized.

Our subgroup analysis revealed that an extended intervention duration of 6 months in exercise protocols significantly improves and maintains cardiorespiratory fitness. However, compared to the control group, no significant difference was observed after the 3-month rehabilitation training. This could be attributed to the reinforcement of patient self-awareness of CR through extended telehealth guidance and monitoring. Slobinec et al [48] found that motivational orientation and self-efficacy of exercise behavior affect exercise maintenance and physical activity levels. Self-regulation theory [21] is supported by physical and mental aspects to motivate patients to realize their potential, actively face diseases and adverse reactions, and improve physical and mental health. Janssen et al [49] showed that a theory-based lifestyle program could stimulate and sustain improvements in exercise adherence. Therefore, cardiac telehabilitation delivered through modern network technology has the potential to enhance long-term effectiveness by tailoring, coaching, monitoring, and providing objective feedback programs that enhance patients' self-efficacy and subjective initiative. Maddison et al [50] indicated that mobile health interventions have a positive therapeutic effect on leisure-time physical activity and walking, which may be moderated by changes in self-efficacy, which also strengthens our conclusions.

We found no strongly favorable evidence of a difference in cardiovascular risk factor management. For cardiovascular risk factors, this meta-analysis indicated no significant differences in reduction in blood pressure, BMI, and blood lipid analysis changes over 12 months. Evaluation and management of risk factors are crucial for the prognosis of patients with CVD [5,51]. Furthermore, with the younger age of patients with CVD and the increase in human life expectancy worldwide, long-lasting beneficial changes are needed for targeted preventive activities, so future research projects in this field should focus on extending the efficacy of risk factor management and maintenance effects.

No effectiveness was demonstrated in anxiety and depression score changes compared to the control group. Negative emotions and the occurrence and development of CVDs are 2-way causes [52]. Penninx et al [53] carried out a 4-year follow-up of 2397 patients with undiagnosed CVD and found that patients with negative emotions are more likely to suffer from CVD than patients without mood disorders. Another study [54] found that CR can help people with anxiety and depression shift their attention, better vent their emotions, and effectively alleviate mood disorders. Internet-based cardiac telehabilitation may enhance communication and feedback between patients and medical staff and achieve emotional problem solving on time [55]. There are few studies on telehabilitation and emotions of patients with CVD. In addition to improving cardiopulmonary fitness and cardiovascular risk factor management, 1 of the ultimate goals of telehabilitation is to improve the long-term QoL of people with CVD. There is a significant statistical difference between groups in long-term follow-up results. However, the effect of cardiac telehabilitation on the QoL of patients with CVD may be influenced by different assessment tools, and there is no consensus at present. The relevant pathogenesis and treatment guidelines are imperfect, so further research is needed.

We found high participation rates in CR during long-term security follow-up in our study. Compliance with rehabilitation training is a key factor in improving the rehabilitation effect [56], due to the patients’ need to go to the hospital regularly for rehabilitation training, resulting in a poor participation rate and compliance, and medium- to long-term recovery rates after discharge are low [57]. Telehabilitation compliance is high, which effectively improves the efficiency of the CR of patients. Ivers et al [58] showed that large multicenter RCT telehealth interventions can improve the completion rate of CR in patients with myocardial infarction, albeit only using simple and convenient remote methods, such as Short Messaging Service (SMS) and email, which was also verified in the summary results of the review by Santiago et al [59]. At the same time, cardiac telehabilitation has a low incidence of adverse events if it is fully evaluated before implementation. For example, Piotrowicz et al [60] found no significant difference in the incidence of adverse events between 2 groups (12.5% vs 12.4%) during the 12- to 24-month follow-up after 9 weeks of cardiac telehabilitation intervention in patients with heart failure compared to usual care. The most effective way to improve the safety of telehabilitation is to fully assess the patient’s status, such as using CPET, noninvasive cardiac output, physical assessment, etc.

CR is a vital part of the rehabilitation process of patients with CVD. Based on the development and application of the internet and tele-equipment, cardiac telehabilitation, as a new means of rehabilitation, can effectively carry out CR in the home-based environment, improve the participation and compliance of patients with CVD to undergo CR, and improve their functional status. Our study adds evidence to the advancement of telehabilitation, in the hope that the popularization of telehabilitation and the improvements in CR treatment for patients with CVD can improve the quality of rehabilitation, save medical time and medical costs, and solve the problem of some young patients being unable to participate in conventional center-based CR due to work. It is necessary for future studies to promote the “internet + cardiac rehabilitation” model to overcome the clinical problems of actual patients seeking medical treatment and effectively implement the model for every patient who needs CR.

Limitations

There are some limitations of the study. First is the large variability and complexity of the interventions due to cardiac telehabilitation delivering exercise intervention details according to the frequency, intensity, timing, and type (FITT) principle. Because relatively few trials are investigating the long-term outcomes of cardiac telehabilitation, it is difficult to unify specifically detailed research protocols; this requires
future investigations to verify the long-term effectiveness of cardiac telerehabilitation under different administration conditions and to develop a uniform personalized plan. Second, our study did not include as outcome measures long-term improvements in major adverse cardiovascular events (MACEs), all-cause mortality, or all-cause hospitalization in people with CVD. Cardiopulmonary fitness indicates that peak VO\(_2\) corresponds to a 13% reduction in all-cause mortality and a 15% reduction in cardiovascular mortality [61]. Therefore, future studies are required to include this indicator based on a sufficient sample size. Finally, we did not consider economic cost-effectiveness. Collecting data on patients’ medical cost burden and rehabilitation cycle during cardiac telerehabilitation and conducting financial analysis from a societal perspective are constructive. For example, Batalik et al [62] mentioned that cost-benefit analysis is essential for policy makers, systematic review of exercise-based telehealth CR is cost-effective, and the 12 studies included in their research showed no clear difference between telerehabilitation and center-based CR.

**Conclusion**
Cardiac telerehabilitation, as a promising treatment method, plays a crucial role in the comprehensive rehabilitation of patients with CVD. It addresses the diverse rehabilitation needs of patients and helps enhance their recovery. Our results demonstrated a significant difference in peak VO\(_2\) and QoL in terms of long-term improvements but no significant differences in changes in cardiovascular risk factor management and the psychological scales of depression and anxiety. Our results provide initial evidence supporting the use of cardiac telerehabilitation as an alternative model to center-based CR. By extending the benefits of cardiorespiratory effectiveness, cardiac telerehabilitation can promote patients’ long-term awareness of rehabilitation, thereby maximizing the prognosis for each patient.

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**Authors’ Contributions**
WZ and QW designed the study. WZ, HC, and QW performed the research and analyzed the data. LX and RL provided help and advice on the tables and figures. CH provided resources. WZ, LW, and QW wrote the manuscript. All authors contributed to editorial changes in the manuscript. All authors have read and approved the final manuscript.

**Conflicts of Interest**
None declared.

Multimedia Appendix 1
Complete search strategy.
[DOCX File, 21 KB - mhealth_v11i1e46359_app1.docx]

Multimedia Appendix 2
Descriptive characteristics of the 10 studies.
[DOCX File, 27 KB - mhealth_v11i1e46359_app2.docx]

**References**


Abbreviations

AT: anaerobic threshold
CAD: coronary artery disease
CPET: cardiopulmonary exercise test
CR: cardiac rehabilitation
CVD: cardiovascular disease
MD: mean difference
PCI: percutaneous coronary intervention
peak VO2: peak oxygen uptake
PEDro: Physiotherapy Evidence Database
PRISMA: Preferred Reporting Items for Systematic Review and Meta-Analyses
QoL: quality of life
RCT: randomized controlled trial
SMD: standardized mean difference

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Effects of a Mobile-Based Intervention for Parents of Children With Crying, Sleeping, and Feeding Problems: Randomized Controlled Trial

Michaela Augustin¹, MSc; Maria Licata-Dandel¹⁻², PhD; Linda D Breeman³, PhD; Mathias Harrer⁴⁻⁵, MSc; Ayten Bilgin⁶, PhD; Dieter Wolke³⁻⁶, PhD; Volker Mall¹⁻², Dr med; Margret Ziegler², Dr med; David Daniel Ebert⁴, PhD; Anna Friedmann¹, PhD

¹Social Pediatrics, TUM School of Medicine, Technical University of Munich, Munich, Germany
²kbo-Kinderzentrum Munich, Munich, Germany
³Health, Medical, and Neuropsychology Unit, Leiden University, Leiden, Netherlands
⁴Psychology & Digital Mental Health Care, Department of Sports and Health Sciences, Technical University of Munich, Munich, Germany
⁵Clinical Psychology and Psychotherapy, Institute for Psychology, Friedrich-Alexander-University Erlangen-Nuremberg, Erlangen, Germany
⁶School of Psychology, University of Kent, Canterbury, United Kingdom
⁷Division of Health Sciences, Warwick Medical School, University of Warwick, Coventry, United Kingdom
⁸Department of Psychology, University of Warwick, Coventry, United Kingdom

Corresponding Author:
Michaela Augustin, MSc
Social Pediatrics
TUM School of Medicine
Technical University of Munich
Heiglhofstr.65
Munich, 81377
Germany
Phone: 49 8971009149
Email: michaela.augustin@tum.de

Abstract

Background: Excessive crying, sleeping, and feeding problems in early childhood are major stressors that can result in parents feeling socially isolated and having low self-efficacy. Affected children are a risk group for being maltreated and developing emotional and behavioral problems. Thus, the development of an innovative and interactive psychoeducational app for parents of children with crying, sleeping, and feeding problems may provide low-threshold access to scientifically based information and reduce negative outcomes in parents and children.

Objective: We aimed to investigate whether following the use of a newly developed psychoeducational app, the parents of children with crying, sleeping, or feeding problems experienced less parenting stress; gained more knowledge about crying, sleeping, and feeding problems; and perceived themselves as more self-effective and as better socially supported and whether their children’s symptoms decreased more than those of the parents who did not use the app.

Methods: Our clinical sample consisted of 136 parents of children (aged 0-24 months) who contacted a cry baby outpatient clinic in Bavaria (Southern Germany) for an initial consultation. Using a randomized controlled design, families were randomly allocated to either an intervention group (IG; 73/136, 53.7%) or a waitlist control group (WCG; 63/136, 46.3%) during the usual waiting time until consultation. The IG was given a psychoeducational app that included evidence-based information via text and videos, a child behavior diary function, a parent chat forum and experience report, tips on relaxation, an emergency plan, and a regional directory of specialized counseling centers. Outcome variables were assessed using validated questionnaires at baseline and posttest. Both groups were compared at posttest regarding changes in parenting stress (primary outcome) and secondary outcomes, namely knowledge about crying, sleeping, and feeding problems; perceived self-efficacy; perceived social support; and child symptoms.

Results: The mean individual study duration was 23.41 (SD 10.42) days. The IG reported significantly lower levels of parenting stress (mean 83.18, SD 19.94) after app use compared with the WCG (mean 87.46, SD 16.67; \(P=.03\); Cohen \(d=0.23\)). Furthermore,
parents in the IG reported a higher level of knowledge about crying, sleeping, and feeding (mean 62.91, SD 4.30) than those in the WCG (mean 61.15, SD 4.46; P<.001; Cohen d=0.38). No differences at posttest were found between groups in terms of parental efficacy (P=.34; Cohen d=0.05), perceived social support (P=.66; Cohen d=0.04), and child symptoms (P=.35; Cohen d=0.10).

Conclusions: This study provides initial evidence of the efficacy of a psychoeducational app for parents with child crying, sleeping, and feeding problems. By reducing parental stress and increasing knowledge of children’s symptoms, the app has the potential to serve as an effective secondary preventive measure. Additional large-scale studies are needed to investigate long-term benefits.

Trial Registration: German Clinical Trials Register DRKS00019001; https://drks.de/search/en/trial/DRKS00019001

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KEYWORDS
children; crying problems; sleeping problems; feeding problems; feeding; regulatory problems; intervention study; Mobile Health Care; health app; mobile app; patient education; psychoeducation; eHealth; mobile health; mHealth; parenting; baby; babies; sleep; crying; newborn; mobile phone

Introduction

Definition
Excessive crying, sleeping, and feeding problems are common sources of stress for parents during early childhood [1,2]. They are characterized by self-regulation difficulties [2], which may manifest as fussiness, prolonged crying, difficulties transitioning to sleep or maintaining sleep, or refusal of new or selective foods [3]. Some children may experience a single problem, whereas others experience multiple problems simultaneously or persistently from early childhood to toddlerhood [2,4].

Prevalence
The prevalence rates of crying, sleeping, and feeding problems vary widely depending on the exact definition of the problems, diagnostic procedures, and the study population. For excessive crying, the incidence rates range from 5% to 26% in the first 18 months of life [5-7]. Sleeping problems in early childhood are evident in 10% to 33.3% of children aged <24 months [7-11], whereas mild to moderate feeding difficulties occur in 20% to 43% of children in the first year of life [7,10,12,13]. Two or more simultaneous problems of feeding, sleeping, or excessive crying emerge in approximately 1% to 26.6% of children in their first 2 years of life [7,10,14]. Although in many cases early crying, sleeping, and feeding problems are transient [14-16], persistent problems are associated with short- and long-term negative consequences for child health and development.

Associated Short- and Long-term Risks
Several factors are associated with the development of excessive crying, sleeping, and feeding problems, and they include neurodevelopmental vulnerability, high levels of parenting stress, parental pre- and postnatal psychopathology such as depression and anxiety, and impaired parent-child relationships [10,14,17-20]. In addition to enormous exhaustion and dejection, parents often feel helpless and incompetent in their parenting skills, which can be reinforced by persistent crying despite all their efforts to calm and satisfy their babies [2,21-23]. Furthermore, affected families often report that they feel increasingly socially isolated and lack support from their social environment [2,24,25]. Affected families bear a high risk of stressful experiences in which childcare demands outbalance parental resources. Thus, children who cry excessively are considered a specific risk group for child maltreatment, for example, by shaking the child, which can have severe long-term and even life-threatening consequences (shaken baby syndrome) [26-29]. Impairment of the parent-child relationship may persist for several years [14,30-32]. Other long-term consequences include the persistence of sleeping and feeding problems beyond the first few months of life up to preschool and even elementary school age [15,16,33] and an increased risk of developing other mental health problems, such as emotional and behavioral problems, as well as cognitive deficits [1,4,33-37]. There is emerging evidence that multiple or persistent crying, sleeping, and feeding problems may have long-lasting effects on attention and avoidant personality symptoms in adulthood [4,27,38]. In summary, early crying, sleeping, and feeding problems are associated with high family stress and increase the risk of impaired child development.

Psychoeducation as a Suitable Intervention Tool for Affected Families
Thus, it is necessary to provide support to affected families as early as possible to reduce parenting stress. This can contribute to preventing crisis situations as well as child and parent mental health problems in the short and long term [39-41]. Psychoeducation is generally an essential tool for the prevention and treatment of mental illness and stress. In addition to increasing knowledge about the child’s problem or disorder [42,43], psychoeducational interventions can promote empowerment by improving subjective coping strategies [44-46]. This is also relevant for families of children with early crying, sleeping, and feeding problems, as parents consider corresponding reliable information helpful for understanding children’s symptom patterns and signals [24,47,48]. Moreover, Gilkerson et al [49] found that an early psychoeducational intervention program for parents of excessively crying children improved parenting self-efficacy. Findings suggest that psychoeducational interventions not only have a positive impact on parental parameters but can also reduce early child symptoms such as sleeping problems [50]. Furthermore, Hiscock et al [47] demonstrated the positive effects of a psychoeducational...
intervention on sleeping and crying problems in a subgroup of children who were fed very frequently.

Need for a Low-Threshold Intervention

Although early intervention is necessary and helpful for affected families, there could be barriers to seeking professional counseling. For example, parents might fear that they will be judged negatively by their social environment as well as by professional health care workers [24]. One possible way to reach affected families at an early stage is by a smartphone app. In Germany, approximately 87% of people have smartphones in their households [51,52]. With >101,000 health- and fitness-related offers in app stores worldwide in 2020 [53], apps are an increasingly popular way to obtain health-related information. Research indicates positive impacts of psychoeducational apps on both parent and child outcomes. Shorey et al [54] showed that an app-based educational program increases parental self-efficacy, social support, and parenting satisfaction during the postpartum period. App-based sleep interventions were found to reduce sleeping problems in children and improve sleep patterns in children aged 6 to 12 months [55] and from the age of 2 years [56]. Furthermore, parents who used features such as tracking feeding behavior reported higher perception of control and self-efficacy [57]. These results indicate that digitized psychoeducational interventions could be effective tools to support families with children with early crying, sleeping, and feeding problems. However, most apps provided in app stores are neither tested for effectiveness nor based on scientifically sound content [58]. Furthermore, most apps such as specialized sleeping or feeding apps target only one of the symptoms [55,56], although the symptoms frequently occur simultaneously in a complex manner [2,4,14]. To our knowledge, no apps are available to date that specifically target crying, sleeping, and feeding problems as common symptom patterns in early childhood. In addition, many apps (such as mere tracking apps) are limited to a few functions, instead of combining psychoeducational and interactive tools [59], and rarely address both child symptoms and parental outcomes, for example, parenting stress. Thus, we developed a new psychoeducational app targeting both parental and child outcomes as a low-threshold early support offer for affected families. In addition to scientifically based information on crying, sleeping, and feeding problems, the app included interactive tools such as a symptom diary function, relaxation strategies for parents, an emergency plan, and contact information for professional counseling centers.

Study Aim

In this study, we aimed to evaluate the effectiveness of the app in a clinical sample by including an intervention group (IG) and a waitlist control group (WCG). We hypothesized that, compared with the WCG, the IG using the app would have a significant reduction in the primary outcome, that is, parenting stress. Furthermore, we aimed to explore the app’s effects on secondary outcomes, including parental knowledge about crying, sleeping, and feeding problems; parental self-efficacy; perceived social support; and child crying, sleeping, and feeding problems.

Methods

Study Design

The app was evaluated in a monocentric, prospective, and randomized controlled intervention study using a pretest-posttest (posttest [t2]) design and a WCG from 2019 to 2022. The methods and results of this study are presented in accordance with the CONSORT (Consolidated Standards of Reporting Trials) Statement [60], the CONSORT-EHEALTH (CONSORT of Electronic and Mobile Health Applications and Online Tele Health) checklist (Multimedia Appendix 1), and the Guidelines for Executing and Reporting Research on Internet Interventions [61].

Ethics Approval

The study protocol was approved by the Ethics Committee of the Technical University of Munich (vote number: 56/18 S). The study was registered with the German Register of Clinical Studies (DRKS; register number: DRKS00019001; Multimedia Appendix 2).

Recruitment and Procedure

The target group were German-speaking parents of children aged 0 to 24 months who contacted a cry baby outpatient clinic in Bavaria (Southern Germany) for the first consultation because of crying, sleeping, or feeding problems. To avoid confounding the effects of app use with the effects of counseling, the individual study phase ended before the first appointment at the outpatient clinic (posttest [t2]). Participants whose possible study duration was very short (<10 days from first contact with the study team until counseling appointment in the outpatient clinic) were excluded because the applied questionnaires referred to a report period of at least 1 week. During the initial phone contact with the clinic, interested parents who met the inclusion criteria were referred to the study team. After verbal consent, study information, declaration of consent, and baseline test questionnaires (t1) were sent to their home addresses. As soon as the study team received the original signed informed consent and t1 questionnaires, families were included and randomly assigned to the IG or the WCG. Randomization was conducted by an independent researcher using Research Randomizer [62]. Participants were not blinded to the study conditions, and they received access to the app by email at different time points. While the IG obtained the app for the duration of the regular waiting period until the first counseling appointment, the WCG received it only after the first counseling appointment. A few days before the counseling appointment, t2 questionnaires were sent by post to the participants, and completed forms were collected by the study team just before the counseling appointment. To avoid sequence effects, all questionnaires were administered in permuted order. The individual study duration corresponded to the average waiting time for an initial counseling appointment (mean 3 weeks). During the study, participants were contacted repeatedly via email to receive a confirmation or reminder: (1) after 1 week if they had not returned the t1 questionnaires by then; (2) after the t1 questionnaires arrived; (3) five days after the app was unlocked to see whether the installation was successful; (4) one week before the initial counseling appointment in the outpatient clinic.
to remind them to bring the completed t2 questionnaire; and (5) after the study ended with a brief thank you note for participation.

**Intervention**

The overall aim of the app was to provide psychoeducation regarding early childhood crying, sleeping, and feeding problems (for screenshot examples, see Figure 1). In line with the Medical Research Council guidelines [63], the app was developed in a working consortium of international scientists and clinical health care professionals (n=10) in the field of early crying, sleeping, and feeding problems and was piloted regarding its first impression by parents and clinical experts (n=15; M Augustin et al, unpublished data, December 2022). The first final version of the app consisted of the following main components: (1) informational texts including tips on how to deal adequately with a child’s behavior were provided in a short version in simple language as well as in a more detailed version; (2) video interviews with experienced clinical experts addressing frequent questions; (3) an emergency plan in acute situations of excessive demands providing guidance for de-escalation; (4) a profile and diary function enabling parents to document their child’s symptoms; (5) self-care strategies suitable for everyday use addressing parents’ own needs; (6) an experience report of one family with a child with crying problems showing frequent problems of affected families; (7) a chat forum providing the opportunity to contact other affected parents; and (8) a regional register of counseling centers in Bavaria aiming to encourage affected parents to seek professional support at an early stage. Parents had the app at their free disposal and could decide how often they wanted to use it.

Figure 1. App intervention: screenshot examples. (A) Main screen and (B) menu for psychoeducational content concerning child crying.

**Measures**

**Primary Outcome: Parenting Stress**

Parenting stress was assessed at t1 and t2 with the Eltern-Belastungs-Inventar (EBI) [64], which is a German adaptation of the Parenting Stress Index [65]. The questionnaire contained 48 items covering the child domain (stress emanating from the child’s behavior) and the parent domain (impairments of parental functions). In this study, the overall parent domain score was applied as the outcome variable, and the 7 parent domain subscales (attachment, isolation, parental competence, depression, health, role restriction, and spouse-related stress) were used in the secondary exploratory analysis. Responses were given on a 5-point-Likert scale (1=strongly agree to 5=strongly disagree). The internal consistency (Cronbach α) of the EBI parent domain has been shown to be excellent (.93). External validity has been examined in validation studies using different samples. Results showed, among others, moderate to high correlations of the EBI with other stress indicators, as well as related constructs of parenting stress [66].
Secondary Outcomes

Knowledge About Crying, Sleeping, and Feeding
A multiple-choice test on crying, sleeping, and feeding (self-developed and based on the contents of the app) assessed the parents’ level of knowledge at t1 and t2 using 18 questions with 4 answer options, of which one or more were correct. An example item is as follows: “It is natural for children to cry (eg, due to tummy ache). However, at a certain age, the crying frequency decreases in most babies. When does this occur?—after 6 weeks—from 3 months of life—from 6 months of life—from 12 months of life.” The maximum possible score was 72. The internal reliability was acceptable, with a Cronbach α of .72.

In a face validity test, participants rated all items as very suitable or mostly suitable (Table S1 in Multimedia Appendix 3).

Parental Self-efficacy
The Perceived Maternal Parenting Self-Efficacy Questionnaire (PMP-SE) [67] measured parental self-efficacy in dealing with the child at t1 and t2. A total score was computed based on 20 items with 4 subscales (caretaking procedures, evoking behaviors, reading behaviors or signaling, and situational beliefs). Items were scored on a 5-point Likert scale ranging from 1 (do not agree at all) to 5 (totally agree). Internal reliability has been proven to be excellent, with a Cronbach α of .91. The predictive and criterion validity have been previously reported [67].

Perceived Social Support
Perceived social support was assessed at t1 and t2 with the K-22 short form of the Social Support Questionnaire (F-SozU) [68], and the total score was computed based on 22 items with 3 subscales (practical support, emotional support, and social integration). All items were rated on a 5-point Likert scale (1=does not apply to 5=is exactly correct). Internal reliability of the total score has been proven to be excellent with a Cronbach α of .91 [69]. Its validity has been confirmed in numerous studies [68,69].

Child Crying, Sleeping, and Feeding Problems
The Questionnaire for Crying, Feeding, and Sleeping (CFS; German Version) [70] assessed early child problems with respect to crying, sleeping, and feeding at t1 and t2. A total score was computed based on 3 scales: “Crying, Whining, and Sleeping” (24 items), “feeding” (13 items), and “coregulation” (12 items). Cronbach α has been shown to vary from .81 to .89 for the subscales, and α is .90 for the complete questionnaire, indicating high internal reliability. The questionnaire has been validated by correlations with behavioral diaries and clinical diagnoses [70].

Sociodemographic Questionnaire (Self-developed)
Parental age, participant’s relation to child, nationality, mother tongue, educational qualifications, current employment situation, partnership status, child’s age and gender, siblings, and information about the child’s problems were recorded at t1.

App Use
App use was measured at t2 with 1 item derived from an app evaluation questionnaire (self-developed) using 5 categories: daily (4), several times a week (3), once a week (2), <once a week (1), and app not used (0).

Statistical Analysis

Power
An a priori case number calculation was performed using G*Power software (version 3.1.9.2; Kiel University) [71]. A repeated-measures mixed ANOVA (between-group × within-subject factor) was assumed. However, to exclude between-subject effects with sufficient certainty, case number planning was completed for the between-subject factor analyses, providing lower power. The estimation was based on a type 1 error of α=.01 and a power of 1–β=.80. Findings from a randomized controlled trial (RCT) of the effectiveness of a psychoeducational app for parents in the postpartum period [54] and another RCT on the effectiveness of an information video–based intervention for early child crying [72] were used to estimate effect sizes [54]. On the basis of statistical values reported in these studies, calculations yielded medium to high effect sizes. Accordingly, in this study, the number of cases was estimated more conservatively for medium treatment effects (Cohen f=.03), using the ANOVA design described previously. The calculation of the number of cases resulted in a sample size of 136 participants.

Analysis Plan
To evaluate the effectiveness of the app-based intervention in the IG compared with the WCG, analyses were based on the intention-to-treat (ITT) principle. All analyses were performed using R software (version 4.0.1; R Foundation for Statistical Computing) [73]. The code used for the analyses has been made openly available in an Open Science Framework repository [74]. Missing values were assumed to be missing at random, which is typically plausible for trials with off-treatment assessments [75,76]. Missing values were therefore imputed using groupwise multivariate imputation by chained equations algorithm (fully conditional specification) [77], with 50 iterations and 50 (m) imputation sets. Several auxiliary variables were included in the imputation model to approximate the missing data in random missingness patterns.

Main Effectiveness Analysis
We tested whether the outcomes of app-based intervention in the IG was superior to those of the WCG in terms of its effects on parenting stress and secondary outcomes from pre- to posttests. For the confirmatory primary outcome analysis, a 1-sided test was used, whereas 2-sided testing was used for exploratory secondary outcome analyses. As an additional exploratory analysis, we examined the differences between groups on the subscales of the primary outcome (EBI parental stress). The effect differences between the 2 study conditions were assessed using univariate analysis of covariance. Baseline scores were used as covariates. Child age was entered as an additional covariate for the child symptom outcome analysis (CFS). All the models were fitted to each of the multiple imputed data sets. Model estimates were then aggregated via
Rubin’s combination rules [78] using a large-sample \( \chi^2 \)-approximation to combine the \( F \)-statistics [79]. To calculate the between-group standardized mean difference (Cohen \( d \)), we pooled the unstandardized group coefficients of a linear model without covariate adjustment using Rubin’s rules. This estimate was then standardized using the pooled outcome SD to obtain Cohen \( d \) and CI.

**Sensitivity Analysis**

To examine the robustness of the main analysis, 2 sensitivity analyses were conducted. First, we conducted a completer analysis of individuals who had no missing data and provided data at all assessment points. Second, a per-protocol analysis was conducted, focusing on individuals in the IG who accessed the app at least once (while retaining all participants in the WCG). The applied methods exactly mirrored the ones of the main effectiveness evaluation.

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**Results**

**Participant Enrollment and Characteristics**

After the first screening by the outpatient clinic, a total of 41.3% (276/669) of participants were assessed for eligibility by the study team. A total 136 individuals who met the inclusion criteria were randomly allocated to the IG (n=73, 53.7%) and WCG (n=63, 46.3%; Figure 2 shows the CONSORT participant flowchart). Participants (mean age 33.97, SD 4.03 years) were predominantly mothers (127/136, 93.3%) of German nationality (113/136, 83.1%) with higher education (105/136, 77.2% qualified for university entrance) and currently not employed or on parental leave (97/136, 71.3%). Children (70/136, 51.5% boys) aged on average 10.32 (SD 5.06) months, had no siblings (95/136, 69.9%), and experienced sleeping (61/136, 44.9%) or combined (40/136, 29.4%) problems. The demographics divided by group are presented in Table 1.
Table 1. Participant characteristics.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Intervention group (n=73)</th>
<th>Waitlist control group (n=63)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parental age (years), mean (SD)</td>
<td>33.71 (3.86)</td>
<td>34.27 (4.22)</td>
</tr>
<tr>
<td>Participant's relation to child, n (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mother</td>
<td>68 (93.2)</td>
<td>59 (93.7)</td>
</tr>
<tr>
<td>Father</td>
<td>5 (6.8)</td>
<td>4 (6.3)</td>
</tr>
<tr>
<td>Academic qualification, n (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Qualified for university entrance</td>
<td>57 (78.1)</td>
<td>48 (76.2)</td>
</tr>
<tr>
<td>Other or missing</td>
<td>16 (21.9)</td>
<td>15 (23.8)</td>
</tr>
<tr>
<td>Nationality, n (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>German</td>
<td>63 (86.3)</td>
<td>50 (79.4)</td>
</tr>
<tr>
<td>Other</td>
<td>10 (13.7)</td>
<td>13 (20.6)</td>
</tr>
<tr>
<td>First language, n (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>German</td>
<td>58 (79.5)</td>
<td>52 (82.5)</td>
</tr>
<tr>
<td>Other</td>
<td>15 (20.5)</td>
<td>11 (17.5)</td>
</tr>
<tr>
<td>Employment, n (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parental leave or currently not employed</td>
<td>53 (72.6)</td>
<td>44 (69.8)</td>
</tr>
<tr>
<td>Currently employed or apprenticeship</td>
<td>19 (26.0)</td>
<td>17 (27)</td>
</tr>
<tr>
<td>Other or missing</td>
<td>1 (1.4)</td>
<td>1 (1.6)</td>
</tr>
<tr>
<td>Single parent, n (%)</td>
<td>0 (0)</td>
<td>2 (3.2)</td>
</tr>
<tr>
<td>Child age (months), mean (SD)</td>
<td>10.21 (4.95)</td>
<td>10.44 (5.21)</td>
</tr>
<tr>
<td>Child gender, n (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Girl</td>
<td>36 (49.3)</td>
<td>30 (47.6)</td>
</tr>
<tr>
<td>Boy</td>
<td>37 (50.7)</td>
<td>33 (52.4)</td>
</tr>
<tr>
<td>Siblings, n (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>22 (30.1)</td>
<td>19 (30.2)</td>
</tr>
<tr>
<td>No</td>
<td>51 (69.9)</td>
<td>44 (69.8)</td>
</tr>
<tr>
<td>Child’s symptom duration (months), mean (SD)</td>
<td>6.91 (4.20)</td>
<td>7.76 (5.46)</td>
</tr>
<tr>
<td>Reason for consultation, n (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sleeping problems</td>
<td>34 (46.6)</td>
<td>27 (42.9)</td>
</tr>
<tr>
<td>Feeding problems</td>
<td>9 (12.3)</td>
<td>7 (11.1)</td>
</tr>
<tr>
<td>Crying or whining</td>
<td>5 (6.8)</td>
<td>3 (4.8)</td>
</tr>
<tr>
<td>Combined problems</td>
<td>21 (28.8)</td>
<td>19 (30.2)</td>
</tr>
<tr>
<td>Other or missing</td>
<td>4 (5.5)</td>
<td>7 (11.1)</td>
</tr>
</tbody>
</table>

**Descriptive Statistics**

Mean study duration from pre- to posttest was 23.41 (SD 10.42; range 10-49) days. In the IG, most parents used the app at least once a week (once a week: 24/73, 33%; several times a week: 21/73, 29%; daily: 7/73, 10%), whereas 27% (20/73) used the app less than once a week and 1 person did not use the app for unknown reasons. Descriptive statistics of outcome variables are displayed in Table 2.
Table 2. Mean scores in intention-to-treat sample per study group for outcome variables (pretest and posttest).

<table>
<thead>
<tr>
<th>Outcome variable</th>
<th>Descriptive statistics of outcomes</th>
<th>Intervention group, mean (SD)</th>
<th>Waitlist control group, mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>t1 (pretest)</td>
<td>t2 (posttest)</td>
</tr>
<tr>
<td>EBI(^a) parental scale</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Attachment</td>
<td>10.05 (3.16)</td>
<td>10.35 (3.24)</td>
<td>9.86 (3.28)</td>
</tr>
<tr>
<td>Isolation</td>
<td>10.86 (4.04)</td>
<td>10.57 (3.86)</td>
<td>11.11 (3.38)</td>
</tr>
<tr>
<td>Parental competence</td>
<td>11.14 (3.94)</td>
<td>10.80 (3.91)</td>
<td>11.27 (3.76)</td>
</tr>
<tr>
<td>Depression</td>
<td>13.14 (4.00)</td>
<td>12.32 (4.01)</td>
<td>12.96 (3.06)</td>
</tr>
<tr>
<td>Health</td>
<td>13.10 (3.28)</td>
<td>12.23 (3.33)</td>
<td>13.19 (3.59)</td>
</tr>
<tr>
<td>Role restriction</td>
<td>13.15 (4.31)</td>
<td>13.27 (4.08)</td>
<td>13.48 (3.51)</td>
</tr>
<tr>
<td>Spouse-related stress</td>
<td>13.88 (3.51)</td>
<td>13.65 (3.90)</td>
<td>14.52 (3.10)</td>
</tr>
<tr>
<td>Knowledge test</td>
<td>59.39 (4.60)</td>
<td>62.91 (4.30)</td>
<td>60.66 (5.04)</td>
</tr>
<tr>
<td>PMP-SE(^b)</td>
<td>65.38 (6.78)</td>
<td>66.96 (7.15)</td>
<td>65.89 (6.74)</td>
</tr>
<tr>
<td>F-SozU(^c)</td>
<td>4.35 (0.58)</td>
<td>4.35 (0.60)</td>
<td>4.18 (0.68)</td>
</tr>
<tr>
<td>CFS(^d)</td>
<td>2.28 (0.27)</td>
<td>2.25 (0.28)</td>
<td>2.29 (0.23)</td>
</tr>
</tbody>
</table>

\(^a\)EBI: Eltern-Belastungs-Inventar.
\(^b\)PMP-SE: Perceived Maternal Parenting Self-Efficacy Questionnaire.
\(^c\)F-SozU: Social Support Questionnaire.
\(^d\)CFS: Questionnaire for Crying, Feeding, and Sleeping.

Main Effectiveness Evaluation

Primary Outcome

Participants in the IG reported significantly lower levels of parenting stress at t2 compared with participants in the WCG \((F_{1,2683.50}=3.38; P=.03; Cohen d=-0.23)\). Exploratory analysis of EBI parent domain subscales revealed a significant reduction in the social isolation subscale \((F_{1,1072.48}=4.68; P=.03; Cohen d=-0.32)\), but not in the other domains (Table 3).
### Table 3. Analysis of covariance (ANCOVA) results for intention-to-treat sample.

<table>
<thead>
<tr>
<th>Variable</th>
<th>F test (df)</th>
<th>P value</th>
<th>Cohen d</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>EBI</strong>&lt;sup&gt;b&lt;/sup&gt; parental subscale</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Attachment</td>
<td>0.10 (1,12563.63)</td>
<td>.76</td>
<td>0.04</td>
<td>−0.30 to 0.38</td>
</tr>
<tr>
<td>Isolation</td>
<td>4.68 (1,1072.48)</td>
<td>.03&lt;sup&gt;d&lt;/sup&gt;</td>
<td>−0.32</td>
<td>−0.66 to 0.02</td>
</tr>
<tr>
<td>Parental competence</td>
<td>0.25 (1,4046.88)</td>
<td>.62</td>
<td>−0.08</td>
<td>−0.42 to 0.26</td>
</tr>
<tr>
<td>Depression</td>
<td>0.11 (1,6522.79)</td>
<td>.74</td>
<td>0.03</td>
<td>−0.31 to 0.37</td>
</tr>
<tr>
<td>Health</td>
<td>2.24 (1,1536.52)</td>
<td>.13</td>
<td>−0.22</td>
<td>−0.56 to 0.12</td>
</tr>
<tr>
<td>Role restriction</td>
<td>2.31 (1,5263.57)</td>
<td>.13</td>
<td>−0.22</td>
<td>−0.57 to 0.11</td>
</tr>
<tr>
<td>Spouse-related stress</td>
<td>3.17 (1,1136.55)</td>
<td>.08</td>
<td>−0.36</td>
<td>−0.71 to −0.02</td>
</tr>
<tr>
<td>Knowledge test</td>
<td>19.46 (1,402.98)</td>
<td>&lt;.001&lt;sup&gt;d&lt;/sup&gt;</td>
<td>0.38</td>
<td>0.05 to 0.73</td>
</tr>
<tr>
<td>PMP-SE&lt;sup&gt;e&lt;/sup&gt;</td>
<td>0.93 (1,7680.23)</td>
<td>.34</td>
<td>0.05</td>
<td>−0.29 to 0.39</td>
</tr>
<tr>
<td>F-SozU&lt;sup&gt;f&lt;/sup&gt;</td>
<td>0.20 (1,11479.08)</td>
<td>.66</td>
<td>0.04</td>
<td>−0.10 to 0.17</td>
</tr>
<tr>
<td>CFS&lt;sup&gt;g&lt;/sup&gt;</td>
<td>0.86 (1581.14)</td>
<td>.35</td>
<td>0.10</td>
<td>−0.23 to 0.45</td>
</tr>
</tbody>
</table>

<sup>a</sup> Approximated df based on multivariate imputation.
<sup>b</sup> EBI: Eltern-Belastungs-Inventar.
<sup>c</sup> 1-tailed test based on the t distribution.
<sup>d</sup> 2-tailed test (F test).
<sup>e</sup> PMP-SE: Perceived Maternal Parenting Self-Efficacy Questionnaire.
<sup>f</sup> F-SozU: Social Support Questionnaire.
<sup>g</sup> CFS: Questionnaire for Crying, Feeding, and Sleeping.

**Secondary Outcomes**

In the IG, a significantly higher level of knowledge about crying, sleeping, and feeding was noticeable at t2 compared with the WCG ($F_{1,402.98}=19.46; P<.001; \text{Cohen } d=0.38$).

No differences were found in parental efficacy, perceived social support, and child symptoms (Table 3).

**Sensitivity Analysis**

In the completer analysis, the primary and secondary outcomes remained stable. In line with the ITT analyses, in the IG, significantly lower levels of parenting stress ($P=.01$) and a significantly higher level of knowledge about crying, sleeping, and feeding ($P<.001$), but not in the other domains, were noticeable at t2 compared with the WCG. Furthermore, in the exploratory completer analysis referring to EBI parental subscales, in line with the ITT analysis, significantly lower scores on the social isolation subscale were noticeable ($P=.004$), and, in contrast to the ITT analysis, significantly lower levels on the role restriction ($P=.04$) and spouse-related stress ($P=.01$) subscales were evident in the IG at t2 (Table S2 in Multimedia Appendix 3).

In the per-protocol analysis, one person in the IG who did not use the app was excluded. In line with the ITT and completer analyses, in the IG, significantly lower levels of parenting stress ($P=.04$) and a significantly higher level of knowledge about crying, sleeping, and feeding ($P<.001$), but not in the other domains, were evident at t2 compared with the WCG. In the exploratory analysis of the EBI subscales, a significantly lower score on the spouse-related stress subscale became evident ($P=.04$), which is contrary to the ITT analysis but consistent with the completer analysis (Table S3 in Multimedia Appendix 3).

**Discussion**

**Principal Findings**

To the best of our knowledge, this is the first randomized controlled clinical study to target an app-based intervention for families having children with crying, sleeping, and feeding problems as common symptom patterns in early childhood. We found significantly lower levels of parenting stress after app use in the IG compared with the WCG. Furthermore, parents in the IG reported a significantly higher level of knowledge about crying, sleeping, and feeding than the parents in the WCG. However, there were no significant differences between the 2 groups in terms of parental efficacy; perceived social support; and child crying, sleeping, and feeding symptoms.

Consistent with other research on families of children with crying, sleeping, and feeding problems [18,80,81], initial parenting stress levels in our sample were very high compared with normative values (EBI parental subscale scores >85 were above the 98 percentile and above the cutoff for individuals with very high stress levels). The finding that the use of our psychoeducational app contributed to the reduction in parenting stress is in line with several previous studies investigating the effects of psychoeducational interventions on stress [82,83]. Psychoeducation can bring various positive effects, such as...
emotional relief and promotion of coping strategies, beyond a mere increase in knowledge [84,85]. In addition, research shows that parents of children aged <5 years very frequently read web-based information on child health but tend to miss the accuracy of the content they find, are only moderately satisfied with its reliability, and often feel the need to cross-check information [86], which might be potentially time-consuming and tedious. By providing a collection of evidence-based and reliable information about their child’s problem behavior as well as intervention strategies, the app use could potentially have spared parents’ time and effort. Further research would need to be sought in this regard.

Exploratory analysis revealed a significant reduction in the parental stress (EBI) subscale of social isolation, and in the sensitivity analysis, effects on the EBI subscales of role restriction and spouse-related stress became evident. Regarding social isolation, this finding is in line with Shorey et al [54], confirming the effects of psychoeducational interventions on perceived support from the social environment. Regarding role restriction, some studies addressing different target groups indicate positive intervention effects (eg, effects of a web-based mindful parenting training for parents of toddlers [87]); however, there is a lack of comparative studies targeting role restriction in the context of child crying, sleeping, or feeding problems. Addressing spouse-related stress, findings indicate that psychoeducational interventions in the pre- and postpartum periods, including both partners, have a positive impact on partnership quality [88,89]. However, we have no information on whether in our sample both partners used the app together, so the result of reduced spouse-related stress in the context of app use still needs further investigation.

With regard to the secondary outcomes, app use led to an increase in knowledge about crying, sleeping, and feeding problems. As summarized in a systematic review by McDowall et al [43], several studies have shown increased knowledge about children’s sleep after educational interventions. For instance, a pilot study by Jones et al [42] revealed that a brief brochure-based psychoeducational intervention enhanced parental knowledge about their children’s sleep in a clinical sample. Although the mechanisms of psychoeducation lack systematic research [90], these findings are in line with the “Information Models” of psychoeducation, which emphasizes the importance of providing families with knowledge about psychological symptoms and their management to create awareness and to contribute to the management of the problems [85].

In this study sample, no effects of app use on parental perceived self-efficacy, social support, or children’s symptoms were evident. With regard to self-efficacy, the absence of effects contrasts with the findings of Gilkerson et al [49] but is in line with the findings of a study by Missler et al [91] who also found no effects of a low-intensity psychoeducational program on parental self-efficacy. In terms of perceived social support, our findings differ from those of other studies focusing on apps for the postpartum period: Shorey et al [54] found that the use of a psychoeducational app increased perceived social support. Regarding child symptoms, studies investigating the effectiveness of psychoeducational interventions on the symptoms of excessive crying, sleeping, and feeding problems have shown inconsistent results. Although some studies indicate that educational interventions can reduce sleeping and crying problems in children [50,55], other studies cannot confirm these effects. In line with our results, Missler et al [91] found no effects of a low-intensity psychoeducational program on perceived problems of child crying, sleeping, and feeding. Hiscock et al [47] found effects only for specific subgroups, namely, very frequently fed children, showing changes in daytime sleep but not in nighttime sleep problems.

One explanation for the missing effects of app use on parental self-efficacy and perceived social support could be that, surprisingly and in contrast with other studies reporting impairment in self-efficacy and social support [24,25,92-95], the mean values of both these outcomes were in the normal range when compared with those of validation studies and normative values [67,96], indicating that these were not major issues in our clinical sample. This difference could be attributed to the characteristics of our sample, which included predominantly highly educated mothers in partnerships. Studies indicate that higher socioeconomic status is associated with higher self-efficacy and social support [97-99]. In addition, sleeping problems were predominant in our sample. Although associations between perceived social support and child crying as well as feeding problems have been investigated in various studies [24,25], studies addressing child sleeping problems are scarce. However, the effects of app use became evident in the EBI social isolation subscale, which might give us an indication that the app could have a positive effect on perceived social isolation. Further research would be useful at this point.

Another possible explanation for the absence of the effects on parental self-efficacy, perceived social support, and child problems could be that these constructs may not be as susceptible to short-term influence as parenting stress or knowledge. A meta-analysis by Amin et al [100] found that educational interventions for parents lasting at least 10 weeks produced significantly greater effects on parental self-efficacy than shorter interventions. To date, there are no comparative data on the extent to which the length of the intervention affects perceived social support. Regarding child symptom reduction, child problem behavior might be moderated by parenting stress; a regularly associated factor is poor parenting behavior, which in turn is linked to poorer child development and more behavioral problems [101,102]. Hence, an effect on child symptoms could become evident after the transfer of learned functional behavioral strategies in everyday life. A longer app use duration could have yielded different results; however, implementation was not possible in this study because the participation of the clinical sample was linked to the waiting time for an initial consultation appointment at the outpatient clinic.

Furthermore, the absence of effects could be anchored in the relevance of child problems to parental outcomes. Self-efficacy theory states that the success of strategies and actions is a major factor in increasing self-efficacy [103]. In the context of crying, sleeping, and feeding problems, this means that child symptoms would need to change because of parental strategies. Because CFS scores indicated clinically relevant problems in our sample.
and no changes in child symptoms were evident in this study, the effects on self-efficacy may have been absent. The lack of effect on child symptom reduction could also be related to the absence of effect on perceived social support in our study. Owing to the persistence of the child symptoms, parental networking behavior may not have changed.

Finally, we must acknowledge the possibility that an app-based psychoeducational intervention for this clientele is not sufficient to influence child symptoms, self-efficacy, or perceived social support. Parental feelings of helplessness, incompetence, and uncertainty about how to act are crucial therapeutic themes in affected families [2,21-23]. Working on these topics may require more intensive and individualized support such as parent-child psychotherapy or specialized counseling.

Our findings are of specific clinical relevance for the following reasons. First, increased knowledge may, to some extent, lead to altered and more favorable parenting behavior and thus might promote more adequate handling of the child in challenging situations [39-41,85]. Second, stress reduction provides the basis for breaking the vicious cycle of dysfunctional parent-child interactions, which is in turn an important protective factor for child mental health in the context of regulatory skills [2,40,41]. Reducing parenting stress is a prerequisite for increasing parental sensitivity, including the ability to adequately focus on a child’s needs and signals [104]. Third, regarding the long-term consequences of early crying, sleeping, and feeding problems, there is evidence that parenting stress partially mediates the association between early behavioral problems and later mental health problems [102]. Thus, stress reduction might be an important factor in the prevention of long-term effects on healthy child development.

The effect sizes on parenting stress are considered small in this study. Other studies investigating the effects of psychoeducational interventions on stress have also found small effect sizes [83]. Nevertheless, our finding that an effect was evident even after a short application period is promising in terms of app use as a secondary preventive service. From a health economic perspective, it should be pointed out that an app, which is relatively cost-efficient, can reach many people in the community; thus, even small effect sizes can be highly effective at the population level. In terms of knowledge gain, the small effect size might be related to sample characteristics, and research indicates that knowledge about child sleeping problems is positively associated with parental educational level in a clinical sample [105]. In our highly educated sample, it is conceivable that the parental level of knowledge about crying, sleeping, and feeding was already high at baseline, and therefore, only a small effect on knowledge level was obtained. However, we did not compare the different educational levels in our study. Therefore, future research should be conducted in this regard. Furthermore, our sample had been dealing with the child’s symptoms for an average of 7 months before seeking professional help in the outpatient clinic. Research shows that parents of children tend to seek internet-based information about child mental health daily or weekly [86]. Thus, one could assume that with such a long duration of symptoms, parents had likely already gathered information before app use, which might have resulted in a small effect on the knowledge level in our sample. Future research will have to corroborate this assumption.

**Strengths and Limitations**

Evaluating the app’s effectiveness using a RCT design is considered the gold standard for testing the effectiveness of new interventions [106]. However, to date, few RCT intervention studies have been conducted regarding early childhood crying, sleeping, and feeding problems. To the best of our knowledge, this is the first randomized controlled clinical study to target an app-based intervention for families having children with crying, sleeping, and feeding problems as common symptom patterns in early childhood. The newly developed app stands out from other web-based offers because it contains evidence-based strategies; addresses the complexity of co-occurring symptoms of crying, sleeping, and feeding; and combines psychoeducational input with interactive elements. Data collection for effectiveness testing was based on validated measurements. To avoid sequence effects, the questionnaires were administered in permuted order.

However, our results should be interpreted against the background of some limitations of the study. First, it must be mentioned that the study was conducted in a specific clinical setting, and predominantly, mothers of German nationality who had a high level of education and were in a partnership with a sense of social support and self-efficacy participated in the study. Caution is necessary when generalizing our results to other clinical populations. However, these sample characteristics are consistent with other studies on early childhood crying, sleeping, and feeding problems, which also report predominantly academic or higher-educated families in stable partnerships [107,108].

Furthermore, regarding post hoc power, given our sample size, only medium-size effects could be detected with sufficiently high probability ($\beta=0.82$ to $0.99$ for medium effects), whereas power was too low to detect small effect sizes with sufficient probability ($\beta=up to 0.79$ for small effects).

Finally, because the study was implemented in a clinical setting, a variation in individual study duration is evident; the measurements were linked to clinic appointments and thus linked to individual variance and deviation because of appointment postponements. However, as pointed out in the Medical Research Council guidelines [63], ensuring very strict standardization might not be appropriate, and a specified degree of adaptation to local settings is preferred.

**Conclusions**

In its first practical use in an RCT, a psychoeducational app for parents of children with crying, sleeping, and feeding problems contributes to parents’ better understanding of their child’s symptoms, has the potential to take the edge off parenting stress, and could therefore also serve as an effective secondary preventive measure. It can be recommended by pediatricians, gynecologists, maternity clinics, or child welfare services as an initial low-threshold information and support service when the first symptoms are developing, or it can be used to bridge waiting times for professional counseling appointments. In the
future, the app will be made available free of charge as a low-threshold offer.

Acknowledgments
The authors would like to thank all participants in the study for their time and effort. They would also like to thank the outpatient clinic, especially Dominika Hess, for their recruitment support; the project staff Katharina Richter, Anne-Sophie Wenzel, Sinja Schwarzwälder, Catherine Buechel, Lena Wagner, and Kristina Scherer for their contributions to the study; and Paula Kuper and Lea Schuurmans for their contributions to the analyses.

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Authors' Contributions
MA, AF, MLD, DW, and VM conceptualized and designed the study. MA and AF coordinated data collection. MA, MH, DDE, AF, MLD, and LDB contributed to the analyses and interpretation of the data. MA, AF, and MH wrote the manuscript. MLD, VM, DW, LDB, AB, and MZ reviewed and revised the manuscript for important intellectual content. AF, MLD, MA, DW, LDB, AB, VM, and MZ developed the app used in the trial. All authors approved the final manuscript as submitted and agreed to be accountable for all aspects of the work.

Conflicts of Interest
DDE reports to have received consultancy fees or served on the scientific advisory board from several companies such as Novartis, Sanofi, Lantern, Schön Kliniken, Minddistrict, and German health insurance companies (BARMER, Techniker Krankenkasse). DDE and MH are stakeholders of the Institute for Health Trainings Online (GET.ON), which aims to implement scientific findings related to digital health interventions in routine care. MH is an employee of the Institute for Health Trainings Online (GET.ON). AF, MLD, MA, DW, LDB, AB, VM, and MZ developed the app used in the trial.

Editorial Notice
This randomized study was only retrospectively registered, explained by authors by the fact that at the time of the study’s submission, registration was not yet required by their ethics committee. On recommendation, the study was registered a few months after study initiation and well before any results were obtained. From the start of the study until the time of registration, no fundamental changes to the study design were implemented. The editor granted an exception from ICMJE rules mandating prospective registration of randomized trials. However, readers are advised to carefully assess the validity of any potential explicit or implicit claims related to primary outcomes or effectiveness, as retrospective registration does not prevent authors from changing their outcome measures retrospectively.

Multimedia Appendix 1
CONSORT eHEALTH checklist (V 1.6.1).
[PDF File (Adobe PDF File), 1712 KB - mhealth_v11i1e41804_app1.pdf]

Multimedia Appendix 2
Trial registration.
[PDF File (Adobe PDF File), 90 KB - mhealth_v11i1e41804_app2.pdf]

Multimedia Appendix 3
Knowledge test face validity and sensitivity analysis results.
[DOCX File , 25 KB - mhealth_v11i1e41804_app3.docx]

References


Abbreviations

CFS: Questionnaire for Crying, Feeding, and Sleeping
CONSORT: Consolidated Standards of Reporting Trials
CONSORT-EHEALTH: Consolidated Standards of Reporting Trials of Electronic and Mobile Health Applications and Online Tele Health
DRKS: German Register of Clinical Studies
EBI: Eltern-Belastungs-Inventar
F-SozU: Social Support Questionnaire
IG: intervention group
ITT: intention-to-treat
PMP-SE: Perceived Maternal Parenting Self-Efficacy Questionnaire
RCT: randomized controlled trial
$t_1$: baseline test
$t_2$: posttest
WCG: waitlist control group

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Clinical Study of a Wearable Remote Rehabilitation Training System for Patients With Stroke: Randomized Controlled Pilot Trial

Liquan Guo1,2*, MS; Jiping Wang1,2, MS; Qunqiang Wu1, BS; Xinning Li4, PhD; Bochao Zhang1,2, BS; Linfu Zhou5*, PhD; Daxi Xiong1,2*, PhD

1School of Biomedical Engineering (Suzhou), Division of Life Sciences and Medicine, University of Science and Technology of China, Suzhou, China
2Suzhou Institute of Biomedical Engineering and Technology, Chinese Academy of Sciences, Suzhou, China
3Department of Rehabilitation Medicine, Tangdu Hospital Airforce Medicine University, Xi’an, China
4Department of Rehabilitation Medicine, Xi’an Gaoxin Hospital, Xi’an, China
5Department of Respiratory and Critical Care Medicine, The First Affiliated Hospital, Nanjing Medical University, Nanjing, China
*these authors contributed equally

Corresponding Author:
Daxi Xiong, PhD
School of Biomedical Engineering (Suzhou)
Division of Life Sciences and Medicine
University of Science and Technology of China
No.88, Keling Road
Suzhou, 215163
China
Phone: 86 18662576055
Email: xiongdx@sibet.ac.cn

Abstract

Background: In contrast to the large and increasing number of patients with stroke, clinical rehabilitation resources cannot meet their rehabilitation needs. Especially for those discharged, ways to carry out effective rehabilitation training without the supervision of physicians and receive guidance from physicians remain urgent problems to be solved in clinical rehabilitation and have become a research hot spot at home and abroad. At present, there are many studies on home rehabilitation training based on wearable devices, Kinect, among others, but these have disadvantages (eg, complex systems, high price, and unsatisfactory rehabilitation effects).

Objective: This study aims to design a remote intelligent rehabilitation training system based on wearable devices and human-computer interaction training tasks, and to evaluate the effectiveness and safety of the remote rehabilitation training system for nonphysician-supervised motor rehabilitation training of patients with stroke through a clinical trial study.

Methods: A total of 120 inpatients with stroke having limb motor dysfunction were enrolled via a randomized, parallel-controlled method in the rehabilitation institutions, and a 3-week clinical trial was conducted in the rehabilitation hall with 60 patients in the experimental group and 60 in the control group. The patients in the experimental group used the remote rehabilitation training system for rehabilitation training and routine clinical physical therapy (PT) training and received routine drug treatment every day. The patients in the control group received routine clinical occupational therapy (OT) training and routine clinical PT training and routine drug treatment every day. At the beginning of the training (baseline) and after 3 weeks, the Fugl-Meyer Motor Function Rating scale was scored by rehabilitation physicians, and the results were compared and analyzed.

Results: Statistics were performed using SAS software (version 9.4). The total mean Fugl-Meyer score improved by 11.98 (SD 8.46; 95% CI 9.69-14.27) in the control group and 17.56 (SD 11.65; 95% CI 14.37-20.74) in the experimental group, and the difference between the 2 groups was statistically significant (P=.005). Among them, the mean Fugl-Meyer upper extremity score improved by 7.45 (SD 7.24; 95% CI 5.50-9.41) in the control group and 11.28 (SD 8.59; 95% CI 8.93-13.62) in the experimental group, and the difference between the 2 groups was statistically significant (P=.01). The mean Fugl-Meyer lower extremity score improved by 4.53 (SD 4.42; 95% CI 3.33-5.72) in the control group and 6.28 (SD 5.28; 95% CI 4.84-7.72) in the experimental group, and there was no significant difference between the 2 groups (P=.06). The test results showed that the experimental group was better than the control group, and that the patients’ motor ability was improved.
Conclusions: The remote rehabilitation training system designed based on wearable devices and human-computer interaction training tasks can replace routine clinical OT training. In the future, through medical device registration certification, the system will be used without the participation of physicians or therapists, such as in rehabilitation training halls, and in remote environments, such as communities and homes.

Trial Registration: Chinese Clinical Trial Registry ChiCTR2200061310; https://tinyurl.com/34ka2725

(JMIR Mhealth Uhealth 2023;11:e40416) doi:10.2196/40416

KEYWORDS
remote rehabilitation; wearable devices; human-computer interaction; rehabilitation training; stroke

Introduction
Stroke is a disease of cerebral blood circulation disorder and brain tissue function and structural damage caused by cerebral vascular obstruction or rupture. It is the third leading cause of death and the second leading cause of disability worldwide. The high disability rate increases economic burden and mental pressure on both society and families [1]. According to the “Report on Stroke Prevention and Treatment in China 2021” [2], in 2020, the standardized prevalence of stroke among people aged over 40 years in China was 2.61%, the incidence rate was 505.23/100,000, and there were about 17.8 million patients with stroke. In addition, 3.4 million new patients are diagnosed with stroke each year in China, compared with approximately 13.7 million annually worldwide.

According to statistics, about 70%-85% of patients with first-time stroke have limb motor dysfunction, which seriously affects the quality of life and brings a heavy burden for the family and society. Timely and effective rehabilitation training can help them restore certain motor functions [3]. However, compared with the large and increasing number of patients with stroke, the resources of rehabilitation medical care are very limited. Therefore, rehabilitation training with the participation of nonrehabilitation physicians or therapists, especially remote and home-based rehabilitation, has received increasing attention.

According to some studies [4,5], the effect of rehabilitation training in a remote environment is comparable to or even better than that in a hospital environment. Relevant studies show [6-8] that sustained and effective remote rehabilitation can activate the neuroplasticity of patients with stroke and greatly improve the rehabilitation effect. Remote rehabilitation training can save medical resources, promote the motor function of patients, and improve the rehabilitation level after discharge in view of poor compliance of discharged patients [9-11]. Indeed, patient adherence and acceptability of rehabilitative practices need to be actively enhanced, overcoming pitfalls due to motor (eg, endurance), nonmotor (eg, fatigue, pain, dysautonomic symptoms, and motivational), and cognitive deficits [12].

Active and effective rehabilitation with nonphysician involvement, such as remote and home rehabilitation, and uploading training data and results to physicians for analysis and guidance are effective solutions to the problems of lack of clinical rehabilitation resources and poor adherence of discharged patients and are hot spots of international research; however, they still face many challenges.

Currently, to carry out effective rehabilitation training with nonphysician involvement, 2 main technical support solutions are proposed for training data acquisition and human-computer interaction control around application scenarios such as patient limb movements [13-15], activity detection [16-18], and motion recognition [19-22].

The first is vision-based solution, such as using a depth camera or Kinect. Placidi et al [23] designed a simple motion analysis system based on the use of a depth camera and a 3D real-time model of the human body. Their experimental results showed no significant differences in more than 95% of the data. However, the experiment could not achieve the rehabilitation training goals for fine motor movements and was not suitable for patients with severe disabilities. Webster and Celik [24] summarized the application of Kinect in geriatric care and stroke rehabilitation, based on which it was pointed out that the current application should be simulated toward the real situation, there was the need to capture obscuring movements, and in addition, the Kinect application is vulnerable to the spatial environment.

The second is a wearable sensor-based solution that integrates inertial sensors such as accelerometers to assess functional activities related to patient mobility in terms of type, intensity, time, and quality of the activity. Rau et al [25] developed a triaxial accelerometer-based remote assessment system for acquiring kinematic data on upper extremity anterior extension activities related to patient mobility in terms of type, intensity, time, and quality of the activity. Yang et al [14] proposed a stroke rehabilitation system combining inertial measurement sensors with physiological sensors, with an average recognition accuracy of 96.20% for hand gesture movements. However, this study only focused on identifying patient-specific movements and the training and validation data were from the same patients.

In addition, most studies have been conducted in clinical settings under physician supervision, and there is a lack of studies on rehabilitation training without physician supervision and validation in standardized clinical trials [26,27]. Therefore, to conduct effective rehabilitation training without physician supervision for use in remote and home settings, wearable devices based on the inertial measurement unit (IMU) and flex sensor are designed to be worn on the affected limb. Patients undergo interactive rehabilitation training based on standard training videos combined with human-computer interaction games. The feasibility, efficacy, and safety of the system are
evaluated by conducting a 120-case parallel-controlled, 2-center clinical trial.

Methods

Overview of the System Framework

In this study, we designed wearable devices such as rehabilitation training gloves and upper and lower limb rehabilitation training modules. Further, a remote rehabilitation system integrating training equipment hardware, man-machine communication training games, rehabilitation training software, a remote rehabilitation management platform, and a mobile app were developed. The overall architecture of the system is shown in Figure 1. The system consists of 3 parts, the patients with stroke side, the physician side, and the cloud server. Through the remote server, the rehabilitation physician in the hospital can view, analyze, and guide the patients’ rehabilitation training remotely in the training hall, community, and home, and prescribe new rehabilitation exercises for the patients. Through this system, patients can perform rehabilitation training without physician involvement.

Figure 1. Remote rehabilitation training system for patients with stroke.
Training Equipment Hardware

The wearable remote rehabilitation training equipment mainly includes the IMU modules for upper and lower limb rehabilitation training, rehabilitation training gloves for hand rehabilitation training, and Zigbee wireless receiver, among others. There are 2 IMU modules containing 9-axis motion sensors, including a 3-axis accelerometer, a 3-axis angular velocity meter, and a 3-axis magnetometer. The 2 IMU sensors are fixed to the upper and lower arms, respectively, by straps during upper limb training, and to the thigh and calf, respectively, during lower limb training. The rehabilitation glove contains 1 IMU and 5 flex sensors inside to monitor the movement of the wrist and individual fingers. The gloves are designed for left and right hands, with large, medium, and small sizes available to suit different patients.

The sensor is fixed on the affected side by the patients or their family according to the instructions and the wearing process is not complicated. In addition, the sensor works in headless mode, and its current position is automatically defined as the initial position through coordinate transformation at the beginning of each movement, so the deviation of the placement position does not affect the rehabilitation training.

Each wearable device has a 400-mAh battery and a power consumption of 20 mAh, with a full charge meeting the rehabilitation training for about 20 hours. Patients can train 2 times a day for half an hour each time, so the wearable devices can be used continuously for 10 days with a full charge. Each sensor was previously networked through the ZigBee2007 wireless communication protocol, which is very convenient for expansion and synchronous data collection. The sampling rate of each wearable device is 30 times per second, which is sufficient for rehabilitation training exercise data collection and analysis.

The rehabilitation training process based on the wearable device and interactive game is shown in Figure 2. Panels A-C are the schematic diagrams of the wearable device worn on the affected upper limb, hand, and lower limb, respectively, while D is the schematic diagram of the human-computer interaction rehabilitation training process. Patients wear the wearable device according to the instruction manual and undergo rehabilitation training according to the standard training video on the software. The sensor collects the rehabilitation training data, receives them through the Zigbee wireless receiver, and transmits them to the computer through USB. The rehabilitation training software on the PC side collects, stores, and displays data; improves signal quality through preprocessing such as sliding filtering; and then extracts patient motion features. The system controls rehabilitation training games through motion features, conducts human-computer interaction training for patients, and provides video and auditory feedback to patients to improve their enthusiasm for rehabilitation training.

Figure 2. Rehabilitation training process based on wearable devices and interactive games. (A) Instructions for wearing upper limbs; (B) Instructions for wearing gloves; (C) Instructions for wearing lower limbs; (D) Human-computer interaction rehabilitation training process. IMU: inertial measurement unit.
Under the advice of the rehabilitation physician and according to the characteristics of rehabilitation training movements, the motion features extracted by the system mainly include motion amplitude, direction, dynamic energy, motion smoothness, and motion force size, as shown in Table 1. The training difficulty is set according to the Fugl-Meyer score of the patient at the time of enrollment, and the system automatically adjusts the difficulty of the next training according to the previous training, with different features selected for different rehabilitation training movements and difficulty levels. For example, the simple mode of the Bobath handshake training uses AMP (amplitude) as the training game control parameter, while the hard mode collects all 5 features (amplitude, mean value, root-mean-square, JERK, strength) for weighted calculation results as the training game control parameter, with the weighting coefficients of 0.5, 0.2, 0.1, 0.1, and 0.1, respectively.

Table 1. Extracted motion features and physical meaning.

<table>
<thead>
<tr>
<th>Number</th>
<th>Feature</th>
<th>Definition</th>
<th>Physical meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>AMP&lt;sup&gt;a&lt;/sup&gt;</td>
<td>AMP=max(x) – max(x)</td>
<td>Describes the magnitude of the movement</td>
</tr>
<tr>
<td>2</td>
<td>MEAN&lt;sup&gt;b&lt;/sup&gt;</td>
<td></td>
<td>Describes the direction of the movement</td>
</tr>
<tr>
<td>3</td>
<td>RMS&lt;sup&gt;c&lt;/sup&gt;</td>
<td></td>
<td>Describes motion dynamic energy</td>
</tr>
<tr>
<td>4</td>
<td>JERK</td>
<td></td>
<td>Describes motion smoothness</td>
</tr>
<tr>
<td>5</td>
<td>Strength</td>
<td>Value</td>
<td>Describes the magnitude of the exercise effort</td>
</tr>
</tbody>
</table>

<sup>a</sup>AMP: amplitude.  
<sup>b</sup>MEAN: mean value.  
<sup>c</sup>RMS: root-mean-square.

**Rehabilitation Training Software**

This is a rehabilitation equipment system that integrates human-computer interaction. It uses software games to simulate daily life scenarios and guide patients in rehabilitation operation training. The computer software collects the strength, speed, distance, and other movement features of the rehabilitation training to control the game tasks, and gives feedback to the patients in a visual or auditory form, so as to guide the patients to continuously adjust their movements. Virtual games can provide clear training goals and tasks. The process of patients completing game tasks is the process of rehabilitation training. The higher the similarity between the patient’s rehabilitation training data and the standard data in terms of characteristics, the higher the patient’s score on the game task. Therefore, the training mode of human-computer interaction can greatly mobilize the enthusiasm of patients for rehabilitation training. In the absence of visual and auditory feedback, the patient is often has a trunk or proximal limb compensation, and is more prone to fatigue [28].

During the trial, the patient opens the Rehabilitation Training and Assessment client software (Figure 3), wears the wearable devices (2 IMU modules and rehabilitation training gloves) based on the physician’s prescription for rehabilitation training, and trains according to the standard rehabilitation video. The software can choose different games and can set different game difficulties according to the patient’s recovery status. Patients are rehabilitated by a threshold to determine whether the training action is effective or not. The thresholds are specifically 80% for difficult, 60% for moderate, and 40% for easy. By completing a valid action, the game will increase the corresponding score, and if the action is invalid, the score will remain the same. Patients will try to follow the movements of the standard training video to get a higher score during training. During the training process, the patient and the game perform human-computer interaction and receive feedback, and can simultaneously see the effect of each rehabilitation training action.
Figure 3. Rehabilitation training and assessment of client software: (A) rehabilitation prescription; (B) virtual game; (C) patient training; (D) exercise time; (E) action guidance; and (F) equipment operating status.

For example, in the apple picking game, each effective rehabilitation training exercise is defined as picking an apple. After the training is completed, the training score is given according to the parameters and features of the patient’s rehabilitation training, and the training data and results are automatically uploaded to the remote server so that the physician increases or decreases the length and intensity of the relevant movements according to the patient’s rehabilitation score. The new exercise prescription is automatically updated in the patient’s rehabilitation software. The clinical Fugl-Meyer score at enrollment and the game score during training were used as the basis for updating the exercise prescription. Adjustments were made once a day, and no adjustment was required for score changes of 5 points or less.

The software, games, and cloud platform included in the rehabilitation training system have been inspected by the National Medical Device Inspection Center and tested in accordance with the testing standard GB/t 25000.1-2010 Software Engineering-Software Product Quality Requirements and Evaluation (SQuaRE) [29], which meets the relevant requirements of software and network security and can be used for clinical research.

Remote Rehabilitation Cloud Management Platform

To help physicians view and analyze the rehabilitation training situation of remote patients more timely and effectively, data are visualized through the remote rehabilitation cloud management platform, thus allowing them to manage the rehabilitation training of their patients. The remote rehabilitation management platform consists of a front-end interactive interface and a back-end data analysis system. The front-end interactive interface comprises multiple pages for users to query and edit related information. The back-end data analysis system mainly realizes the functions of analyzing multisource sensor data and generating analysis reports and pushes the evaluation results to the corresponding rehabilitation physicians.

The remote rehabilitation cloud management platform (Figure 4) includes the web terminal and the mobile app, both of which have the functions of patient information management, updating rehabilitation prescriptions, remote video guidance, viewing rehabilitation data, generating analysis reports, and constructing patient rehabilitation files to assist physicians in better managing remote rehabilitation and guiding them in rehabilitation training. Patients or their families can also log-in to the management platform to consult and communicate with rehabilitation physicians.
Clinical Trial: Parallel Controlled 2-Center Study

Participants and Setting

For this pilot study, we chose patients in Tangdu Hospital and Xi’an Gaoxin Hospital with limb motor dysfunction caused by stroke 15-180 days after the onset (recovery period) and requiring rehabilitation training.

Patient inclusion criteria were as follows: (1) stroke diagnosed by computed tomography or magnetic resonance imaging within 90 days; (2) age between 30 and 75 years, male or female; (3) stable rehabilitation patients with limb motor dysfunction (with hemiplegic motor function evaluated according to the Brunnstrom upper or lower extremity grading stages II–VI) caused by stroke 15-180 days after its onset (recovery period); (4) cognition is clear and can follow the research protocol; (5) the patient can understand the study’s purpose, as well as showing sufficient compliance with the study protocol and signed the informed consent.

The following patients were excluded: (1) significant impairment of cognition and consciousness so that the Fugl-Meyer test could not be completed, (2) other significant limb lesions, such as fractures, severe arthritis, or amputation; (3) formation of limb joint contractures; (4) patients with disability, as specified by the International Classification of Functioning, Disability, and Health; (5) patients with a combination of severe primary diseases involving the cardiovascular, liver, kidney, and hematopoietic systems and mentally ill patients, as well as other circumstances that the investigator considers inappropriate to participate in this trial.

Experimental Design

This clinical trial is planned to be carried out in 2 clinical trial institutions at the same time and is divided into an experimental group and a control group. Patients in the experimental group received exercise training guided by the remote rehabilitation training system, routine clinical physical therapy (PT) training, and routine drug treatment. By contrast, patients in the control group received routine clinical occupational therapy (OT) training, routine clinical PT training, and routine drug treatment (see Multimedia Appendix 1 for the CONSORT [Consolidated Standards of Reporting Trials] checklist).

According to the inclusion criteria, this study selects all patients who conform to the entire trial process, that is, those who conform to the trial protocol, have good compliance, and can complete the corresponding tasks for analysis. The patients are randomly allocated to the experimental and control group in a 1:1 ratio, and the main efficacy index (Fugl-Meyer score of patients) was used as the basis for case estimation, with the sample size calculated according to the following formula [30]:

\[
\begin{align*}
\text{Sample size} &= \frac{z_{\alpha/2}^2 \cdot \text{SD}^2}{\delta^2} \\
\text{Sample size} &= \frac{(1.96)^2 \cdot 5.5^2}{2.2^2}
\end{align*}
\]

According to class II medical devices recognized by the industry, when the probability of type I error \( \alpha \) is set to 1-sided .025, \( z_{\alpha/2} = 1.96 \), and the probability of type II error \( \beta \) is set to .2, that is, the power \( 1-\beta = 80\% \) is 80%, \( z_{\beta} = 0.84 \). According to the aforesaid formula for the number of classic cases, this study predicted that the Fugl-Meyer change value of the experimental group is \( \mu_1 = 11.0 \), the mean change of the control group is \( \mu_2 = 10.0 \), and the mean SD () = 5.5. The noninferiority margin was 40% of the mean SD, and if \( \delta = 2.2 \), the number of cases was calculated as \( n = 47 \). Assuming a 20% dropout rate, the number of patients in each group should be at least 59. This clinical trial determined 60 cases in the experimental group and 60 in the control group, thus there were a total of 120 cases.

Considering whether the patients were exposed to PT/OT training and reducing the associated effects, this clinical trial protocol used a randomized grouping approach in which all patients who met the inclusion criteria were randomly assigned to either the test or control group according to randomization rules. The randomization method and steps were as follows: (1) Patients were randomized according to the stratified block randomization method. First, the random seed was set, then the block length was determined and stratified according to the center. SAS version 9.4 (SAS Institute) was used to generate a random grouping table of 120 patients receiving the trial (experimental group or control group). Each center was assigned consecutive random numbers that connect with each other. The patients were randomly assigned to either the experimental group or the control group according to the order in which the cases were enrolled and the randomization table.
As the training methods were different for the 2 groups, an open randomized trial was used. After randomizing patients to 1 of the 2 groups, neither the investigator nor the patients knew the grouping when baseline scoring was performed. At the beginning of the training, the randomized envelope for rehabilitation training corresponding to each randomization number was opened to know the corresponding training method. Thus, the investigator and patients only became aware of the grouping and scoring results after starting training. The statistical analysts, however, before unblinding, were not aware of the patients’ grouping.

Figure 5. Clinical trial flowchart.

According to related studies [28], active exercise training is more conducive to functional improvement and cortical function remodeling than passive training. According to the general rehabilitation guidelines and operating norms at home and abroad [31-33], in combination with the current commonly used clinical rehabilitation training movements and training methods, and under the advice and recommendation of many rehabilitation experts and physicians, 16 typical rehabilitation exercises were designed. The designed rehabilitation movements are used for the coordinated movement training of upper extremity, hand, and lower extremity. The training actions of the remote rehabilitation training system were as follows:

Upper extremity movements: (1) Bobath handshake training, (2) Bobath flexion and extension, (3) Bobath external anterior flexion and extension, (4) Bobath pre- and postrotation, (5) breast expansion exercise, (6) shoulder joint internal and external rotation, (7) shoulder touch training, and (8) elbow joint flexion and touch. Hand movements: (1) flexion-pressure rotation forward and backward, (2) wrist flexion and extension, (3) elbow flexion and wrist compression training, (4) finger-to-finger training, and (5) ball gripping training. Lower extremity movements: (1) squat training, (2) knee flexion and extension, and (3) knee internal and external rotation.
The experimental group adopted the training method of the remote rehabilitation training system and routine clinical PT training, whereas the control group used routine clinical rehabilitation training methods for limb motor dysfunction (ie, routine clinical OT training and routine clinical PT training).

For the inpatients in the experimental and control groups, the specific diagnosis and treatment methods were based on the condition and the test content, and the corresponding training and rehabilitation exercise methods that could be completed independently were selected in the rehabilitation hall. In addition, they performed system-guided training or routine clinical OT training 2 times a day (each session lasted 30 minutes) and conventional PT training 2 times a day (each session lasted 30 minutes). They trained no less than 10 times a week, for a total of no less than 30 times, for a total of 3 weeks.

In this study, the simplified Fugl-Meyer Motor Function Assessment scale was used for evaluation. The scale has good reliability and validity, Cronbach reliability coefficient >.80, and intraclass correlation coefficient >0.70 [34]. The scale consists of 50 items, including 33 for the upper extremities and 17 for the lower extremities, with each item rated on a scale of 0 (unable to complete the specified movement), 1 (able to partially complete), or 2 (can fully complete). The total score is 100 points. The higher the score, the better the motor function of the patient. At baseline and after 3 weeks of training, the patients were assessed by the rehabilitation physician according to the Fugl-Meyer Assessment (FMA) scale and the related results were recorded, respectively.

To study the rehabilitation training under the real nonphysician involvement scenario, the rehabilitation physician or therapist was next to the patient during the whole rehabilitation training process, only to ensure the patient’s safety. In addition, the rehabilitation data from the experimental group were uploaded to the rehabilitation website so that the physician could view the training data and update the exercise prescription as necessary from the office. The actual training of patients with stroke is shown in Figure 6. Figure 6A shows the control group receiving conventional OT training and Figure 6B shows the experimental group wearing the wearable device and following the video and human-computer interaction game for autonomous rehabilitation training.

### Figure 6. Practical application of the 2 training methods: (A) patients in the control group using conventional occupational therapy training; (B) patients in the experimental group using a remote rehabilitation training system.

**Statistical Analysis**

In this study, the rehabilitation status of patients with limb motor dysfunction (based on the change in the Fugl-Meyer Motor Function Rating scale score) after 3 weeks of clinical observation was used as the primary endpoint. The Fugl-Meyer score was used as the evaluation index to evaluate the clinical effectiveness of the remote rehabilitation training and evaluation system, and the safety of the system was judged by the number of adverse events and the relationship with the test system.

Descriptive statistics were used in this study to characterize demographic parameters and other baseline characteristic values. In this pilot study, a total of 109 patients ultimately completed the full trial, and statistical analyses and discussions of the data were conducted for these patients.

For descriptive statistics, demographic data, and other baseline characteristic values, parametric analysis was performed using targeted statistical methods, and the P value of inferential statistics was listed as the descriptive result. For the change in Fugl-Meyer score from baseline to 3 weeks of treatment, the difference between the 2 groups and its bilateral 95% CI were calculated.

SAS version 9.4 was used for analysis in this study. All statistical tests were 2-sided, and a P value ≤.05 was considered statistically significant.

**Ethics Approval**

This study was approved by the Ethics Committees of Tangdu Hospital (approval number 201912-08) and Xi’an Gaoxin Hospital (2020 ethics review number 001). All patients participating in this study have signed the informed consent form.

**Results**

### Baseline Data Analysis

The statistical results of demographic parameters and other baseline characteristic values are presented in Table 2. Different parameters of the experimental and control groups were statistically analyzed by different statistical methods. There was no significant difference in age (P=.81), BMI (P=.39), systolic blood pressure (P=.25), and diastolic blood pressure (P=.41) between the 2 groups by (1-sided) t test (P>.05).

https://mhealth.jmir.org/2023/11/e40416
Table 2. Analysis of demographic parameters of patients with stroke (n=60).

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Control group</th>
<th>Experimental group</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Valuesa</td>
<td>95% CI (lower-upper)</td>
</tr>
<tr>
<td></td>
<td>Valuesa</td>
<td>95% CI (lower-upper)</td>
</tr>
<tr>
<td>P value</td>
<td>.81</td>
<td>&gt;.99</td>
</tr>
<tr>
<td>Age (year)</td>
<td>55.82 (9.68)</td>
<td>34.00-73.00 (55.00)</td>
</tr>
<tr>
<td>Gender (male)</td>
<td>43 (71.67)</td>
<td>15.00-169.00 (41.00)</td>
</tr>
<tr>
<td>Course of disease (days)</td>
<td>61.20 (46.67)</td>
<td>96.00-151.00 (127.00)</td>
</tr>
<tr>
<td>Systolic blood pressure (mmHg)</td>
<td>127.47 (11.56)</td>
<td>82.45 (9.51)</td>
</tr>
<tr>
<td>Diastolic blood pressure (mmHg)</td>
<td>81.05 (9.00)</td>
<td>60.00-105.00 (80.00)</td>
</tr>
<tr>
<td>BMI (kg/m²)</td>
<td>24.68 (4.08)</td>
<td>18.34-44.92 (23.70)</td>
</tr>
<tr>
<td>Stroke type (cerebral infarction)</td>
<td>37 (61.67)</td>
<td>32 (53.33)</td>
</tr>
<tr>
<td>Hypertension</td>
<td>44 (73.33)</td>
<td>43 (71.67)</td>
</tr>
<tr>
<td>Hyperlipidemia</td>
<td>7 (11.67)</td>
<td>4 (6.67)</td>
</tr>
<tr>
<td>Arteriosclerotic coronary disease/myocardial infarction</td>
<td>10 (16.67)</td>
<td>12 (20.00)</td>
</tr>
</tbody>
</table>

aData are mean (SD) or n (%).

bNot applicable.

Although the mean course of stroke in the 2 groups was 61.20 and 46.22, respectively, in the Wilcoxon test for these 2 nonnormally distributed data, \( P = .15 \) (\( P > .05 \)), indicating that there was no statistically significant difference between the 2 groups. The reason for the difference in the means of the 2 groups was that there were 2 cases in the control group with stroke duration days close to 180 days, which increased the mean, but did not affect the overall experimental results.

The chi-square test showed that there was no significant difference between the 2 groups in gender (\( P > .99 \)), stroke type (\( P = .36 \)), hypertension (\( P = .84 \)), and arteriosclerotic coronary disease/myocardial infarction (\( P = .64 \)). Fisher test showed that there was no significant difference in hyperlipidemia between the 2 groups (\( P = .53 \)). These statistical results showed that in terms of various parameters, there was no statistical difference between the control group and the experimental group.

Results of the Clinical Trial

At baseline and 21 days, patients in the experimental group and patients in the control group were evaluated for motor function according to the FMA scale by experienced clinical rehabilitation physicians. The results of the experimental and control groups were statistically analyzed using the \( t \) test, and the relevant results are presented in Table 3. A total of 55 patients (92%) in the control group completed all trials, whereas a total of 54 patients (90%) in the experimental group completed all trials. Physician Fugl-Meyer mean total score changes in the control group were 11.98 (SD 8.46; 95% CI 9.69-14.27), whereas those in the experimental group were 17.56 (SD 11.65; 95% CI 14.37-20.74; \( P = .005 \)). Physician Fugl-Meyer mean upper extremity score changes in the control group were 7.45 (SD 7.24; 95% CI 5.50-9.41), whereas those in the experimental group were 11.28 (SD 8.59; 95% CI 8.93-13.62; \( P = .01 \)). Physician Fugl-Meyer mean lower extremity score changes in the control group were 4.53 (SD 4.42; 95% CI 3.33-5.72), whereas those in the experimental group were 6.28 (SD 5.28; 95% CI 4.84-7.72; \( P = .06 \)).
Table 3. Statistical analysis of physician scores according to the Fugl-Meyer scale.

<table>
<thead>
<tr>
<th>Analysis</th>
<th>Control group</th>
<th>Experimental group</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (SD)</td>
<td>95% CI (lower-upper)</td>
<td>Range (median)</td>
</tr>
<tr>
<td>Total score</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 days</td>
<td>41.11 (27.49)</td>
<td>33.68-48.54</td>
<td>8.00 to 96.00 (35.00)</td>
</tr>
<tr>
<td>21 days</td>
<td>53.09 (28.40)</td>
<td>45.41-60.77</td>
<td>8.00 to 99.00 (48.00)</td>
</tr>
<tr>
<td>21 to 0 days</td>
<td>11.98 (8.46)</td>
<td>9.69-14.27</td>
<td>0.00 to 39.00 (10.00)</td>
</tr>
<tr>
<td>Upper extremity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 days</td>
<td>23.67 (19.93)</td>
<td>18.28-29.06</td>
<td>4.00 to 65.00 (16.00)</td>
</tr>
<tr>
<td>21 days</td>
<td>31.13 (21.67)</td>
<td>25.27-36.99</td>
<td>4.00 to 66.00 (25.00)</td>
</tr>
<tr>
<td>21 to 0 days</td>
<td>7.45 (7.24)</td>
<td>5.50-9.41</td>
<td>0.00 to 36.00 (5.00)</td>
</tr>
<tr>
<td>Lower extremity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 days</td>
<td>17.44 (9.36)</td>
<td>14.91-19.97</td>
<td>4.00 to 34.00 (17.00)</td>
</tr>
<tr>
<td>21 days</td>
<td>21.96 (8.36)</td>
<td>19.70-24.22</td>
<td>4.00 to 34.00 (23.00)</td>
</tr>
<tr>
<td>21 to 0 days</td>
<td>4.53 (4.42)</td>
<td>3.33-5.72</td>
<td>–7.00 to 16.00 (4.00)</td>
</tr>
</tbody>
</table>

Figure 7 shows the change distribution of Fugl-Meyer scores in the control group and the experimental group after 21 days of rehabilitation training, including the total score, upper limb score, and lower extremity score. The test results showed that the experimental group was better than the control group in the improvement of the total score, upper limb score, and lower extremity score. In the general evaluation and upper limb rehabilitation training, there were significant differences in the changes between the 2 groups (P=.005 and .01, respectively), and there was no significant difference in the changes in the lower extremity score between the 2 groups (P=.06). The reason may be that, on the one hand, there are only 3 lower extremity rehabilitation exercises, and on the other hand, because the patients also undergo exercise rehabilitation training for the lower extremities in daily walking and other activities, there is no significant difference in the lower extremity rehabilitation effects between the 2 groups (P=.06).
To analyze the effect of a single patient’s use of a remote rehabilitation training system on motor function recovery, this study compared the results of the total score, upper limb score, and lower limb score of all patients in the experimental group before and after rehabilitation, as shown in Figure 8. Combined with data in Table 3, the average score of patients before rehabilitation was 43.28, and the average score after rehabilitation training was 60.83, with an average increase of 17.56. The average score of upper limbs before rehabilitation was 25.48, and the average score of upper limbs after rehabilitation training was 36.76, with an average increase of 11.28. The average score of the front lower extremity was 17.80, and the average score of the lower extremity after rehabilitation training was 24.07, an average increase of 6.28. These results show that for all patients using the remote rehabilitation training system, after 21 days of rehabilitation training, the FMA total score, the upper limb score, and the lower extremity score have improved significantly, that is, the patient’s exercise ability has been effectively recovered.

Figure 8. (A) Comparison of total scores of the Fugl-Meyer Scale before and after rehabilitation of patients in the experimental group; (B) comparison of Fugl-Meyer Scale upper limb scores of patients in the experimental group before and after rehabilitation; (C) comparison of Fugl-Meyer Scale lower extremity scores before and after rehabilitation in the experimental group.
To compare the effects of using the remote rehabilitation training system and receiving conventional OT training on the recovery of patients’ exercise ability, this study compared the control group and the experimental group before and after rehabilitation, as shown in Figure 9. Compared with receiving conventional OT training, the patient’s exercise ability improved significantly through the remote rehabilitation training system, and the difference was significant ($P=0.005$; Table 3). Among them, the Fugl-Meyer score change value of the upper limb was greater than that of the lower extremity, and all patients using the remote rehabilitation training system had a better rehabilitation effect on the upper limb remote rehabilitation.

Figure 9. (A) Changes in the total score of different rehabilitation methods in the control group and the experimental group; (B) changes in upper limb scores in different rehabilitation methods in the control group and experimental group; (C) changes in lower extremity scores in different rehabilitation methods in the control group and experimental group.

Finally, adverse events in this trial were analyzed. Adverse events are unfavorable medical events that occur during a clinical trial, whether related to a device or not. During the entire clinical trial, 28 adverse events were reported in the control group, with an incidence rate of 46.67%, and 22 adverse events in the experimental group, with an incidence rate of 36.67%; however, there was no significant difference between the 2 groups ($P=0.27$). The adverse events that occurred were judged by the investigator to be irrelevant to this test system.

Discussion

Principal Findings

In this study, aiming at the rehabilitation training of patients with limb movement dysfunction such as stroke, a number of wireless wearable devices were developed based on IMU inertial device and bending sensor. Using the Zigbee wireless networking technology, the movement data from patients’ rehabilitation training can be collected at the same time. Through data fusion and signal processing, real-time rehabilitation training exercise monitoring and exercise ability analysis are realized. Using rehabilitation training games based on daily life scenes, human-computer interaction rehabilitation training is realized. Further, the patient’s rehabilitation training data and results are recorded and uploaded to the remote server platform, so that the remote-end rehabilitation physician can view, analyze, and guide the patient to undergo effective rehabilitation training in a timely manner and improve the patient’s enthusiasm and compliance for rehabilitation training.

In addition, the game scenes correspond to the rehabilitation training actions, and the actions and games are matched according to the parts of the patient’s body that need rehabilitation. At the same time, the patient can modify the default game and the system will automatically save the record of the game selected by the patient and use it for subsequent rehabilitation training. With the improvement of the patient’s exercise ability, the difficulty of training will increase, and the rehabilitation exercise prescription will become more diversified. Presenting continually challenging new tasks helps patients stay motivated and interested in rehabilitation therapy. The virtual training scene based on daily life can reduce the danger caused by the wrong operation of patients with stroke in the real environment.
Based on the clinical trial of 109/120 (90.8%) patients with stroke, those in the experimental and control groups were scored according to the FMA scale at baseline and 21 days, respectively, and the scores of the 2 groups were compared and statistically analyzed. The results showed that the experimental group outperformed the control group in terms of changes relative to baseline in Fugl-Meyer total scores, upper extremity scores, and lower extremity scores, and that the patients’ upper and lower extremity motor abilities were better restored and improved, with significant improvement in upper extremity and total scores and some improvement in lower extremity scores. Other studies also found that lower extremity training improved motor function [35,36]. This clinical trial shows that the remote rehabilitation training system is used for the rehabilitation training of limb motor function of patients with stroke, and that the effect is better than that of routine clinical OT training.

In addition, in terms of safety, no adverse events related to this system occurred during the entire trial. Therefore, the designed remote rehabilitation training system based on wearable devices and human-computer interaction is used for rehabilitation training of patients with stroke and other limb motor dysfunction, which has good efficacy and good safety.

Comparison With Prior Work

According to the literature [37], long-term and specific rehabilitation training can maximize the recovery of patients’ health and confidence. However, patients are less willing to participate in rehabilitation programs for daily repetitive and passive training [38,39]. By contrast, active training of patients is more effective than passive training and can enhance patient outcomes [40,41].

Chae et al [42] proposed a smartwatch and machine learning–based remote rehabilitation system for home training of patients’ upper limbs. However, the number of patients was small, and the system is only for upper limb training; besides, the actual accuracy of home motion detection was not evaluated. Held et al [43] proposed a method of gait rehabilitation for patients with stroke, combining mobile augmented reality technology and sensor technology to adjust and train patients to walk. However, the device requires set up and calibration, making it more difficult for patients to use. The use of robotic technology for the rehabilitation of patients with stroke has been greatly developed. Ren et al [13] developed a wearable ankle joint rehabilitation robot to perform active and passive training on patients, but only for patients with acute stroke requiring ankle rehabilitation. Zhang et al [44] designed a desktop rehabilitation robot to train and evaluate the motor function of the upper limbs of patients.

Most experimental systems are complicated to use, expensive, inconvenient for patients to perform home training, and have few training movements, and therefore, they cannot undergo comprehensive training for the whole body. In addition, most of the aforesaid studies were performed under the supervision of physicians on-site, and cannot be applied in remote environments such as home.

In similar clinical trials of the efficacy of home remote rehabilitation, Cramer et al [45] conducted a comparison trial with clinical rehabilitation modalities for patients with stroke having upper extremity motor deficits and showed that activity-based training significantly improved arm motor function, but the trial was only for upper extremity and lacked further analysis for patients requiring lower extremity rehabilitation. In a trial comparing lower extremity rehabilitation, Kang et al [46] compared patients’ activities of daily living abilities through treadmill training, and reported that the Nordic treadmill training was an effective aid. However, the trial was performed for patients with mild issues under the supervision of the therapist, and there was no random allocation method, so caution should be exercised when interpreting the findings. In terms of human-computer interaction, Lee’s study [35] found that mobile phone–based virtual reality applied to patients’ stationary bicycle training improved lower extremity motor function recovery, but the movement of both legs was easily dominated by the healthy side of the body and lacked targeted training for the affected side of the body.

Therefore, the wearable remote rehabilitation training system for patients with stroke designed in this study can effectively overcome the aforesaid technology problems. Besides, the system was further designed and optimized based on the previous versions. Consequently, patients can receive effective training and guidance at home or in the community. In addition, the effectiveness and safety of the designed stroke active rehabilitation training system were verified by analyzing the results of the finalized clinical trial of 109 patients with stroke.

Limitations and Prospects

During the clinical experiment, almost all patients in the experimental group and rehabilitation physicians expressed strong interest in the designed rehabilitation training system owing to wearable devices and human-computer interaction training games.

However, according to the recommendations of rehabilitation physicians and patients, the system still has some limitations and needs further improvement for its better application in remote and home environments. In future work, the following improvements will be made.

First, according to the patients’ suggestion, the size/resolution of the standard training video on the software interface needs to be increased, with the action details and precautions also displayed, to facilitate the patient to standardize the rehabilitation training according to the standard video. Second, the software needs to have built-in instructions and videos on how to wear the wearable device so that patients who are unfamiliar with the system can adapt more quickly and actively participate in rehabilitation training. Third, we need to add more rehabilitation training actions and more human-computer interaction sports games in daily life scenarios to meet the needs for more refined and diversified rehabilitation training.

In terms of the experimental design, the following limitations apply:

1. The pilot was set up in a hospital rehabilitation hall rather than in a remote and decentralized home setting to more fully assess the effectiveness of patient rehabilitation training and the overall management of the rehabilitation process.

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JMIR Mhealth Uhealth 2023 | vol. 11 | e40416 | p.1111
(page number not for citation purposes)
2. Considering that hospital patients usually recover in the hospital for about 3 weeks, the trial was shorter than other studies [47,48]. After the trial, only 3 months of telephone follow-up was conducted for patients, and no abnormalities related to the trial were found. The clinical follow-up results are not taken into account in this study, which is one of the limitations of the design scheme of this study.

3. This trial only studied the patients’ performance in the FMA scale. The follow-up research will include the Activities of Daily Living scale, the Wolf Motor Function Test, the patients’ psychological status and satisfaction level, the impact of stroke publicity and education, among others, to further explore the rehabilitation effect of the remote rehabilitation training system.

Conclusions
This study found that the use of the remote intelligent rehabilitation training system designed based on wearable devices and human-computer interaction training tasks has a significant effect on the rehabilitation of motor function of patients with stroke, which can replace routine clinical OT training and improve the motivation, compliance, and rehabilitation effect of the training. In the future, improvements to the system will be made based on physician and patient recommendations, and through the medical device registration certification, it will be used without the participation of physicians or therapists, such as in rehabilitation training halls, and in remote environments, such as communities and homes.

Acknowledgments
This study was supported by the National Key Research and Development Program of China (2018YFC1313602), and the clinical trial was approved by the Ethics Committee of Tangdu Hospital and the Ethics Committee of Xi’an Gaoxin Hospital. All patients participating in the clinical trial research have signed the informed consent. We thank them for their contributions to this study.

Conflicts of Interest
None declared.

Multimedia Appendix 1
CONSORT-eHEALTH checklist (V 1.6.1).
[PDF File (Adobe PDF File), 584 KB - mhealth_v11i1e40416_app1.pdf ]

References


Abbreviations

AMP: amplitude
FMA: Fugl-Meyer Assessment
IMU: inertial measurement unit
MEAN: mean value
OT: occupational therapy
PT: physical therapy
RMS: root-mean-square
SQuaRE: Software Engineering-Software Product Quality Requirements and Evaluation
Clinical Study of a Wearable Remote Rehabilitation Training System for Patients With Stroke: Randomized Controlled Pilot Trial


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Background: Musculoskeletal (MSK) conditions are the number one cause of disability worldwide. Digital care programs (DCPs) for MSK pain management have arisen as alternative care delivery models to circumvent challenges in accessibility of conventional therapy. Despite the potential of DCPs to reduce inequities in accessing care, the outcomes of such interventions in rural and urban populations have yet to be studied.

Objective: The aim of this study was to assess the impact of urban or rural residency on engagement and clinical outcomes after a multimodal DCP for MSK pain.

Methods: This study consists of an ad hoc analysis of a decentralized single-arm investigation into engagement and clinical-related outcomes after a multimodal DCP in patients with MSK conditions. Patients were coded according to their zip codes to a specific rural-urban commuting area code and grouped into rural and urban cohorts. Changes in their engagement and clinical outcomes from baseline to program end were assessed. Latent growth curve analysis was performed to estimate change trajectories adjusting for the following covariates: age, gender, BMI, employment status, and pain acuity. Outcomes included engagement, self-reported pain, and the results of the Generalized Anxiety Disorder 7-item, Patient Health Questionnaire 9-item, and Work Productivity and Activity Impairment scales. A minimum clinically important difference (MCID) of 30% was considered for pain.

Results: Patients with urban and rural residency across the United States participated in the program (n=9992). A 73.8% (7378/9992) completion rate was observed. Both groups reported high satisfaction scores and similar engagement with exercise sessions, with rural residents showing higher engagement with educational content ($P<.001$) and higher program completion rates ($P=.02$). All groups showed a significant improvement in all clinical outcomes, including pain, mental health, and work productivity, without statistically significant intergroup differences. The percentage of patients meeting the MCID was similar in both groups (urban: 67.1%, rural: 68.3%; $P=.30$).
Conclusions: This study advocates for the utility of a DCP in improving access to MSK care in urban and rural areas alike, showcasing its potential to promote health equity. High engagement, satisfaction, and completion rates were noted in both groups, as well as significant improvements in clinical outcomes.

Trial Registration: ClinicalTrials.gov NCT04092946; https://clinicaltrials.gov/ct2/show/NCT04092946

(JMIR Mhealth Uhealth 2023;11:e44316) doi:10.2196/44316

KEYWORDS
physical therapy; physiotherapy; remote care; telerehabilitation; digital therapy; eHealth; telehealth; telemedicine; musculoskeletal; musculoskeletal conditions; urban; rural; pain; health inequity; digital care; pain management; clinical outcome; health equity; engagement

Introduction
Musculoskeletal (MSK) conditions are highly prevalent worldwide, resulting in significant disability and suffering [1], and were associated with up to US $380.9 billion of total medical expenditures in 2016 in the United States alone [2]. Exercise-based physical therapy is the mainstay treatment for such conditions [1,3-6]. Recently, telerehabilitation and digital physical therapy have emerged as alternative care delivery systems for a wide range of MSK conditions [7-10]. These alternative care delivery systems have shown to be effective and feasible compared to traditional physical therapy [11-18] while increasing access and affordability to patients and easing the burdens of conventional programs [19]. Accessibility is increased by reducing travel limitations and time barriers while eliminating any geographic restrictions. Additionally, digital therapy can increase compliance by allowing patients to undergo treatment at their convenience and at their own pace, increasing patient empowerment and self-management [8,10,20].

Despite the many benefits of telehealth, inequities in health other than underlying health status still exist based on age, geography, respective availability of health care facilities, and socioeconomic factors [21-27]. In fact, compared to those in urban areas, patients from rural areas tend to be older, are more likely to be obese, have higher rates of disability, have more chronic health conditions, and have higher fall rates [24,28]. Rural areas are known to have higher proportions of uninsured and underinsured individuals and higher costs of health care services when compared to urban areas [29]. Overall, 65% of rural US counties are designated as health professional shortage areas [30], and rural areas have lower patient-to-primary care physician ratios [31]. Patients in rural areas of the United States have fewer opportunities for in-person physical activity programs due to limited access to indoor facilities and limited transportation when compared to urban patients [32]. These inequities are further compounded by lower educational levels, higher rates of poverty, and lower rates of internet access in rural areas [24,33]. Also, individuals with limited or no digital literacy or with limited access to digital technology may not have the means to pursue and maintain a telerehabilitation intervention [23]. It is therefore crucial to identify strategies for improved access and quality of physical therapy in these historically disinvested areas.

To our knowledge, no study has been conducted on the impact of urban or rural location on engagement and clinical outcomes following a telerehabilitation program for MSK conditions. We have previously reported a multimodal digital care program (DCP) combining exercise-based physical therapy with psychoeducational components, which provided a comprehensive approach to pain management. This program encourages patients to develop strategies and self-management skills to manage their pain and has been validated in several acute and chronic MSK conditions [15-17,34-36]. Additionally, the impact of race and ethnicity [37], as well as baseline mental health [38] and fear-avoidance beliefs [39], on final clinical outcomes have also been explored. The purpose of this study was to assess the impact of geographical location on engagement and clinical outcomes after a multimodal DCP, with the hypothesis being that patients from both rural and urban areas would have similar engagement and significant improvement in outcomes after program completion.

Methods

Study Design
This study is an ad hoc analysis of a decentralized, single-arm investigation into clinical and engagement-related outcomes following a multimodal DCP in patients with musculoskeletal (MSK) pain conditions. The DCP was administered at the patients’ homes and delivered between March 1, 2021, and March 10, 2022.

Ethics Approval
This study is part of a trial that was prospectively registered on ClinicalTrials.gov (NCT04092946) on September 17, 2019, and approved by the New England Institutional Review Board (120190313) on June 18, 2020.

Population
The study population included adults (≥18 years of age) who were beneficiaries of employer health plans from 50 US states and the District of Columbia. Employees and their dependents who reported either acute or chronic MSK pain in the spine, upper limbs, or lower limbs were eligible and were invited to apply to the DCP of Sword Health (located in Draper, Utah) through a dedicated website. Throughout enrollment, participants were asked to provide demographic data, including zip codes and baseline clinical information (eg, initial pain levels). Participants were informed about the study and invited to provide consent. The exclusion criteria were as follows: (1) a health condition (eg, cardiac or respiratory) not allowing a participant to engage in at least 20 minutes of light to moderate exercise, (2) being under treatment for active cancer, and (3)
rapid loss of strength or numbness in the arms or legs or change in bowel or urinary function in the previous 2 weeks.

**Intervention**

The DCP has been described previously [15-17,34-36]. In brief, this multimodal program consisted of 4-, 8-, or 12-week telerehabilitation interventions comprising exercise, education, and cognitive behavioral therapy (CBT). This program digitally interfaced between the patient and an assigned physical therapist (PT), who monitored the patient for the study duration. Participants who lacked internet access at home were given a Wi-Fi hotspot. A US Food and Drug Administration–listed class II medical device that consisted of inertial motion trackers, a mobile app in a dedicated tablet, and a cloud-based portal was made available to all patients. Briefly, the personalized exercises were displayed on the tablet, with trackers allowing real-time video and audio biofeedback on performance. At session end, the data related to the exercise sessions, such as compliance, presence or absence of movement errors, and level of pain and fatigue during the exercise, were registered and stored in a cloud-based portal. This portal enabled remote and asynchronous monitoring by the assigned PT, who revised the prescribed exercises if needed. Patients were recommended a frequency of 3 exercise sessions per week. The education and CBT components of the program were developed by a multidisciplinary team following current clinical guidelines and state-of-the-art research [40-44]. The education component delved into topics focused on anatomy, physiology, symptoms, evidence-based treatments, fear avoidance, and active coping skills (including managing feelings of anxiety and depression). The CBT program was based on third-generation techniques—mindfulness, acceptance, and commitment therapy; empathy-focused therapy; fear-avoidance behavior; and constructive coping. The education and CBT materials were delivered to the patients through written articles, audio content, and interactive modules. Bidirectional communication with the assigned PT was ensured through built-in secure chat within a smartphone app and through video calls. Participants who did not perform any exercise session for 28 consecutive days were considered dropouts.

**Demographic Data**

Demographic data included age, BMI, patient gender, educational level, and employment status. The gender category included “man,” “woman,” “nonbinary,” “other,” and “prefer not to specify.” The employment status categories were defined as the following: full-time employed, part-time employed, or not employed. The educational levels were (1) high school or less (including technical or vocational training), (2) some college, including a bachelor’s degree, community college, or an associate degree, (3) some graduate school, including a master’s or doctoral degree, and (4) “not available” or “prefer not to answer.”

Patients were coded according to their zip codes to a specific rural-urban commuting area (RUCA) code [45]. RUCA codes characterize all census areas regarding their rural and urban status and relationships. This classification system uses the standard Bureau of Census urbanized area and urban cluster definitions in combination with work-commuting information [46,47]. Rural areas have been defined as having an urban core of 50,000 people or less [24]. Therefore, using primary RUCA codes, we defined urban areas by scores from 1 to 3, and rural areas by aggregating codes 4 to 10 (Multimedia Appendix 1, Table S1 [47]).

**Outcomes**

Outcomes were collected at baseline and 4, 8, and 12 weeks, and mean changes were calculated between baseline and program end. Engagement and clinical outcomes are described in Table 1.

### Table 1. Engagement and clinical outcomes in this study.

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Description</th>
</tr>
</thead>
</table>
| Engagement | Measured through the following:  
- Completion of the program (considered as the retention rate)  
- Number of completed exercise sessions over the 12-week digital care program  
- Weekly session frequency  
- Time spent performing exercise sessions  
- Interactions with the physical therapist  
- Satisfaction, assessed through the question “On a scale from 0 to 10, how likely is it that you would recommend this intervention to a friend or neighbor?” |
| Numerical Pain Rating Scale [48,49] | Assessed through the question “Please rate your average pain over the last 7 days, from 0 (no pain at all) to 10 (worst pain imaginable);” the number of patients reaching the minimum clinically important difference of 30% between baseline and treatment end was also assessed |
| Generalized Anxiety Disorder 7-item scale (range 0-21) [50] | Used to assess anxiety; higher scores are associated with worse outcomes |
| Patient Health Questionnaire 9-item scale (range 0-27) [51] | Used to assess depression; higher scores are associated with worse outcomes |
| WPAP* for general health questionnaire (version 2.0) [52] | Evaluated in employed participants to assess overall work impairment (WPAI overall: total presenteeism and absenteeism from work), presenteeism (WPAI work), absenteeism (WPAI time), and non–work-related activity impairment (WPAI activity); higher scores represent higher impairment. |

*WPAI: Work Productivity and Activity Impairment.
Statistical Analysis

Analyses of baseline characteristics (demographics and clinical data), as well as engagement metrics, were performed using a 2-tailed, 2-sample t test, a 2-way analysis of variance (ANOVA) with Bonferroni post hoc test, a chi-square test, or a 2-proportion z test. Patients who completed the program were defined as “completers” and those that did not were defined as “noncompleters.”

Latent growth curve analysis (LGCA) was used to estimate trajectories of each outcome over time [35,53]. The LGCA has been recognized as one of the most powerful methods to analyze longitudinal data, since it provides a measure of fitness and addresses missing data through full information maximum likelihood (FIML) [54-57]. FIML uses all available data at each time point from all participants to calculate maximum likelihood estimates, outperforming multiple imputation by chained equations or listwise deletion [58,59]. In addition, the LGCA uses a structural equation model to define trajectories through intercept, slope, and curvature for each variable, allowing analysis of the recovery pace and leveling of the effect for each outcome. In order to account for unbalanced group sizes, a multiple-group LGCA was conducted. This allows for creating separate models for rural and urban groups while simultaneously performing intergroup comparisons (e.g., mean change). A conditional analysis was conducted to assess the influence of age, gender, BMI, employment status, and education level and was fitted as a random effect. Additionally, analysis of subpopulations was performed by focusing on participants who met the following criteria at baseline: Generalized Anxiety Disorder 7-item (GAD-7) and Patient Health Questionnaire 9-item (PHQ-9) scores equal or greater than 5 points [50,51] and a Work Productivity and Activity Impairment (WPAI; comprising overall, work, time, and activity) score greater than 0 points. A robust sandwich estimator was used in all models for standard errors.

All statistical analyses were conducted using commercially available software (SPSS version 22; IBM Corp), and the level of significance was set at \( P < .05 \) for all tests. The LGCA was coded using R (version 4.2.2; R Foundation for Statistical Computing).

Results

Participant Inclusion

A total of 14,754 participants were screened for eligibility (Figure 1). Of these, 2151 were excluded, for a total of 12,603 (85.4%) eligible patients, of whom 2611 were excluded due to unavailable RUCA data or not starting the program, resulting in a total of 9992 patients at program start. A total of 7378 of 9992 (73.8%) patients completed the program. The study flow diagram is presented in Figure 1.

Baseline Characteristics

Patients’ baseline demographics grouped by urban and rural areas are presented in Table 2, while baseline characteristics stratified by completers and noncompleters can be found in Multimedia Appendix 1, Table S2.
### Table 2. Baseline characteristics for urban and rural groups following an intention-to-treat analysis. Filtered cases correspond to participants who reported relevant impairment at baseline (>0 or ≥5 points). Statistically significant $P$ values are italicized.

<table>
<thead>
<tr>
<th></th>
<th>Total (n=9992)</th>
<th>Urban (n=8809)</th>
<th>Rural (n=1183)</th>
<th>$P$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years), mean (SD)</td>
<td>48.55 (12.45)</td>
<td>48.11 (12.37)</td>
<td>51.85 (12.57)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Age categories (years), n (%)</td>
<td></td>
<td></td>
<td></td>
<td>&lt;.001</td>
</tr>
<tr>
<td>&lt;25</td>
<td>127 (1.3)</td>
<td>114 (1.3)</td>
<td>13 (1.1)</td>
<td></td>
</tr>
<tr>
<td>25-40</td>
<td>2753 (27.6)</td>
<td>2520 (28.6)</td>
<td>233 (19.7)</td>
<td></td>
</tr>
<tr>
<td>40-60</td>
<td>5279 (52.8)</td>
<td>4649 (52.8)</td>
<td>630 (53.3)</td>
<td></td>
</tr>
<tr>
<td>&gt;60</td>
<td>1833 (18.3)</td>
<td>1526 (17.3)</td>
<td>307 (26)</td>
<td></td>
</tr>
<tr>
<td>BMI (kg/m$^2$), mean (SD)</td>
<td>29.18 (6.74)</td>
<td>28.96 (6.60)</td>
<td>30.83 (7.48)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>BMI categories (kg/m$^2$), n (%)</td>
<td></td>
<td></td>
<td></td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Underweight (&lt;18.5)</td>
<td>90 (0.9)</td>
<td>84 (1)</td>
<td>6 (0.5)</td>
<td></td>
</tr>
<tr>
<td>Normal (18.5-25)</td>
<td>2798 (28)</td>
<td>2548 (28.9)</td>
<td>250 (21.1)</td>
<td></td>
</tr>
<tr>
<td>Overweight (25-30)</td>
<td>3373 (33.8)</td>
<td>3011 (34.2)</td>
<td>362 (30.6)</td>
<td></td>
</tr>
<tr>
<td>Obese (30-40)</td>
<td>2957 (29.6)</td>
<td>2525 (28.7)</td>
<td>432 (36.5)</td>
<td></td>
</tr>
<tr>
<td>Obese grade III (&gt;40)</td>
<td>743 (7.4)</td>
<td>614 (7)</td>
<td>129 (10.9)</td>
<td></td>
</tr>
<tr>
<td>Gender, n (%)</td>
<td></td>
<td></td>
<td></td>
<td>.12</td>
</tr>
<tr>
<td>Woman</td>
<td>5502 (55.1)</td>
<td>4818 (54.7)</td>
<td>684 (57.8)</td>
<td></td>
</tr>
<tr>
<td>Man</td>
<td>4457 (44.6)</td>
<td>3963 (45)</td>
<td>494 (41.8)</td>
<td></td>
</tr>
<tr>
<td>Nonbinary</td>
<td>24 (0.2)</td>
<td>19 (0.2)</td>
<td>5 (0.4)</td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>3 (0)</td>
<td>3 (0)</td>
<td>0 (0)</td>
<td></td>
</tr>
<tr>
<td>Prefer not to specify</td>
<td>6 (0.1)</td>
<td>6 (0.1)</td>
<td>0 (0)</td>
<td></td>
</tr>
<tr>
<td>Employment status, n (%)</td>
<td></td>
<td></td>
<td></td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Employed full-time</td>
<td>6271 (62.8)</td>
<td>5616 (63.8)</td>
<td>655 (55.4)</td>
<td></td>
</tr>
<tr>
<td>Employed part-time</td>
<td>2348 (23.5)</td>
<td>2076 (23.6)</td>
<td>272 (23)</td>
<td></td>
</tr>
<tr>
<td>Not employed</td>
<td>1067 (10.7)</td>
<td>853 (9.7)</td>
<td>214 (18.1)</td>
<td></td>
</tr>
<tr>
<td>Education level, n (%)</td>
<td></td>
<td></td>
<td></td>
<td>.001</td>
</tr>
<tr>
<td>High school or less</td>
<td>866 (8.7)</td>
<td>700 (7.9)</td>
<td>166 (14)</td>
<td></td>
</tr>
<tr>
<td>Some college, including bachelor’s or associate degree</td>
<td>4543 (45.5)</td>
<td>4031 (45.8)</td>
<td>512 (43.3)</td>
<td></td>
</tr>
<tr>
<td>Some graduate school, including master’s or doctoral degree</td>
<td>2082 (20.8)</td>
<td>1876 (21.3)</td>
<td>206 (17.4)</td>
<td></td>
</tr>
<tr>
<td>Not available or prefer not to answer</td>
<td>2501 (25)</td>
<td>2202 (25)</td>
<td>299 (25.3)</td>
<td></td>
</tr>
<tr>
<td>Acuity, n (%)</td>
<td></td>
<td></td>
<td></td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Acute</td>
<td>2147 (21.5)</td>
<td>1952 (22.2)</td>
<td>195 (16.5)</td>
<td></td>
</tr>
<tr>
<td>Chronic</td>
<td>7845 (78.5)</td>
<td>6857 (77.8)</td>
<td>988 (83.5)</td>
<td></td>
</tr>
<tr>
<td>Anatomical pain region, n (%)</td>
<td></td>
<td></td>
<td></td>
<td>.003</td>
</tr>
<tr>
<td>Ankle</td>
<td>422 (4.2)</td>
<td>380 (4.3)</td>
<td>42 (3.6)</td>
<td></td>
</tr>
<tr>
<td>Elbow</td>
<td>286 (2.9)</td>
<td>259 (2.9)</td>
<td>27 (2.3)</td>
<td></td>
</tr>
<tr>
<td>Hip</td>
<td>900 (9)</td>
<td>786 (8.9)</td>
<td>114 (9.6)</td>
<td></td>
</tr>
<tr>
<td>Knee</td>
<td>1438 (14.4)</td>
<td>1292 (14.7)</td>
<td>146 (12.3)</td>
<td></td>
</tr>
<tr>
<td>Low back</td>
<td>3976 (39.8)</td>
<td>3441 (39.1)</td>
<td>535 (45.2)</td>
<td></td>
</tr>
<tr>
<td>Neck</td>
<td>936 (9.4)</td>
<td>834 (9.5)</td>
<td>102 (8.6)</td>
<td></td>
</tr>
<tr>
<td>Shoulder</td>
<td>1632 (16.3)</td>
<td>1461 (16.6)</td>
<td>171 (14.5)</td>
<td></td>
</tr>
</tbody>
</table>
### Clinical outcomes (score)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Total (n=9992)</th>
<th>Urban (n=8809)</th>
<th>Rural (n=1183)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Wrist or hand</strong></td>
<td>402 (4)</td>
<td>356 (4)</td>
<td>46 (3.9)</td>
<td></td>
</tr>
<tr>
<td><strong>Pain, mean (SD)</strong></td>
<td>4.83 (1.99)</td>
<td>4.83 (1.99)</td>
<td>4.85 (1.98)</td>
<td>.72</td>
</tr>
<tr>
<td><strong>GAD-7 ≥5, n (%)</strong></td>
<td>2751 (27.5)</td>
<td>2430 (27.6)</td>
<td>321 (27.1)</td>
<td>.74</td>
</tr>
<tr>
<td><strong>GAD-7, mean (SD)</strong></td>
<td>8.89 (4.08)</td>
<td>8.89 (4.07)</td>
<td>8.89 (4.19)</td>
<td>.99</td>
</tr>
<tr>
<td><strong>PHQ-9 ≥5, n (%)</strong></td>
<td>3.03 (4.35)</td>
<td>3.04 (4.35)</td>
<td>2.98 (4.37)</td>
<td>.69</td>
</tr>
<tr>
<td><strong>PHQ-9, mean (SD)</strong></td>
<td>2071 (20.7)</td>
<td>1790 (20.3)</td>
<td>281 (23.8)</td>
<td>.006</td>
</tr>
<tr>
<td><strong>PHQ-9, mean (SD)</strong></td>
<td>9.21 (4.30)</td>
<td>9.20 (4.29)</td>
<td>9.31 (4.41)</td>
<td>.69</td>
</tr>
<tr>
<td><strong>WPAI overall &gt;0, mean (SD)</strong></td>
<td>2.37 (4.15)</td>
<td>2.33 (4.11)</td>
<td>2.7 (4.41)</td>
<td>.004</td>
</tr>
<tr>
<td><strong>WPAI overall, mean (SD)</strong></td>
<td>29.89 (20.11)</td>
<td>29.9 (20.11)</td>
<td>29.80 (20.16)</td>
<td>.91</td>
</tr>
<tr>
<td><strong>WPAI work &gt;0, mean (SD)</strong></td>
<td>17.32 (21.26)</td>
<td>17.23 (21.25)</td>
<td>17.9 (21.39)</td>
<td>.34</td>
</tr>
<tr>
<td><strong>WPAI work, mean (SD)</strong></td>
<td>28.63 (18.80)</td>
<td>28.62 (18.77)</td>
<td>28.71 (19.05)</td>
<td>.91</td>
</tr>
<tr>
<td><strong>WPAI time &gt;0, mean (SD)</strong></td>
<td>16.27 (20.05)</td>
<td>16.16 (20.0)</td>
<td>17.04 (20.35)</td>
<td>.21</td>
</tr>
<tr>
<td><strong>WPAI time, mean (SD)</strong></td>
<td>18.08 (18.07)</td>
<td>18.45 (18.45)</td>
<td>15.38 (14.94)</td>
<td>.11</td>
</tr>
<tr>
<td><strong>WPAI activity &gt;0, mean (SD)</strong></td>
<td>1.91 (8.07)</td>
<td>1.94 (8.22)</td>
<td>1.65 (6.82)</td>
<td>.31</td>
</tr>
<tr>
<td><strong>WPAI activity, mean (SD)</strong></td>
<td>37.37 (22.86)</td>
<td>37.33 (22.85)</td>
<td>37.70 (22.91)</td>
<td>.65</td>
</tr>
<tr>
<td><strong>Medications, n (%)</strong></td>
<td>29.04 (25.46)</td>
<td>28.92 (25.45)</td>
<td>29.93 (25.48)</td>
<td>.20</td>
</tr>
</tbody>
</table>

---

When comparing completers with noncompleters, the latter were younger (46.23, SD 12.61 years vs 49.38, SD 12.29 years, respectively; P<.001) and reported higher BMI (30.22, SD 7.36 kg/m² vs 28.81, SD 6.47 kg/m², respectively; P<.001). A larger proportion of noncompleters were employed full-time (1732/2614, 66.3% vs 4539/7378, 61.5%, respectively; P<.001) and reported a lower educational level. Noncompleters also reported higher levels of impairment in productivity (WPAI overall, P=.004 and WPAI work, P=.001) and non–work-related activities (WPAI activity, P=.01) at baseline.

### Engagement

Individuals from rural areas were more likely to complete the program than patients from urban areas (906/1183, 76.6% vs 6472/8809, 73.5%, respectively; P=.02). However, independently of dropout rates, both groups had a similar pattern of engagement. Engagement data stratified by patients from urban and rural areas is presented in Table 3. The 2 groups had similar time dedicated to exercise (P=.48), number of sessions (P=.77), sessions per week (P=.11), and interactions with the PT (P=.14). Average satisfaction scores were similarly high in both groups (rural score 8.6, SD 1.7 and urban score 8.6, SD 1.8; P=.95). The single significant difference in engagement between groups was the number of educational articles consulted, with patients from rural areas reading more articles than patients from urban areas (P<.001; Table 3).
Table 3. Engagement data across the groups. Statistically significant $P$ values are italicized.

<table>
<thead>
<tr>
<th>Engagement outcomes</th>
<th>Urban, mean (SD)</th>
<th>Rural, mean (SD)</th>
<th>$P$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sessions, n</td>
<td>33.88 (32.23)</td>
<td>34.18 (30.94)</td>
<td>.77</td>
</tr>
<tr>
<td>Sessions per week, n</td>
<td>2.76 (1.14)</td>
<td>2.78 (1.12)</td>
<td>.11</td>
</tr>
<tr>
<td>Training time, minutes</td>
<td>472.02 (485.56)</td>
<td>482.54 (485.96)</td>
<td>.48</td>
</tr>
<tr>
<td>Articles read, n</td>
<td>2.72 (5.27)</td>
<td>3.44 (6.18)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Interactions with physical therapist, n</td>
<td>11.79 (12.54)</td>
<td>12.37 (13.90)</td>
<td>.14</td>
</tr>
<tr>
<td>Average satisfaction score</td>
<td>8.6 (1.7)</td>
<td>8.6 (1.8)</td>
<td>.95</td>
</tr>
</tbody>
</table>

Clinical Outcomes

Mean changes in clinical outcomes for both urban and rural groups following an intent-to-treat analysis are presented in Table 4, while the corresponding model estimates and model fitness are presented in Multimedia Appendix 1, Tables S3 and S4, respectively [60,61]. Change trajectories of each outcome are depicted in Figure 2. The impact of the covariates in clinical outcomes is presented in Multimedia Appendix 1, Table S5. The same analysis following a per-protocol approach is presented in Multimedia Appendix 1, Tables S6-S8. Similar results were observed from both intention-to-treat and per-protocol approaches. Since intention-to-treat analysis offers an overview change of the entire cohort, the following section is focused on these results.

Table 4. Mean changes between baseline and program end and mean differences between groups for the studied clinical outcomes following an intent-to-treat analysis. Statistically significant $P$ values are italicized.

<table>
<thead>
<tr>
<th>Scores</th>
<th>Urban</th>
<th>Rural</th>
<th>Mean difference</th>
<th>$P$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pain</td>
<td>Mean change (95% CI)</td>
<td>$P$ value</td>
<td>Mean change</td>
<td>$P$ value</td>
</tr>
<tr>
<td></td>
<td>2.2 (2.2 to 2.3)</td>
<td>&lt;.001</td>
<td>2.3 (2.1 to 2.5)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>GAD-7$^a$</td>
<td>1.26 (1.16 to 1.37)</td>
<td>&lt;.001</td>
<td>1.16 (0.86 to 1.47)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>GAD-7 ≥5</td>
<td>4.5 (3.7 to 5.4)</td>
<td>&lt;.001</td>
<td>4.6 (4.3 to 4.9)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>PHQ-9$^b$</td>
<td>0.93 (0.82 to 1.03)</td>
<td>&lt;.001</td>
<td>1.14 (0.84 to 1.45)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>PHQ-9 ≥5</td>
<td>4.5 (3.39 to 5.53)</td>
<td>&lt;.001</td>
<td>4.9 (4.5 to 5.2)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>WPAI$^c$ overall</td>
<td>7.37 (6.65 to 8.09)</td>
<td>&lt;.001</td>
<td>7.19 (5.28 to 9.11)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>WPAI overall &gt;0</td>
<td>14.6 (11.7 to 17.4)</td>
<td>&lt;.001</td>
<td>15.6 (14.5 to 16.7)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>WPAI work</td>
<td>13.73 (12.99 to 14.47)</td>
<td>&lt;.001</td>
<td>13.59 (11.67 to 15.51)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>WPAI work &gt;0</td>
<td>14.3 (11.6 to 17.0)</td>
<td>&lt;.001</td>
<td>15.4 (14.3 to 16.4)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>WPAI time missed</td>
<td>7.14 (6.47 to 7.81)</td>
<td>&lt;.001</td>
<td>6.82 (5 to 8.63)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>WPAI time missed &gt;0</td>
<td>11.4 (6.9 to 16.0)</td>
<td>&lt;.001</td>
<td>11.8 (9.9 to 13.7)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>WPAI activity</td>
<td>0.66 (0.37 to 0.96)</td>
<td>&lt;.001</td>
<td>0.42 (–0.34 to 1.19)</td>
<td>.28</td>
</tr>
<tr>
<td>WPAI activity &gt;0</td>
<td>19.4 (18.6 to 20.3)</td>
<td>&lt;.001</td>
<td>18.4 (16.1 to 20.7)</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

$^a$GAD-7: Generalized Anxiety Disorder 7-item scale.

$^b$PHQ-9: Patient Health Questionnaire 9-item scale.

$^c$WPAI: Work Productivity and Activity Impairment scale.
**Pain**

Pain levels decreased similarly in both groups from baseline to program end ($P=.62$), corresponding to a significant mean change of 2.2 points (95% CI 2.2-2.3) in the urban cohort and 2.3 points (95% CI 2.1-2.5) in the rural cohort (Table 4 and Figure 2A). The rate of patients meeting pain MCID at program end was not statistically different between urban and rural cohorts (67.1% versus 68.3%, $P=.30$).

**Mental Health**

Among those who reported at least mild or moderate anxiety (GAD-7 score $\geq 5$) at baseline, we observed a significant decrease in anxiety in both groups (urban score 4.5, 95% CI 3.7-5.4; $P<.001$ and rural score 4.6, 95% CI 4.3-4.9; $P<.001$); this decrease was similar in the groups ($P=.85$). Likewise, among those reporting at least mild or moderate depression at baseline (ie, PHQ-9 score $\geq 5$), we observed a significant decrease in depression scores in both groups (urban score 4.5, 95% CI 3.39-5.53; $P<.001$ and rural score 4.9, 95% CI 4.5-5.2; $P<.001$); this decrease was also similar in the groups ($P=.48$). In patients from urban areas, chronic MSK conditions were associated with steeper initial recovery of depression, followed by a stronger leveling effect. In contrast, in patients from rural areas, chronic pain was associated with slower improvement that was more sustained over time (Figure 2C, difference in slope between groups $-0.07$, $P=.004$; difference in curve...
between groups 1.06, *P*<.001; Multimedia Appendix 1, Table S5).

**Productivity**

Productivity improvements were observed in both groups with no differences between them (Figure 2D-F). For WPAI overall, mean changes of 14.6 points (95% CI 11.7-17.4) and 15.6 points (95% CI 14.5-16.7) were reported for urban and rural groups, respectively (*P*=.50). Presenteeism, measured through WPAI work, improved by 14.3 points (95% CI 11.6-17.0) in the urban group and by 15.4 points (95% CI 14.3-16.4) in the rural group (*P*=.46). Absenteeism, measured through WPAI time missed, was reduced by 11.4 points (95% CI 6.9-16.0) and 11.8 points (95% CI 9.9-13.7) in the urban and rural groups, respectively. Similarly, impairment in non–work-related activities (ie, WPAI activity) had improvements of 19.4 points (95% CI 18.6-20.3) and 18.4 points (95% CI 16.1-20.7) in the urban and rural groups, respectively.

In urban areas, individuals with higher BMI reported a greater leveling effect on absenteeism improvement than those from rural areas (the difference in curve between groups was 0.14, *P*=.04; Multimedia Appendix 1, Table S5). In patients from rural areas, the presence of chronic pain was associated with a faster recovery in absenteeism in comparison with that in patients from urban areas (the difference in slope between groups was 0.16, *P*=.03; Multimedia Appendix 1, Table S5).

**Discussion**

**Principal Findings**

The multimodal DCP herein reported was able to reach all US states in both urban and rural locations and had a completion rate of 73.8% (7378/9992), which is similar to previous studies reporting the use of digital interventions for MSK pain management [37,62]. The percentage of participants in urban areas was significantly higher than in rural locations, which was expected given that only approximately 19.6% of the US population is located in rural areas according to the US Census Bureau [63].

Health inequities between urban and rural populations are prevalent in the United States. [64]. Rural populations have been reported to have demographics associated with a poorer prognosis for MSK pain [65-69]. In accord with this, in this study, patients from rural areas were older [67], had higher BMI [69], had lower educational levels [65], and had a higher prevalence of depression [67]. Some of these factors have previously been associated with lower chances of receiving physical therapy [33]. Lower education (and consequently lower digital literacy) have been associated with lower adherence, for example [21-23].

Studies have shown that patients in rural areas of the United States may face additional difficulties in recovery due to fewer opportunities for in-person physical activity programs as a consequence of limited access to indoor facilities, limited transportation, and a lower overall health status when compared to urban patients [24,32]. Additionally, rural residents are less likely to report having home broadband than those living in urban or suburban areas [70], which seriously impacts their access to digital health care tools and electronic communication with health providers [71].

In this study, engagement was similar between both rural and urban areas (eg, the number of sessions and interactions with a PT), and completion rates were higher in the rural cohort. The reasons behind these observations may be multifactorial, but one can speculate that the lack of access to alternative health care resources, as well as the provision of a Wi-Fi hotspot to those without internet, might have prompted patients from rural areas to not only engage with the exercise sessions but also to achieve higher completion rates [70,71]. Also, despite lower educational levels, patients from rural areas engaged more with curated health educational articles advocating for telerehabilitation programs as enablers of health literacy.

Despite the worse clinical outcomes reported at baseline by those in rural communities, in line with what has been described before [32,66-69], similar improvements in pain, mental health, and productivity impairment were observed in both groups, again reinforcing the notion that higher MSK pain burden in rural areas may be associated with lack of access to care. Pain improvements were above a 2-point change independently of the studied group, with 67.1% to 68.3% of participants meeting the MCID for pain [48,49]. The percentages of patients meeting the MCID were within the ranges previously reported for digital interventions (49%-75.6%) [72-74] and in-person physical therapy [75].

The prevalence of depression and anxiety has been reported to be higher in residents of rural areas compared to urban areas [76], with those from rural areas facing a shortage of mental health services [77]. Since mental health and MSK pain are tightly associated [38,78], the scarcity of psychological support can seriously impact the recovery rates of rural populations. This study confirms a higher depression burden in patients from rural areas but found similar improvement in mental health scores in both rural and urban patients, reinforcing the notion that lack of access to mental health resources may be the main driver for the higher burden of disease in rural areas. Additionally, MSK pain has been reported to be a main driver for loss of work productivity [79,80]. The factors weighing on absenteeism recovery were BMI and the presence of chronic pain, both previously reported to negatively impact MSK pain recovery [81,82]. Nevertheless, we did not observe significant differences in improvement in any productivity domains between urban and rural groups; all of these domains showed significant improvement following the DCP.

Despite the wide reach of telerehabilitation, many areas across the United States are still facing unmet needs. The results observed herein support the need for further research and investment in digital rehabilitation to mitigate inequities in health care access and care delivery optimization.

**Strengths and Limitations**

There are many strengths to this study, namely the novelty of investigating the urban-rural dichotomy within a digital therapy program in a large sample size from a real-world context, including patients from 50 US states and the District of Columbia, which allows for a diverse population and thus better
generalizability. Another strength is the DCP itself, which uses a multimodal approach that includes exercises with real-time biofeedback, mental support, regular communication with the PT, and a digital format. All these components favor accessibility and maximize engagement and clinical outcomes, allowing us to study different aspects of the problem, from pain to mental health to productivity.

The classification of rural and urban areas is a challenging topic considering the multitude of factors that can highly influence the obtained readings. Despite the application of a recognized classification system [45-47], we cannot rule out the existence of other confounding factors with contributions that were not taken into account during this exploratory analysis, including desirability bias. Other limitations include the lack of control groups (to account for nonspecific treatment effects) and the lack of long-term outcome and objective outcome measures (ie, through activity trackers). Nevertheless, this exploratory study may lay a foundation for future work in this field, identifying areas in need of improvement for future telerehabilitation programs. Further prospective controlled studies are warranted to better characterize the effect of rural and urban inequities on digital therapy outcomes.

Conclusion
This study provides important insights regarding the impact of a multimodal digital program for MSK pain management in rural and urban settings. The DCP was able to reach all areas across the United States with high completion rates in both settings. Despite the inherent health inequities between patients from rural and urban areas, similarly high satisfaction and engagement, alongside significant improvements in pain, mental health, and productivity, were observed in both groups. This showcases the potential of the DCP to mitigate inequities by improving the accessibility of MSK care independently of geographic location.

Acknowledgments
The authors acknowledge the team of physical therapists responsible for managing the participants. The authors also acknowledge the contributions of João Tiago Silva and Guilherme Freches in data validation (both employees of Sword Health). Critical revision of the manuscript for important intellectual content was done by all authors. All authors were involved with the final approval of the manuscript. The study sponsor, Sword Health, was involved in the study design, data collection, and interpretation and writing of the manuscript.

Data Availability
The data sets generated during or analyzed during this study are available from the corresponding author upon reasonable request.

Authors’ Contributions
All authors made a significant contribution to the work. FC, FDC, and JL were responsible for the study concept and design. MM acquired the data. RM performed the statistical analysis. JS, FC, ACA, DJ, MM, and FC interpreted the data. JS was responsible for drafting the work. VB was responsible for funding.

Conflicts of Interest
Sword Health owns the Digital Care Program and as such this program is only available to those covered by a commercial agreement with Sword Health. FC, DJ, AA, MM, FDC, VB, and VY are employees of Sword Health, the sponsor of this study. DJ, FC, FDC, VY, and VB also hold equity in Sword Health. RM is an independent scientific consultant responsible for the statistical analysis. JS and JL are independent scientific and clinical consultants who received adviser honorariums from Sword Health.

Multimedia Appendix 1
Information regarding (1) Rural-urban commuting area (RUCA) codes, (2) baseline characteristics of completers and non-completers, (3) Latent growth curve analysis (LGCA) model following intent-to-treat analysis with corresponding model fitness and conditional analysis, and (4) 12-week mean changes for the per-protocol analysis and corresponding LGCA model and model fitness.
[DOCX File, 78 KB - mhealth_v11i1e44316_app1.docx ]

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Abbreviations

ANOVA: analysis of variance
CBT: cognitive behavioral therapy
DCP: digital care program
FIML: full information maximum likelihood
GAD-7: Generalized Anxiety Disorder 7-item
LGCA: latent growth curve analysis
MCID: minimum clinically important difference
MSK: musculoskeletal
PHQ-9: Patient Health Questionnaire 9-item
PT: physical therapist
RUCA: rural-urban commuting area
WPAI: Work Productivity and Activity Impairment
Engagement and Utilization of a Complete Remote Digital Care Program for Musculoskeletal Pain Management in Urban and Rural Areas Across the United States: Longitudinal Cohort Study

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Original Paper

Smartphone-Tracked Digital Markers of Momentary Subjective Stress in College Students: Idiographic Machine Learning Analysis

George Aalbers1,2, BSc, MSc; Andrew T Hendrickson1, PhD; Mariek MP Vanden Abeele2,3, PhD; Loes Keijsers4, PhD

1Department of Cognitive Science & Artificial Intelligence, Tilburg University, Tilburg, Netherlands
2Department of Communication and Cognition, Tilburg University, Tilburg, Netherlands
3Media, Innovation and Communication Technologies, Department of Communication Sciences, Ghent University, Ghent, Belgium
4Clinical Child and Family Studies, Erasmus School of Social and Behavioural Sciences, Erasmus University Rotterdam, Rotterdam, Netherlands

Corresponding Author:
George Aalbers, BSc, MSc
Department of Cognitive Science & Artificial Intelligence
Tilburg University
Warandelaan 2
Tilburg, 5037 AB
Netherlands
Phone: 31 13 466 9111
Email: h.j.g.aalbers@tilburguniversity.edu

Abstract

Background: Stress is an important predictor of mental health problems such as burnout and depression. Acute stress is considered adaptive, whereas chronic stress is viewed as detrimental to well-being. To aid in the early detection of chronic stress, machine learning models are increasingly trained to learn the quantitative relation from digital footprints to self-reported stress. Prior studies have investigated general principles in population-wide studies, but the extent to which the findings apply to individuals is understudied.

Objective: We aimed to explore to what extent machine learning models can leverage features of smartphone app use log data to recognize momentary subjective stress in individuals, which of these features are most important for predicting stress and represent potential digital markers of stress, the nature of the relations between these digital markers and stress, and the degree to which these relations differ across people.

Methods: Student participants (N=224) self-reported momentary subjective stress 5 times per day up to 60 days in total (44,381 observations); in parallel, dedicated smartphone software continuously logged their smartphone app use. We extracted features from the log data (eg, time spent on app categories such as messenger apps and proxies for sleep duration and onset) and trained machine learning models to predict momentary subjective stress from these features using 2 approaches: modeling general relations at the group level (nomothetic approach) and modeling relations for each person separately (idiographic approach). To identify potential digital markers of momentary subjective stress, we applied explainable artificial intelligence methodology (ie, Shapley additive explanations). We evaluated model accuracy on a person-to-person basis in out-of-sample observations.

Results: We identified prolonged use of messenger and social network site apps and proxies for sleep duration and onset as the most important features across modeling approaches (nomothetic vs idiographic). The relations of these digital markers with momentary subjective stress differed from person to person, as did model accuracy. Sleep proxies, messenger, and social network use were heterogeneously related to stress (ie, negative in some and positive or zero in others). Model predictions correlated positively and statistically significantly with self-reported stress in most individuals (median person-specific correlation=0.15-0.19 for nomothetic models and median person-specific correlation=0.00-0.09 for idiographic models).

Conclusions: Our findings indicate that smartphone log data can be used for identifying digital markers of stress and also show that the relation between specific digital markers and stress differs from person to person. These findings warrant follow-up studies in other populations (eg, professionals and clinical populations) and pave the way for similar research using physiological measures of stress.

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Introduction

Background

Stress is an important predictor of mental health problems such as burnout [1] and depression [2]. How stress influences mental health depends on its duration. Stress with a duration of minutes to hours (acute stress) is commonly considered an adaptive psychophysiological response, whereas stress lasting for weeks to months or even years (chronic stress) is believed to have adverse psychological and physiological consequences [3]. Given its potential effects, early detection and treatment of chronic stress is important to prevent mental health problems.

As asking individuals to consistently self-monitor and self-report stress over extended periods is a difficult, costly, and time-intensive procedure [4], researchers have started developing algorithms to unobtrusively detect stress from passively logged data, such as smartphone app use log data [5]. If successful, such algorithms open opportunities for early detection of the tipping point where acute stress turns into chronic stress, possibly unlocking earlier possibilities for scalable interventions, such as smartphone-based cognitive behavioral therapy with chatbots [6].

Previous research suggests that smartphone use log data (among other passively logged data sources) might be used to recognize how stressed a person feels [5,7-10], with pioneering studies in college students using call and SMS text messaging log data (among others) as predictors [9,10]. However, following technological advances that made smartphones more powerful, use of these devices has evolved, and college students now typically access their smartphone for activities other than calling or SMS text messaging, such as using social media [11]. As a result, more research is required to identify whether stress might be recognized using smartphone app use patterns with high relevance to the current generation of students. We, therefore, extend previous work in the domain [5,7-10] to a large sample of contemporary college students and explore to what extent machine learning models can leverage features of smartphone app use to recognize momentary subjective stress and which of these app use features are most important for predicting momentary subjective stress and represent potential digital markers of stress. Inspired by recent findings in clinical psychology [11,12] and communication science [13-16], we then shed light on the nature of the relations between these potential digital markers and stress and the degree to which these relations differ from one person to another. Following related machine learning research on mood recognition [17], we also assess how important digital markers are relative to temporal features: time of day, day of the week, day of the month, and before COVID-19 versus during COVID-19 lockdown.

Digital Markers

Digital markers are digital footprints, such as features of smartphone use log data, that are related to psychological or biological states [18], such as stress. Such features might represent any quantification of raw log data of digital devices, ranging from simple (eg, time spent using a device) [19] to more complex (eg, daily life patterns derived from device use) [20].

In this study, we investigate two types of potential digital markers of stress: (1) use of different types of smartphone apps (eg, duration and frequency of social network, messenger, and video apps) and (2) sleep proxies derived from smartphone app log data.

Smartphone Use Behaviors as Potential Digital Markers

Smartphones enable individuals to perform a wide range of behaviors with profound psychological meaning and relevance to momentary subjective stress. Extant evidence, however, suggests a complex and nuanced relation between smartphone use and mental health, with different types of app use showing different patterns of association. For example, smartphone use behaviors with particular theoretical relevance to stress are calling, mobile messaging, and using social media, but recent work on passively logged data found depression relates negatively to calling [21], whereas it relates positively to social media use [22]. Moreover, research suggests that relations between smartphone app use and mental health differ from person to person [12-16]. Altogether, with respect to the association between smartphone use and mental health, these and other findings [23,24] indicate that smartphone behaviors could be informative about stress, but open questions remain.

Sleep Proxies as Potential Digital Markers

Smartphone log data not only captures smartphone behavior with relevance to stress but might also be used to quantify sleep, which is a universal behavior related to stress [25]. As the human sleep-wake cycle closely aligns with smartphone app use patterns, different disciplines have leveraged smartphone log data (eg, call records, screen on-off status, and screen taps) to estimate sleep onset, offset, and duration [20]. To explore if such sleep proxies might be useful for stress recognition, we applied a rule-based algorithm (similar but not identical to a recent study by Massar et al [20]) to extract proxies for sleep duration and sleep onset from smartphone app log data and included these as features in our models.

Explainable Artificial Intelligence

One potential avenue to identify digital markers is to (1) train machine learning models to find a mathematical mapping from digital markers to self-reports of momentary subjective stress and (2) apply explainable artificial intelligence (eg, Shapley values [26]) to clarify how these models make predictions. Applying explainable artificial intelligence is necessary because the structure of some powerful models (eg, random forest [RF]) preclude the straightforward interpretation of parameters that linear statistical models have.

By taking this approach, we aim (1) to identify digital markers by testing which features of smartphone use log data a model uses to predict momentary subjective stress and (2) to understand...
the nature of the relation between these digital markers and stress. For instance, time spent on messenger apps might be important for the prediction of stress and negatively related to stress, suggesting that individuals tend to spend less time on these apps when feeling stressed. This could potentially indicate that stress reduces social interaction or vice versa.

Nomothetic Versus Idiographic
When training machine learning models on human-subjects data, it is important to take into account that individuals differ from another. Hence, both machine learning [27] and behavioral scientists [28] have underlined the importance of ensuring that models of human-subjects data are applicable to the individuals they pertain to. This is certainly also important in the domain of digital markers of stress. Behavioral scientists have shown that relations between digital trace data and psychological self-reports differ across individuals [19]. In parallel, machine learning researchers have demonstrated that personalized models, which are known as idiographic models in behavioral science, tend to predict subjective stress more accurately than nonpersonalized models [27], which are also referred to as nomothetic models. Naturally, these findings go hand in hand: a personalized (idiographic) model will more adequately capture person-specific dependencies between digital trace data and stress and therefore should make more accurate predictions than a nonpersonalized (nomothetic) model. In this study, we implement, evaluate, and compare both approaches.

Objectives
This study has four complementary aims to explore: (1) to what extent machine learning models can leverage features of smartphone app use log data to recognize momentary subjective stress in individuals, (2) which of these features are most important for predicting stress and represent potential digital markers of stress, (3) the nature of the relations between these digital markers and stress, and (4) the degree to which these relations differ from one person to another.

Methods
Participants
We followed reporting guidelines recommended for experience sampling studies [29]. For a preregistered data collection [30], we used the university participant pool to recruit 247 student participants with an Android operating system on their primary phone, 224 (90.7%) of whom we included for analysis. Their average age was 21.97 (SD 3.04) years and the majority were female (125/224, 55.8%). We excluded (1) participants with operating systems other than Android on their primary phone and (2) participants with insufficient survey responses for training idiographic machine learning models (<6). Most participants (186/224, 83%) started participation before the first (reported) local infection of SARS-CoV-2 and a minority (38/224, 17%) after. With the exception of 2 participants, all participants had been active in our study before the first nation-wide lockdown. Throughout the study, the original (Wuhan) strain of SARS-CoV-2 was dominant.

Procedure
Ethics Approval
Ethics approval was issued by the Tilburg University Ethics Committee (approval code REDC 2019/94c).

Onboarding
Participants were recruited through the university participant pool. After receiving web-based information through Qualtrics (Qualtrics XM), having been offered a possibility to ask questions, and signing an informed consent form, participants followed web-based instructions to install 2 apps on their smartphone. After completing these instructions, the participants attended an onboarding session in which we provided additional information, offered further opportunity to ask questions, and motivated the participants to participate to the best of their ability.

Technology
All participants installed 2 apps on their Android device: Ethica Data [31] and mobileDNA [32]. Ethica Data is an app that prompts participants to complete brief surveys on their smartphone (ie, experience sampling). MobileDNA is an app that unobtrusively logs a person’s smartphone app use, smartphone notifications, and location (ie, passive logging).

Sampling Scheme
The data collected in this study are part of a larger research project with other questions that required a so-called measurement burst design (1 period of intensive data collection followed by a break followed by another period of intensive data collection) [33]. The important advantage of this procedure is that it reduces participant burden, while capturing information on a larger timescale. Hence, in a 4-month period, Ethica notified the participants 5 times a day for a maximum of 60 days (30 days in month 1 and 30 days in month 4) at pseudorandom times between 8:30 AM and 10:30 PM to complete a 10-item survey (approximately 1 minute to complete) on stress and other constructs (fatigue, procrastination, and mood), whereas mobileDNA continuously logged smartphone app use. Following an initial push notification, each survey was notified the participants 5 times a day for a maximum of 60 days (30 days in month 1 and 30 days in month 4) at pseudorandom times between 8:30 AM and 10:30 PM to complete a 10-item survey (approximately 1 minute to complete) on stress and other constructs (fatigue, procrastination, and mood), whereas mobileDNA continuously logged smartphone app use. Following an initial push notification, each survey was available to the participant for 50 minutes. After 45 minutes, they received a reminder notification. After 50 minutes, the survey expired. The participants were allowed to catch up on 1 missed survey per day by starting and completing a new survey.

Monitoring Protocol
We actively monitored participant compliance and motivated participants with weekly emails containing personalized feedback. When a participant failed to complete many consecutive surveys, we sent an email to inquire why they could not comply with the study protocol and how any issues might be resolved. In a limited number of cases, the participants did not respond to such emails, in which case we contacted them through a phone call. The participants were compensated with course credits for research participation and were entered into a raffle comprising 20 prizes of 15 euros (US $22.06).
Compliance

The participants (N=224) completed a total of 44,381 surveys (198 per person on average). Though data collection spanned the introduction of the COVID-19 pandemic lockdown, the median participant remained in the study across 4 months. In the sample we analyzed, the median participant completed 205 surveys (SD 87.42) and had 3072 hours of smartphone use log data. The median time difference between receiving the initial notification and completing the survey was 6 minutes (SD 14.26; refer to Figure 1 for a histogram). Reasons for noncompliance ranged from technical difficulties (eg, not receiving any notifications and broken or lost smartphone) to not being able to complete a survey (eg, waking up too late and receiving a notification during work or lecture) to personal reasons (eg, attrition because of COVID-19 pandemic–related personal problems or collecting sufficient course credits). Figure 2 visualizes how compliance rate changed from the first to the last day of the study.

Figure 1. Distribution of the time difference between receiving the initial notification and completing the survey (in minutes).

Figure 2. Daily compliance rate over time. To determine daily compliance rate, we computed the percentage of survey responses that were received on a given participation day relative to the total number of surveys to be sent each day based on our original sample size (224×5=1120). If, for instance, all participants completed 4 out of 5 surveys on their first day of participation, daily compliance equals 80%.

Measures

To measure participants’ current (ie, in-the-moment) subjective level of stress, we used the Stress Experience Sampling Scale [34]. This scale consists of 2 items on a 7-point Likert scale ranging from 1 (not at all) to 4 (moderately) to 7 (very much): “Right now, I feel relaxed” and “Right now, I feel stressed (tense, restless, nervous or anxious).” The 2 items have an adequate intraclass coefficient (>50% of variance because of within-person fluctuations) and acceptable within-person reliability as assessed by within-person omega (ω=.71). We calculated an unweighted average of the 2 items and subtracted each participant’s average level of stress from the resulting values (ie, within-person centering).

Textbox 1 provides an overview of the features included in this study. We analyzed three categories of features: (1) smartphone use behavior, (2) sleep, and (3) time. As the raw values of these features are on vastly different scales, which can dramatically
impact model performance, we scaled all features to a range between 0 and 1 using MinMaxScaler in sklearn [35], based on the minimum and maximum values in the training data.

To extract time spent on different smartphone app categories, we first categorized apps using a coding scheme that maps app names (eg WhatsApp [36]) to 1 of the 18 major categories (Textbox 2; these core categories represent 4,046,581/5,277,494, 76.68% of all app events). Then, during the 60 minutes before each self-report of stress, we calculated (1) the total time spent on all apps in a category (duration) and (2) the total number of times apps in a category had been accessed (frequency).

To extract sleep duration and sleep onset proxies from the raw smartphone app log timestamps, we used an algorithm similar (but not identical) to a previously validated rule-based algorithm [11] (refer to Multimedia Appendix 1 for a description of our approach), an algorithm that was found to be strongly associated with actigraphy-based and self-reported sleep duration and onset.

To extract time features (ie, hour of the day, day of the week, day of the month, and lockdown status) from the raw self-report timestamps, we used pandas.datetime in Python 3.9.9 [37]. In the interest of model simplicity, we recoded day of the week into a binary variable (weekday=0 and weekend=1) rather than treating this variable as a categorical variable. We further coded lockdown status as a binary variable (before COVID-19 lockdown=0 and during COVID-19 lockdown=1) based on the lockdown timing in the Netherlands.

Textbox 1. Overview of the features included in models.

<table>
<thead>
<tr>
<th>Smartphone use behavior</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Time (seconds) spent on smartphone app category X in the past 60 minutes</td>
</tr>
<tr>
<td>• Frequency (count) of opening smartphone app category X in the past 60 minutes</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sleep</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Sleep onset (hours and postmidnight hours &gt;24)</td>
</tr>
<tr>
<td>• Sleep duration (hours)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Hour of the day (0 to 23 and starting at midnight)</td>
</tr>
<tr>
<td>• Day of the week (0=weekday and 1=weekend)</td>
</tr>
<tr>
<td>• Day of the month (0 to 31)</td>
</tr>
<tr>
<td>• COVID-19 (before lockdown=0 and during lockdown=1)</td>
</tr>
</tbody>
</table>

Textbox 2. Smartphone app categories and examples of apps per category.

- Browser: Chrome and Opera
- Calling: default dial apps
- Camera: default camera apps
- Dating: Tinder and Grindr
- Email: Gmail and Outlook
- Exercise: RunKeeper
- Food and drink: UberEATS
- Gallery: default gallery apps
- Game: CandyCrush
- Messenger: WhatsApp
- Music and audio: Spotify
- Productivity: Microsoft Word
- Shared transportation: 9292OV (Dutch public transport)
- Social network: Facebook, Instagram, and Twitter
- Tracker: pedometer apps
- Video: YouTube and Netflix
- Weather: default weather apps
- Work: StudentJob and EmployeeApp
Stress Recognition Models

Model Types
We trained 3 different types of machine learning models: least absolute shrinkage and selection operator (LASSO) regression, support vector regression (SVR), and RF regression. We trained all models using a nomothetic and an idiographic approach (explained in the section Model Cross-Validation). For brevity and clarity, we prepend an “N” to the abbreviations of our nomothetic models (ie, N-LASSO, N-SVR, and N-RF) and an “I” to the abbreviations of our idiographic models (ie, I-LASSO, I-SVR, and I-RF).

Model Cross-Validation
Generally, when we perform cross-validation (CV), we (1) split the data into train and test data, (2) specify a range of values for a model’s different hyperparameters (ie, researcher-specified parameters that control model complexity), (3) identify the best hyperparameters per model using k-fold CV within the training set, and (4) evaluate each model based on predictive accuracy for the test data. In what follows, we outline how we cross-validated nomothetic and idiographic models.

To train nomothetic models, we applied a user split to distinguish between train and test data. We first used group k-fold CV (GroupKFold in sklearn [35]) to partition the data into 5 subsets. A total of 4 subsets contained data from 45 participants, and 1 subset contained data from 44 participants. We then selected 4 subsets (train data) to train a model. For training the model, we used 5-fold grid search CV (GridSearchCV in sklearn [35]) to minimize each model’s default sklearn error metric (refer to Multimedia Appendix 2 for tuned hyperparameters and minimized error metrics). After training the model, we let the model make predictions on the data subset we did not include in training (test data; ie, all observations of participants excluded from training). Finally, we evaluated the accuracy of these predictions. We repeated this process until each subset of the data had been left out of training once and did so for all models.

To train idiographic models, we applied a time split to distinguish between train and test data. We iteratively selected 1 participant’s data to train and test models only on these data. For each person, we assigned each participant’s first 80% observations to a train data set and their final 20% observations to a test data set and trained each model (SVR, RF, and LASSO). We applied 5-fold grid search CV to each participant’s train data to optimize hyperparameters. As the number of idiographic models to train is much larger, we applied 5-fold randomized search CV rather than grid search CV for training RFs, which are more computationally expensive than LASSO and SVR. Grid search CV always uses a larger number of hyperparameters than randomized search CV because the latter trains models on a random subset of all the hyperparameter settings used by the former. Randomized search CV considerably speeds up training time and makes training a large number of RF models more feasible. Finally, we let trained models make predictions on the individual’s test data (ie, final 20% observations) and evaluated the accuracy of these predictions.

Model Evaluation
To evaluate the accuracy of models, we used Spearman rho rank-order correlation and mean absolute error (MAE) as evaluation metrics. Spearman rho rank-order correlation indicates whether a model tends to predict greater values when an individual feels more stressed without assuming a linear relation. We consider a model to perform above chance for a given individual if the Spearman ρ between predictions and self-reports between predictions and self-reports has a P value below .05.

Lower MAE values indicate a more accurate model. We consider the MAE to be an intuitive metric to assess predictive accuracy on a target variable measured on a 7-point Likert scale, as it allows us to make statements such as “on average, the model mispredicts momentary subjective stress by ±0.80 points on a 7-point Likert scale.” To evaluate if our models perform better than random guessing, we compare against the MAEs of a “naïve” but person-specific baseline model. This “naïve” baseline model always predicts an individual’s average level of stress.

Model Explanation
One of the challenges of machine learning approaches is to understand the results, as they are more complex and therefore less intuitive than standard statistical approaches. To explain models, we use the Shapley additive explanations (SHAP) library [26] implemented in Python 3.9.9 [37] to calculate and visualize Shapley values. Shapley values can be used to determine (1) which features are most important in a model and (2) how features are related to model predictions.

Results
Recognizing Momentary Subjective Stress
Table 1 provides an overview of how accurately nomothetic models predict out-of-sample data. Model predictions correlated positively and significantly with self-reports in a majority of participants for N-LASSO (116/224, 51.3%), N-SVR (120/224, 53.6%) and N-RF, with N-RF performing best in terms of percent significant results (124/224, 55.4%). The median correlation between predictions and self-reports was weak for all models (between 0.15 and 0.19). Correlations also differed between participants: in 60 participants, the positive correlation was moderate or larger (ρ>0.3), whereas it was negative (range P<.001 to P=.049) in 2.2% (5/224) of people. In the median participant, models on average mispredicted momentary subjective stress by approximately 0.8 points on a 7-point Likert scale (MAE of 0.84; scale range: 1=“Not at all,” 4=“Moderately,” and 7=“Very much”). The MAE of nomothetic models varied across individuals, but for 89.3% (200/224) of participants, the person-specific baseline outperformed all nomothetic models (refer to the sixth column in Table 1), followed by N-LASSO (20/224, 8.9%) and N-SVR (4/224, 1.8%). N-RF did not outperform the other models in terms of MAE.

Thus, nomothetic models make predictions that weakly and positively correlate with actual stress self-reports for the majority of participants (up to 124/224, 55.3%). This means...
that when these participants, who were not included in the training data set, feel stressed, the model tends to output a higher value, and when a participant does not feel stressed, the model tends to output a lower value. However, these models are not highly accurate, as they often do not outperform a person-specific baseline. For most participants, the association between predictions and actual self-reported stress is positive, but it is significantly negative (range $P < 0.001$ to $P = 0.049$) for a very small group ($5/224, 2.2\%$). Thus, for a very small group of participants, the model tends to detect subjective stress when the person does not feel stressed, and vice versa.

We then evaluated how well idiographic models recognize momentary subjective stress in out-of-sample observations. For all models, model predictions of momentary subjective stress correlated positively and significantly with self-reports of momentary subjective stress, but only in a minority of participants. In 60 participants, this correlation was moderate or larger ($P > 0.3$), whereas the overall median correlation was absent to weak (range of median correlations per model, $P = 0.00 - 0.09$). In a minority ($11/224, 4.9\%$), model predictions of stress and self-reported stress were significantly negatively associated. Similar to the nomothetic models, the median person-specific MAE for each idiographic model was slightly >0.8 points. These MAE scores are compared with a person-specific baseline based on the person-specific average level of stress in the participant’s train data (ie, first 80\%) rather than all their data to prevent data leakage from train to test data. MAE varied from individual to individual, but for 80.4\% ($180/224$) of participants at least one of the idiographic models outperformed the person-specific baseline. The I-SVR most frequently outperformed all other models (including person-specific baseline; $92/224, 41.1\%$), followed by I-RF ($47/224, 20.9\%$) and I-LASSO ($43/224, 19.2\%$).

### Table 1. Central tendency and range of out-of-sample predictive accuracy (Spearman $\rho$ correlation and mean absolute error [MAE]) for nomothetic and idiographic models on a person-by-person basis.

<table>
<thead>
<tr>
<th>Model</th>
<th>Spearman $\rho$ rank-order correlation</th>
<th>MAE</th>
<th>Median (range)</th>
<th>Better than baseline (%)</th>
<th>Best model (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>N$^a$-baseline</td>
<td>N/A$^b$</td>
<td>N/A</td>
<td>0.83$^c$ (0 to 3.39)</td>
<td>N/A</td>
<td>89.29</td>
</tr>
<tr>
<td>N-LASSO$^d$</td>
<td>0.15 (−0.45 to 0.65)</td>
<td>51.34</td>
<td>0.84 (0.11 to 2.04)</td>
<td>10.27</td>
<td>8.93</td>
</tr>
<tr>
<td>N-SVR$^e$</td>
<td>0.16 (−0.31 to 0.64)</td>
<td>53.57</td>
<td>0.84 (0.17 to 2.04)</td>
<td>4.91</td>
<td>1.79</td>
</tr>
<tr>
<td>N-RF$^f$</td>
<td>0.19 (−0.37 to 0.57)</td>
<td>55.34</td>
<td>0.84 (0.26 to 2.04)</td>
<td>3.57</td>
<td>0</td>
</tr>
<tr>
<td>I$^g$-baseline</td>
<td>N/A</td>
<td>N/A</td>
<td>0.83 (0 to 3.40)</td>
<td>N/A</td>
<td>19.64</td>
</tr>
<tr>
<td>I-LASSO</td>
<td>0.00 (−1 to 1)</td>
<td>13.84</td>
<td>0.87 (0 to 3.36)</td>
<td>34.37</td>
<td>18.75</td>
</tr>
<tr>
<td>I-SVR</td>
<td>0.09 (−0.79 to 1)</td>
<td>23.21</td>
<td>0.84 (0 to 3.49)</td>
<td>50.45</td>
<td>41.07</td>
</tr>
<tr>
<td>I-RF</td>
<td>0.08 (−1 to 1)</td>
<td>19.64</td>
<td>0.84 (0 to 3.27)</td>
<td>39.73</td>
<td>20.98</td>
</tr>
</tbody>
</table>

$^a$N: nomothetic.  
$^b$N/A: not applicable.  
$^c$Italicized values represent best performance.  
$^d$LASSO: least absolute shrinkage and selection operator.  
$^e$SVR: support vector regression.  
$^f$RF: random forest.  
$^g$I: idiographic.

### Identifying Digital Markers of Momentary Subjective Stress

To demonstrate which aspects of the model have the strongest predictive value, Figure 3 provides an overview of the 10 most important features per nomothetic and idiographic model. In all 6 models, temporal features, COVID-19 lockdown status, messenger and social network use, and sleep proxies were most important to the prediction stress. The largest disagreement between nomothetic and idiographic models was the importance of messenger and social network use relative to sleep duration and onset. The former features were more important in nomothetic models, whereas the latter were more important in idiographic models. Feature importance was relatively consistent for models across data splits (refer to Multimedia Appendix 3 for beeswarm plots per model per data split).
Figure 3. Feature importance ranking for each nomothetic (N) and idiographic (I) model, containing features that appeared in the top 10 features of any model. Numeric values represent the ranking of 1 feature for 1 model. Dark (top) cells represent more important features. N-median and I-median represent the median ranking of a feature across N and I models, respectively, where double values indicate a tie between 2 features. Features are ordered by N-median scores. LASSO: least absolute shrinkage and selection operator; RF: random forest; SVR: support vector regression.

Understanding Digital Markers of Momentary Subjective Stress

Feature importance provides relevant information about which features contribute most to predictions. However, it does not tell us whether small or large values of a feature are indicative of momentary subjective stress. For instance, although we have identified hour of the day as a relatively important predictor of momentary subjective stress, it is still unclear whether people tend to feel more stressed in earlier or later hours of the day. To clarify potential relations between features and momentary subjective stress, we present a beeswarm plot for the nomothetic RF (Figure 4; refer to Multimedia Appendix 3 for all beeswarm plots) to visualize how different features are related to model predictions in 1 split of the data. In this figure, for each feature (listed on the y-axis in decreasing order of importance), a point represents 1 test trial, the color of a point indicates the value of the feature (red for higher values [eg, later hour of the day] and blue for low values [eg, earlier hour of the day]), and the position along the x-axis indicates the SHAP value (positive values correspond with higher stress predictions; larger magnitude values indicate stronger impact). For any 1 feature, red points on the left side of the plot (high feature values and negative SHAP values) indicate a relation where increasing the feature value results in the model predicting lower outcome values (eg, higher hour predicts lower stress), whereas red points on the right side of the plot (high feature values and positive SHAP values) indicate a positive relation (eg, COVID-19 lockdown predicts higher stress). For instance, Figure 4 shows that N-RF predicts greater momentary subjective stress values (1) in earlier hours of the day (indicated in blue), (2) during COVID-19 lockdown, (3) on weekdays, and (4) later in the month. Similarly, when individuals spend more time on messenger (red), these models output greater values for momentary subjective stress.
Interindividual Differences in the Relation Between Digital Markers and Stress

We also investigated whether the nature of relations between features and stress differed from person to person. As the zero-order Spearman rank-order correlations between features and stress are relatively weak (Multimedia Appendix 4), we instead calculated these correlations between feature values and SHAP values for each idiographic model. A positive correlation between feature and SHAP value indicates that when this feature has a higher value, the model predicts that an individual feels more stressed. SHAP values of more complex models have the potential benefit of capturing the nonlinear and interactive relations learned by the model. Correlations with \( P \) values of \( >.05 \) are not included.

Figure 5 shows the frequency of significant positive and negative correlations between digital markers and SHAP values for the prediction of stress for each idiographic model. Interestingly, most bars are both red and blue, which indicates a relatively heterogeneous relation across people between that feature and stress for most features. For instance, there is much heterogeneity in the relation between stress and some of the most important features (Figure 3), including social network use and sleep duration. Some bars are mostly red or mostly blue, suggesting a relatively homogeneous relation across people between these features and stress. For instance, the relation between stress and hour of the day is mostly negative and the relation between stress and shared transportation app use is mostly positive. A few features rarely show any correlation with predicted stress, and this is likely because that model has learned to disregard those features or because the correlation between feature values and SHAP values is either not reliable or monotonic.
Figure 5. Stacked bar plots representing the proportion of participants showing a significant positive (blue bar) or negative (red bar) correlation between feature values and Shapley additive explanations (SHAP) values for each idiographic model. A positive correlation indicates that when a given feature has a higher value, then the model predicts that an individual feels more stressed. A negative correlation indicates that when a given feature has a higher value, then the model predicts that an individual feels less stressed. For instance, the idiographic random forest (I-RF) predicts a lower level of stress at later hours of the day in 53.4% (120/224) of individuals. I-LASSO: idiographic least absolute shrinkage and selection operator; I-SVR: idiographic support vector regression.

Discussion

Principal Findings

The aims of our study were to explore (1) to what extent machine learning models can leverage features of smartphone app use log data to recognize momentary subjective stress, (2) which smartphone app use features are most important for predicting stress and represent potential digital markers of stress, (3) the nature of the relations between smartphone app use features and stress, and (4) the degree to which these relations differ from one person to another. We found that when individuals were more stressed, the best performing nomothetic models tended to predict a higher level of stress (and vice versa) in the majority of individuals (up to 124/224, 55.3%). However, they generally did not predict stress with greater accuracy than a naive baseline model, which always predicted that a person was experiencing their average level of stress. We found these results to be similar for idiographic models, although these models predicted stress with greater accuracy than a naive baseline model. Although performance should be improved to make clinical application feasible, this study does suggest that, in the absence of self-report or physiological data, digital markers can be used to recognize momentary subjective stress on a person-by-person basis in out-of-sample data.

Using explainable artificial intelligence, we found that temporal features, prolonged messenger and social network app use, and smartphone-tracked sleep proxies were the most important features of the best-performing nomothetic and idiographic models. These models consistently ordered these features, with temporal features as most important and app use as less important drivers of stress predictions. The largest disagreement between nomothetic and idiographic models is the importance of app use duration. In nomothetic models, these are more important than sleep features, but in idiographic models, the order is opposite. In sum, though, prolonged use of messenger and social network apps and sleep proxies might be valid digital markers of stress.

Our results suggest that, for an average person, in the earlier hours of the day, on weekdays, on later days of the month, and during COVID-19 lockdown (compared with before COVID-19 lockdown), individuals felt more stressed than they would usually do. Individuals also felt more stressed when spending more time on social apps (ie, messenger and social network apps). The relation between temporal features and (SHAP values...
for the prediction of) stress was rather consistent across individuals, suggesting these could represent universal principles for this population. These may even be explained by biological mechanisms (eg, cortisol awakening response [38]) that universally affect adolescents and young adults. Such features are likely important to include in passive tracking in the context of stress-related mental health problems such as depression and burnout.

One of the unique features of this study was to compare nomothetic and idiographic models in light of increasingly idiographic research practices in behavioral science [29]. Our findings show that model personalization is warranted especially when smartphone app use features are added to the model. That is, the relation between social app use and stress was negative for some individuals and positive or absent for others (Figure 5). We, therefore, find evidence that the idiographic approach of digital phenotyping research, that is, “the moment-by-moment quantification of the individual-level human phenotype in situ using data from personal digital devices, in particular smartphones” [39], is warranted in the context of stress.

In clinical practice, the added value of digital phenotyping of stress is that it might help us to understand how, for a given individual, stress is related to temporal features, how sleep impacts their stress levels, and how their stress relates to their smartphone app use. Identifying the latter relations might serve as a probe for qualitative investigation of how they respond to stress. For instance, if an individual spends less time on messenger apps when stressed, this could suggest that they avoid social contact, whereas seeking social support might be beneficial. If individuals are not aware of this pattern, personalized prediction models could provide novel clinical insights and could potentially help to improve therapy outcomes (eg, within personalized treatment modules [40]).

Finally, our exploratory findings provide important directions for confirmatory research. Contrary to the approach taken here, which is useful for discovering potential digital markers, a confirmatory approach would be to test a small number of (preregistered) hypotheses that make explicit what relation we expect between specific digital markers and momentary subjective stress. Confirmatory research is required to test the robustness of (1) the relation between stress and the potential digital markers identified here and (2) the interindividual variability in this relation.

**Limitations**

This study should be viewed in light of the following limitations. First, our findings have constraints on generality, as they are based on a sample of students at a small university in the Netherlands and, therefore, are more likely to generalize to student than nonstudent populations. Furthermore, we measured these individuals during the COVID-19 pandemic, when the original (Wuhan) strain of the SARS-CoV-2 virus was dominant. As results suggest that the COVID-19 pandemic and resulting lockdown affected participant stress (generally increasing stress but decreasing stress in some individuals), potentially, these results might have been different had there not been a pandemic.

We encourage future research to test if our results replicate in other populations (eg, working adults or individuals diagnosed with mental disorders) and during a period with a limited SARS-CoV-2 infection rate.

Second, it is conceivable that not all students self-reported stress accurately at every assessment. A significant proportion of variance might therefore represent noise that cannot be explained by any variable or model, irrespective of modeling decisions. This is especially an issue for idiographic models that rely on the participants’ final observations, which might be observations of lower quality because of study fatigue [41].

Third, we applied within-person mean centering to the self-reported stress. Although this corrects for differences in how people use a scale, it only allows nomothetic models to predict whether a person is currently experiencing more or less stress than usual and prevents models from predicting whether this person’s stress level is very low or high relative to other people’s stress level.

Fourth, we forced nomothetic models to learn one mapping function from features to outcome for all individuals in our sample. This is problematic because such models learn 1 set of parameters that might be accurate for some individuals but highly inaccurate for others (ie, one-size-fits-all fallacy) [42]. Truly idiographic models, which we also trained in this study, do not have this issue by default. However, this comes at the cost of strongly reduced sample size, which limits model complexity and may lead to overfitting. As collecting more self-report data per individual is not feasible for samples of this size, future studies could (1) focus on smaller samples with exceptionally motivated participants for a longer sampling period, (2) use wearables to measure psychophysiological signals of stress (eg, CortiWatch [43]), or (3) train machine learning models on a full data set without losing sight of interindividual differences in feature-outcome relations (eg, using transfer learning [44]).

**Conclusions**

Our exploratory study has 3 main conclusions. First, temporal features, sleep proxies, and prolonged use of messenger and social network apps are consistently identified as the most important digital markers for predicting momentary subjective stress. Second, for most people (200/224, 89.3%), these markers are not sufficiently informative to recognize momentary subjective stress with appreciable improvements in accuracy over a baseline model but do produce predictions that correlate with subjective stress. Third, the utility and relation with stress of (some) digital markers varies from person to person. On the one hand, 1 digital marker may be relevant to momentary subjective stress in one individual but not in another. On the other hand, the increase of 1 digital marker might imply lower stress for one individual and higher stress for another. Our study thus provides evidence for phenotypic heterogeneity in the relation between how we feel and the digital traces we leave behind. These findings are relevant for the implementation of algorithms in mobile health apps to prevent, monitor, and treat stress-related mental health problems.
Acknowledgments

The authors would like to thank the Tilburg Experience Sampling Center and the mobileDNA team at imec-mict-U Gent for their assistance in setting up the digital phenotyping study. The authors thank their colleagues Ghaith Al Seirawan, Andrei Oprea, Ethel Pruss, Marieke van der Pol, and Kyle van Gaeveren for their outstanding help during data collection.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Description of the algorithm used to estimate sleep duration and onset from smartphone app use log data.

[DOCX File, 16 KB - mhealth_v11i1e37469_app1.docx ]

Multimedia Appendix 2

List of hyperparameters and the grid of hyperparameter values that were searched to optimize models in cross-validation.

[DOCX File, 17 KB - mhealth_v11i1e37469_app2.docx ]

Multimedia Appendix 3

Shapley additive explanations (SHAP) beeswarm plots for all model types and splits of the data.

[DOCX File, 2793 KB - mhealth_v11i1e37469_app3.docx ]

Multimedia Appendix 4

Stacked bar plot of zero-order correlations between features and stress on a person-by-person basis.

[DOCX File, 167 KB - mhealth_v11i1e37469_app4.docx ]

References


https://mhealth.jmir.org/2023/1/e37469

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Abbreviations

**CV:** cross-validation

**LASSO:** least absolute shrinkage and selection operator

**MAE:** mean absolute error

**RF:** random forest

**SHAP:** Shapley additive explanations

**SVR:** support vector regression
Smartwatch-Based Maximum Oxygen Consumption Measurement for Predicting Acute Mountain Sickness: Diagnostic Accuracy Evaluation Study

Xiaowei Ye1*, MD; Mengjia Sun1*, MD; Shiyong Yu1*, PhD; Jie Yang1, PhD; Zhen Liu1, MD; Hailin Lv1, MD; Boji Wu1, MD; Jingyu He1, MD; Xuhong Wang1, MD; Lan Huang1, PhD

Institute of Cardiovascular Diseases of People's Liberation Army, The Second Affiliated Hospital, Army Medical University (Third Military Medical University), Chongqing, China

*these authors contributed equally

Corresponding Author:
Lan Huang, PhD
Institute of Cardiovascular Diseases of People's Liberation Army
The Second Affiliated Hospital
Army Medical University (Third Military Medical University)
No 183, Xinqiao Street, Shapingba District
Chongqing, 400037
China
Phone: 86 23 68755601
Email: huanglan260@126.com

Abstract

Background: Cardiorespiratory fitness plays an important role in coping with hypoxic stress at high altitudes. However, the association of cardiorespiratory fitness with the development of acute mountain sickness (AMS) has not yet been evaluated. Wearable technology devices provide a feasible assessment of cardiorespiratory fitness, which is quantifiable as maximum oxygen consumption (VO2max) and may contribute to AMS prediction.

Objective: We aimed to determine the validity of VO2max estimated by the smartwatch test (SWT), which can be self-administered, in order to overcome the limitations of clinical VO2max measurements. We also aimed to evaluate the performance of a VO2max-SWT–based model in predicting susceptibility to AMS.

Methods: Both SWT and cardiopulmonary exercise test (CPET) were performed for VO2max measurements in 46 healthy participants at low altitude (300 m) and in 41 of them at high altitude (3900 m). The characteristics of the red blood cells and hemoglobin levels in all the participants were analyzed by routine blood examination before the exercise tests. The Bland-Altman method was used for bias and precision assessment. Multivariate logistic regression was performed to analyze the correlation between AMS and the candidate variables. A receiver operating characteristic curve was used to evaluate the efficacy of VO2max in predicting AMS.

Results: VO2max decreased after acute high altitude exposure, as measured by CPET (25.20 [SD 6.46] vs 30.17 [SD 5.01] at low altitude; P<.001) and SWT (26.17 [SD 6.71] vs 31.28 [SD 5.17] at low altitude; P<.001). Both at low and high altitudes, VO2max was slightly overestimated by SWT but had considerable accuracy as the mean absolute percentage error (<7%) and mean absolute error (<2 mL·kg⁻¹·min⁻¹), with a relatively small bias compared with VO2max-CPET. Twenty of the 46 participants developed AMS at 3900 m, and their VO2max was significantly lower than that of those without AMS (CPET: 27.80 [SD 4.55] vs 32.00 [SD 4.64], respectively; P=.004; SWT: 28.00 [IQR 25.25-32.00] vs 32.00 [IQR 30.00-37.00], respectively; P=.001). VO2max-CPET, VO2max-SWT, and red blood cell distribution width—coefficient of variation (RDW-CV) were found to be independent predictors of AMS. To increase the prediction accuracy, we used combination models. The combination of VO2max-SWT and RDW-CV showed the largest area under the curve for all parameters and models, which increased the area under the curve from 0.785 for VO2max-SWT alone to 0.839.

Conclusions: Our study demonstrates that the smartwatch device can be a feasible approach for estimating VO2max. In both low and high altitudes, VO2max-SWT showed a systematic bias toward a calibration point, slightly overestimating the proper
VO₂max when investigated in healthy participants. The SWT-based VO₂max at low altitude is an effective indicator of AMS and helps to better identify susceptible individuals following acute high-altitude exposure, particularly by combining the RDW-CV at low altitude.

**Trial Registration:** Chinese Clinical Trial Registry ChiCTR2200059900; https://www.chictr.org.cn/showproj.html?proj=170253

(JMIR Mhealth Uhealth 2023;11:e43340) doi:10.2196/43340

**KEYWORDS**

VO2max; maximum oxygen consumption; smartwatch; cardiopulmonary exercise test; acute mountain sickness

**Introduction**

In recent years, mountain climbing has become a popular activity for pleasure, work, and athletic competitions. However, inadequate acclimatization to hypobaric hypoxia results in a series of symptoms known as acute mountain sickness (AMS). AMS is relatively common among new travelers, affecting >30% of individuals ascending to 3500 m and >70% of those ascending above 6000 m [1]. AMS is characterized by the presence of headache in combination with other symptoms, including dizziness, fatigue, loss of appetite, and insomnia [2]. Although younger age, female gender, rapid ascent, low oxygen saturation (SpO₂), and abnormal ventilatory response to exercise have been previously associated with AMS and its severity [3-5], susceptible individuals still need to be further identified, especially with more accuracy and practicality.

Maximum oxygen consumption (VO₂max) is defined as the maximum capacity of the cardiovascular, respiratory, and muscular systems to deliver and utilize oxygen, which is reflected by an individual’s cardiorespiratory fitness [6-9]. VO₂max is accurately measured by the cardiopulmonary exercise test (CPET) during a maximal graded exercise until exhaustion, which is considered the gold standard for cardiorespiratory functional assessment [10,11]. However, the use of direct measurements is limited, particularly at high altitude, as it is time-consuming and requires infrastructure and specialized personnel to conduct exercise assessments. Therefore, indirect measurement methods of VO₂max (Firstbeat fitness test [FFT]) have been developed and have become advantageous due to the popularity of smart wearable devices [12,13]. Previous studies have reported that VO₂max estimated by the FFT method is accurate and suitable for athletes owing to its lower exercise intensity [14]. However, for those who require to face the challenge of extreme high-altitude environments over a short period, the maximum intensity of exercise should also be avoided so as not to affect the acclimatization process. Previous studies have shown that the error of the FFT method is less than 5% at low altitudes [14]; however, it remains controversial whether it underestimates the true VO₂max. Additionally, its performance at high altitudes has not been evaluated and compared with that of the gold standard.

VO₂max decreases during acute or chronic exposure to high altitudes, which is mainly attributed to the reduction of PO₂ [15,16]. Moreover, in terms of limiting VO₂max, in addition to environmental factors, more attention is focused on the oxygen delivery pathway, central circulation [17], maximal cardiac output [18], oxygen-carrying capacity of the blood, ability to distribute that blood into the contracting muscles, and finally, the ability of the muscles to consume oxygen [19]. In other words, the above physiological processes and related indices involving oxygen transport may also be potential predictors of AMS [20]. Therefore, this study aims to compare the accuracy and consistency of VO₂max obtained from CPET and smartwatch test (SWT) at different atmospheric pressures and to determine whether VO₂max at low altitudes is correlated with AMS. Further, we tested the hypothesis that the combination of VO₂max-SWT and red blood cell (RBC) distribution width-coefficient of variation (RDW-CV) may be more efficient in predicting AMS.

**Methods**

**Participant Recruitment**

We recruited 46 healthy adults (27 women and 19 men, age range 22-54 years) from Chongqing, China, based on the inclusion and exclusion criteria. All participants had lived at low altitudes (<500 m) for at least 10 years and had no recent history of high-altitude (>2500 m) exposure (in the last 6 months). Participants with any one of the following conditions were excluded: respiratory and cardiovascular diseases, malignant tumors, liver and kidney dysfunctions, and psychiatric disorders or neuroses that would not allow them to complete the questionnaires.

**Ethics Approval**

The study protocol (ChiCTR2200059900) complied with the Declaration of Helsinki and was approved by the ethics committee of Xinqiao Hospital of Army Medical University (approval: 2022-研第-060-01). Written informed consent was obtained from all the participants after the study details, procedures, benefits, and risks were explained.

**Procedures**

This study consisted of 2 exercise tests at low and high altitudes (Figure 1). The participants were instructed to avoid heavy load training 7 days before the tests and during the recovery days and to abstain from caffeine and alcohol for 24 hours before testing. On the first day of the study, each participant underwent a routine blood test before the SWT. After a 24-hour break, CPET was performed. The 2 tests (SWT and CPET) were performed at a similar time of day (SD 30 minutes) and were completed in 2 days. After resting for 3 days, the participants ascended to a high altitude (3900 m, Shigatsзе, China) in 3 hours by plane from a low altitude (300 m, Chongqing, China). On
the second day at high altitude, they took 1 day off to complete the 2018 Lake Louise score assessment. Unfortunately, 2 individuals had knee injury because of the trip; therefore, they did not undergo exercise tests. Besides, 1 participant had an ST segment depression in the electrocardiogram and 2 participants had chest pain; therefore, they could not make it to the end. Finally, the remaining 41 participants repeated the exercise tests completely.

Figure 1. Cohort development diagram for this study. AMS, acute mountain sickness; CPET, cardiopulmonary exercise test; SWT, smartwatch test.

**Blood Routine Examination**

The participants were required to avoid eating or drinking anything (fasting) apart from water for up to 12 hours. Approximately 5 mL of intravenous blood was collected from the inside of the elbow and mixed with 1 mL of dipotassium ethylenediaminetetraacetic acid anticoagulant by using a tight band (tourniquet). Blood samples were analyzed using a BC-3000 plus automated hematology corpuscle analyzer (Mindray). The details of the 19 different parameters are presented in Multimedia Appendix 1. Blood tests at low altitude were performed between 7 AM and 9 AM on the same day before the exercise tests. All biochemical parameters were measured in the blood samples at the Clinical Laboratory of Cardiology Science of Xinqiao Hospital, Army Medical University.

**CPET Analysis**

The CPET was performed on an electronically braked cycle ergometer (EC3000e, Customed) in an erect position with breath-by-breath measurements through a tightly fitted face mask of minute ventilation, \( O_2 \) uptake, and \( CO_2 \) output by using a cardiopulmonary exercise testing system (Metalyzer 3B, Cortex). Before performing CPET, the baseline physiological measures for all devices used in this study were measured for 5 minutes in a resting state and subsequently in a standing position. After the baseline measurement, the test was conducted immediately. The cycle ergometry test protocol included 3 minutes of free-wheel cycling and subsequently proceeded with a continual increase in resistance by 25 W/min (according to the prior known exercise capacity [21], so that the test would last 10-12 minutes) until test completion or exhaustion. \( VO_2\text{max} \) was defined as the highest 30-s average value within the last minute of exercise until the first 15 s of recovery at peak exercise [22]. Standard 12-lead electrocardiogram, blood pressure, and \( SpO_2 \) were obtained at rest, every minute during exercise, and for \( \geq 4 \) minutes during the recovery phase throughout the procedure using a 12-lead connection (custo-Cardio 3000BT-A, Cortex) in real time, blood pressure cuffs (Suntech Tango M2, Cortex) in the upper arm, and a finger clip portable oximeter (Nonin wristOx2), respectively.

**SWT Analysis**

We provided participants with a smartwatch (Huawei Watch GT Runner) and instructed them to wear it correctly on the left wrist, which enables reliable and persistent measurement of
running speed, distance, and heart rate. Therefore, these measurements could be monitored continuously and automatically during each running activity, stored on the participant’s mobile device (Huawei MatePad 11 DBY-W09), and regularly transmitted to a secure cloud server, which was later transferred to the Huawei Health Center software through Bluetooth. Specifically, VO\textsubscript{2max} estimation steps were as follows: (1) the personal background information (age, height, and weight) of the participant was logged in and the exercise type (running outdoors) was selected; (2) the participant started to run with a smartwatch that measured the heart rate and speed on level ground; (3) the start and end points were in the same place, and the smartwatch was stopped by the researchers uniformly with a timely click; (4) the researchers subsequently saved the participants’ running data to an album on the pad, facilitating further statistical analysis; and (5) the smartwatch and mobile device were formatted to prepare for the next test.

The signal processing by Huawei Watch GT Runner is licensed by the Firstbeat Technology’s Fitness Test, which is based on intelligent detection for both data reliability and exercise pattern during successive recording [13]. Briefly, the moving average filter was applied to both heart rate and physical activity data. After filtering the data, only data points at which both heart rate and physical activity data increased were selected as a period of physical activity. This was conducted by differentiating the data and selecting where both differentiated data were positive. The situations where the data series were excluded are listed below: (1) significant heart rate decreases and exceptional striding pattern (identified as a situation of running on a very steep downhill or soft surface automatically), (2) significant heart rate increases while the velocity remained 0 identified as stopping suddenly in the middle), and (3) a short duration of highly increasing intensity (identified as insufficient effort level). After exclusions, the selected data series were further segmented as different heart rate zones according to the effort level. Of them, the reliable data segments that belong to a long series of successive heartbeat intervals (in generally 20 s-10 minutes and preferably 30 s-4 minutes) and with a small heart rate change level were recognized as sufficient effort and used to calculate the VO\textsubscript{2max}. In these reliable segments, speed was measured based on acceleration measurements by using a satellite navigation system. VO\textsubscript{2max} estimates were made for each reliable segment by using the following theoretical VO\textsubscript{2} equation: theoretical VO\textsubscript{2} (mL·kg\textsuperscript{-1}·min\textsuperscript{-1}) = 3.5 * speed (km/h). The obtained VO\textsubscript{2max} for each data segment was weighed and subsequently utilized to make a linear equation for calculating the final VO\textsubscript{2max} (the detailed rule of weighting is shown in patent US9237868B2).

**Lake Louise Consensus Scoring System and AMS**

The presence of AMS at high altitude was assessed using the Lake Louise consensus scoring system 2018 version [23]. According to the 4 main symptoms, namely, headache, gastrointestinal symptoms, fatigue/weakness, and dizziness/vertigo, the scores were 0, 1, 2, and 3 in the order of none, mild, moderate, and severe, respectively. A total score of ≥3 combined with headache can be diagnosed as AMS.

**Statistical Analyses**

Categorical variables were described as numbers and percentages. Descriptive statistics were presented as mean (SD) for variables with skewed distribution and median (IQR) for variables with normal distribution. The Mann–Wilcoxon rank-sum, independent-sample t test (2-sided test), Pearson chi-square test, and Fisher exact tests were used to compare the continuous and categorical variables statistically. The correlation magnitude and coefficient of determination between VO\textsubscript{2max}-CPET and VO\textsubscript{2max}-SWT were assessed using Pearson correlation. The intraclass correlation coefficient and paired-sample t tests (2-sided test) were performed to determine the agreement between VO\textsubscript{2max}-CPET and VO\textsubscript{2max}-SWT at low and high altitudes, respectively. We calculated the mean absolute error and mean absolute percentage error (MAPE) to evaluate the accuracy of the estimation. Furthermore, we used a Bland–Altman plot to investigate the level of agreement with 95% limits of agreement [24].

The relationship between the variables and AMS was examined by binomial logistic regression analysis with univariate analyses. The relationship between VO\textsubscript{2max}-CPET, VO\textsubscript{2max}-SWT, RDW-CV, and AMS was further examined by multivariate analyses. In the preliminary screening, we considered the variable with P<.05 as a potential risk factor, and an adjusted binary logistic regression model subjected the variable to identify the independent risk factors for AMS after the adjustment. Receiver operating characteristic (ROC) curves were constructed, and the Youden index was calculated. The optimal cutoff of variables for diagnosing AMS was determined at the point where the Youden index was maximum on the ROC analysis. We also compared the ROC curves of VO\textsubscript{2max}-CPET, VO\textsubscript{2max}-SWT, and RDW-CV alone or in combination. Differences were considered statistically significant at P<.05. Statistical analyses were performed using the SPSS Statistics software (IBM Corp) for Windows (version 26) and MedCalc software for Windows.

**Results**

**Participant Characteristics**

A total of 46 participants were recruited for this study, of whom 20 (44%) participants developed AMS. The clinical characteristics of participants with AMS and without AMS are presented in Table 1. There were no differences in age, sex, BMI, baseline heart rate, SpO\textsubscript{2}, and blood pressure between the 2 groups. RBC count; hemoglobin, hematocrit, and mean corpuscular hemoglobin levels; mean corpuscular hemoglobin concentration; and RDW-SD did not differ significantly between the participants in the 2 groups, whereas the AMS group had higher RDW-CV at low altitude than the non-AMS group (14.25 [IQR 12.75-21.03] vs 12.70 [IQR 12.25-13.53], respectively; P = 0.02). In addition, the AMS group had lower VO\textsubscript{2max} both measured by CPET (27.80 [SD 4.55] vs 32.00 [SD 4.04], respectively; P = 0.004) and estimated by SWT (28.00 [SD 6.75] vs 32.00 [IQR 30.00-37.00], respectively; P = 0.001) than the non-AMS group.
**Table 1.** Baseline characteristics, blood routine test, and maximum oxygen consumption of the participants at low altitudes.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Total (n=46)</th>
<th>Participants with AMS&lt;sup&gt;a&lt;/sup&gt; (n=20)</th>
<th>Participants without AMS (n=26)</th>
<th>P value&lt;sup&gt;b&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Baseline characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (years), mean (SD)</td>
<td>33.33 (7.80)</td>
<td>33.85 (8.41)</td>
<td>32.92 (7.44)</td>
<td>.70</td>
</tr>
<tr>
<td>Gender, n (%)</td>
<td></td>
<td></td>
<td></td>
<td>.17</td>
</tr>
<tr>
<td>Female</td>
<td>27 (59)</td>
<td>14 (70)</td>
<td>13 (50)</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>19 (41)</td>
<td>6 (30)</td>
<td>13 (50)</td>
<td></td>
</tr>
<tr>
<td>BMI (kg/m&lt;sup&gt;2&lt;/sup&gt;), median (IQR)</td>
<td>22.19 (20.22-23.64)</td>
<td>21.89 (20.15-23.44)</td>
<td>22.40 (20.22-24.01)</td>
<td>.78</td>
</tr>
<tr>
<td><strong>Alcohol use, n (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td>.18</td>
</tr>
<tr>
<td>Current drinker or ex-drinker</td>
<td>10 (22)</td>
<td>2 (10)</td>
<td>8 (31)</td>
<td></td>
</tr>
<tr>
<td>Never</td>
<td>36 (78)</td>
<td>18 (90)</td>
<td>18 (69)</td>
<td></td>
</tr>
<tr>
<td><strong>Smoking status, n (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td>.92</td>
</tr>
<tr>
<td>Current smoker or ex-smoker</td>
<td>6 (13)</td>
<td>2 (10)</td>
<td>4 (15)</td>
<td></td>
</tr>
<tr>
<td>Nonsmoker</td>
<td>40 (87)</td>
<td>18 (90)</td>
<td>22 (85)</td>
<td></td>
</tr>
<tr>
<td><strong>HR&lt;sup&gt;c&lt;/sup&gt; (beats/min), mean (SD)</strong></td>
<td>78.93 (9.69)</td>
<td>81.25 (9.72)</td>
<td>77.15 (9.46)</td>
<td>.16</td>
</tr>
<tr>
<td><strong>SpO&lt;sub&gt;2&lt;/sub&gt;&lt;sup&gt;d&lt;/sup&gt; (%), median (IQR)</strong></td>
<td>97 (96-98)</td>
<td>97 (96-98.75)</td>
<td>97 (96-98)</td>
<td>.72</td>
</tr>
<tr>
<td><strong>SBP&lt;sup&gt;e&lt;/sup&gt; (mm Hg), median (IQR)</strong></td>
<td>112.00 (103.75-121.25)</td>
<td>112.00 (105.00-126.50)</td>
<td>112.00 (102.75-118.75)</td>
<td>.92</td>
</tr>
<tr>
<td><strong>DBP&lt;sup&gt;f&lt;/sup&gt; (mm Hg), mean (SD)</strong></td>
<td>74.11 (11.11)</td>
<td>72.95 (14.24)</td>
<td>75.00 (8.12)</td>
<td>.54</td>
</tr>
<tr>
<td><strong>Blood routine test</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RBC&lt;sup&gt;g&lt;/sup&gt; (10&lt;sup&gt;12&lt;/sup&gt;/L), median (IQR)</td>
<td>4.51 (4.30-4.95)</td>
<td>4.40 (4.25-4.89)</td>
<td>4.71 (4.33-5.08)</td>
<td>.19</td>
</tr>
<tr>
<td>HGB&lt;sup&gt;h&lt;/sup&gt; (g/L), mean (SD)</td>
<td>131.59 (10.03)</td>
<td>128.85 (11.45)</td>
<td>133.69 (8.42)</td>
<td>.11</td>
</tr>
<tr>
<td>HCT&lt;sup&gt;i&lt;/sup&gt; (%), mean (SD)</td>
<td>44.10 (4.32)</td>
<td>43.31 (4.28)</td>
<td>44.70 (4.34)</td>
<td>.28</td>
</tr>
<tr>
<td>MCV&lt;sup&gt;j&lt;/sup&gt; (fL), median (IQR)</td>
<td>94.10 (90.90-96.60)</td>
<td>94.35 (96.50-96.58)</td>
<td>94.00 (91.73-96.78)</td>
<td>.89</td>
</tr>
<tr>
<td>MCH&lt;sup&gt;k&lt;/sup&gt; (pg), median (IQR)</td>
<td>28.77 (27.46-29.82)</td>
<td>28.54 (27.18-29.77)</td>
<td>28.82 (27.58-29.90)</td>
<td>.71</td>
</tr>
<tr>
<td>MCHC&lt;sup&gt;l&lt;/sup&gt; (g/L), median (SD)</td>
<td>304.62 (15.21)</td>
<td>304.46 (14.72)</td>
<td>304.75 (15.86)</td>
<td>.95</td>
</tr>
<tr>
<td>RDW-CV&lt;sup&gt;m&lt;/sup&gt; (%), median (IQR)</td>
<td>13.10 (12.30-14.83)</td>
<td>14.25 (12.75-21.03)</td>
<td>12.70 (12.25-13.53)</td>
<td>.02</td>
</tr>
<tr>
<td>RDW-SD&lt;sup&gt;n&lt;/sup&gt; (fL), median (IQR)</td>
<td>44.40 (41.48-46.68)</td>
<td>44.40 (41.00-46.83)</td>
<td>44.55 (41.48-46.70)</td>
<td>.84</td>
</tr>
<tr>
<td><strong>Cardiorespiratory fitness</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VO&lt;sub&gt;2&lt;/sub&gt;max-CPET&lt;sup&gt;o&lt;/sup&gt; (mL·kg&lt;sup&gt;–1&lt;/sup&gt;·min&lt;sup&gt;–1&lt;/sup&gt;), mean (SD)</td>
<td>30.17 (5.01)</td>
<td>27.80 (4.55)</td>
<td>32.00 (4.64)</td>
<td>.004</td>
</tr>
<tr>
<td>VO&lt;sub&gt;2&lt;/sub&gt;max-SWT&lt;sup&gt;p&lt;/sup&gt; (mL·kg&lt;sup&gt;–1&lt;/sup&gt;·min&lt;sup&gt;–1&lt;/sup&gt;), median (IQR)</td>
<td>30.50 (27.75-34.25)</td>
<td>28.00 (25.25-32.00)</td>
<td>32.00 (30.00-37.00)</td>
<td>.001</td>
</tr>
</tbody>
</table>

<sup>a</sup>AMS: acute mountain sickness.
<sup>b</sup>Differences were considered statistically significant if P<.05.
<sup>c</sup>HR: heart rate.
<sup>d</sup>SpO: oxygen saturation.
<sup>e</sup>SBP: systolic blood pressure.
<sup>f</sup>DBP: diastolic blood pressure.
<sup>g</sup>RBC: red blood cell.
<sup>h</sup>HGB: hemoglobin.
<sup>i</sup>HCT: hematocrit.
<sup>j</sup>MCV: mean corpuscular volume.
<sup>k</sup>MCH: mean corpuscular hemoglobin.
MCHC: mean corpuscular hemoglobin concentration.
RDW-CV: red blood cell distribution width-coefficient of variation.
RDW-SD: red blood cell distribution width-standard deviation.
VO\textsubscript{max}-CPET: maximum oxygen consumption measured by cardiopulmonary exercise test.
VO\textsubscript{max}-SWT: maximum oxygen consumption estimated by smartwatch test.

**Accuracy and Consistency Analyses of VO\textsubscript{2max} Estimation in the SWT at Low and High Altitudes**

Table 2 shows the VO\textsubscript{2max} in the SWT and CPET at low and high altitudes. The values of VO\textsubscript{2max}-SWT were significantly overestimated at both low (constant error=1.11 [SD 1.73] mL·kg\textsuperscript{-1}·min\textsuperscript{-1}; \textit{t}\textsubscript{45}=4.35; \textit{P}<.001) and high (constant error=0.98 [SD 1.54] mL·kg\textsuperscript{-1}·min\textsuperscript{-1}; \textit{t}\textsubscript{40}=4.05; \textit{P}<.001) altitudes. A 6% MAPE (mean absolute error=1.761 mL·kg\textsuperscript{-1}·min\textsuperscript{-1}) at low altitude and a 6.8% MAPE (mean absolute error=1.610 mL·kg\textsuperscript{-1}·min\textsuperscript{-1}) at high altitude were observed, indicating a low average deviation between the 2 methods (Table 2). Furthermore, a strong correlation was found between VO\textsubscript{2max}-SWT and VO\textsubscript{2max}-CPET values (low altitude: \textit{R}\textsuperscript{2}=0.889; \textit{P}<.001; high altitude: \textit{R}\textsuperscript{2}=0.947; \textit{P}<.001; Figure 2). The results of the intraclass correlation coefficient revealed that VO\textsubscript{2max}-SWT had a good level of agreement with the directly measured VO\textsubscript{2max}-CPET at low (0.942; \textit{P}<.001) and high (0.973; \textit{P}<.001) altitudes. Additionally, the Bland–Altman plots demonstrated a small bias of the VO\textsubscript{2max}-SWT values compared to the VO\textsubscript{2max}-CPET at low (bias=1.11 mL·kg\textsuperscript{-1}·min\textsuperscript{-1}, Figure 3A) and high (bias=1.00 mL·kg\textsuperscript{-1}·min\textsuperscript{-1}, Figure 3B) altitudes. VO\textsubscript{2max}-SWT showed even a lower range of bias at high altitudes than at low altitudes (upper to lower limits of agreement: 6.0 mL·kg\textsuperscript{-1}·min\textsuperscript{-1} vs 6.8 mL·kg\textsuperscript{-1}·min\textsuperscript{-1}, respectively).

**Table 2. Correlations and differences between the estimated maximum oxygen consumption in the smartwatch test and the measured maximum oxygen consumption in the cardiopulmonary exercise test.**

<table>
<thead>
<tr>
<th></th>
<th>VO\textsubscript{2max}-CPET\textsuperscript{a} (mL·kg\textsuperscript{-1}·min\textsuperscript{-1}), mean (SD)</th>
<th>VO\textsubscript{2max}-SWT\textsuperscript{b} (mL·kg\textsuperscript{-1}·min\textsuperscript{-1}), mean (SD)</th>
<th>CE\textsuperscript{c} (mL·kg\textsuperscript{-1}·min\textsuperscript{-1}), mean (SD)</th>
<th>\textit{t} (df)</th>
<th>\textit{r}</th>
<th>Intraclass correlation coefficient</th>
<th>Mean absolute error (mL·kg\textsuperscript{-1}·min\textsuperscript{-1})</th>
<th>Mean absolute percentage error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low altitude</td>
<td>30.17 (5.01)</td>
<td>31.28 (5.17)</td>
<td>1.11 (1.73)</td>
<td>4.35 (45)</td>
<td>0.943 (\textit{P}&lt;.001)</td>
<td>0.942 (\textit{P}&lt;.001)</td>
<td>1.761</td>
<td>6</td>
</tr>
<tr>
<td>(n=46)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High altitude</td>
<td>25.20 (6.46)</td>
<td>26.17 (6.71)</td>
<td>0.98 (1.54)</td>
<td>4.05 (40)</td>
<td>0.973 (\textit{P}&lt;.001)</td>
<td>0.973 (\textit{P}&lt;.001)</td>
<td>1.610</td>
<td>6.80</td>
</tr>
<tr>
<td>(n=41)</td>
<td></td>
<td></td>
<td></td>
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</tbody>
</table>

\textsuperscript{a}VO\textsubscript{2max}-CPET: maximum oxygen consumption measured by the cardiopulmonary exercise test.

\textsuperscript{b}VO\textsubscript{2max}-SWT: maximum oxygen consumption estimated by the smartwatch test.

\textsuperscript{c}CE: constant error (arithmetic mean of the difference between estimated and measured VO\textsubscript{2max}).

\textsuperscript{d}Differences were considered statistically significant if \textit{P}<.05.
Figure 2. Linear regression plots between the estimated maximum oxygen consumption measured by smartwatch test and maximum oxygen consumption measured by cardiopulmonary exercise testing. Pearson correlation between the maximum oxygen consumption estimated by smartwatch and measured by cardiopulmonary exercise testing at low altitude (A) and at high altitude (B). The coefficient of determination (R²) and 95% CI bounds (dotted line) are depicted for the regression lines (solid). VO₂max-CPET: maximum oxygen consumption measured by cardiopulmonary exercise testing; VO₂max-SWT: estimated maximum oxygen consumption by smartwatch test.

Figure 3. Bland-Altman plots between the estimated maximum oxygen consumption by smartwatch test and maximum oxygen consumption measured by cardiopulmonary exercise test at low altitude (A) and at high altitude (B). Mean biases (solid line), 95% limits of agreement (dashed line), and equality (dotted line) are also depicted. VO₂max-CPET: maximum oxygen consumption measured by cardiopulmonary exercise test; VO₂max-SWT: estimated maximum oxygen consumption by smartwatch test.

Distribution of VO₂max and Incidence of AMS

There was a significant difference in the VO₂max values at low altitude between the participants with and without AMS. VO₂max-CPET in the AMS group was lower than that in the non-AMS group (27.80 [SD 4.55] vs 32.00 [SD 4.64], respectively; P=.004), and a similar result was revealed by SWT (28.00 [IQR 25.25-32.00] vs 2.00 [IQR 30.00-37.00], respectively; P=.001; Figure 4A). The distribution of the VO₂max values based on the AMS results is shown in Figure 4B. Approximately 90% (16/17) of the participants with VO₂max values <26 mL·kg⁻¹·min⁻¹ developed AMS compared with approximately 20% (3/15) of the participants who developed AMS with a VO₂max >35 mL·kg⁻¹·min⁻¹. Patients with AMS seemed to have a lower VO₂max, regardless of whether it was directly measured by CPET or estimated by SWT.
Figure 4. (A) Distribution of the estimated maximum oxygen consumption measured by smartwatch test and cardiopulmonary exercise test based on the diagnosis of acute mountain sickness. (B) Diagram of the probability of acute mountain sickness occurrence for different ranges of the maximum oxygen consumption value at low altitude (blue: maximum oxygen consumption measured by cardiopulmonary exercise test; orange: maximum oxygen consumption measured by smartwatch test). **Significantly different between acute mountain sickness and non–acute mountain sickness at $P<.01$. AMS: acute mountain sickness; VO$_{2\text{max}}$-CPET: maximum oxygen consumption measured by cardiopulmonary exercise test; VO$_{2\text{max}}$-SWT: estimated maximum oxygen consumption by smartwatch test.

Univariate and Multivariate Logistic Regression Analyses for AMS

To further explore the association between VO$_{2\text{max}}$ and AMS, a univariate analysis was performed. Table 3 shows that VO$_{2\text{max}}$-CPET (odds ratio [OR] 0.807, 95% CI 0.686-0.949; $P=0.01$) and VO$_{2\text{max}}$-SWT (OR 0.765, 95% CI 0.635-0.922; $P=0.005$) at low altitude and baseline RDW-CV (OR 1.177, 95% CI 0.999-1.386; $P=0.05$) were potentially associated with AMS occurrence. Multivariate regression analysis identified VO$_{2\text{max}}$-CPET (OR 0.770, 95% CI 0.640-0.926; $P=0.006$) and RDW-CV (OR 1.263, 95% CI 1.028-1.553; $P=0.03$) as well as VO$_{2\text{max}}$-SWT (OR 0.720, 95% CI 0.578-0.898; $P=0.004$) and RDW-CV (OR 1.273, 95% CI 1.027-1.577; $P=0.03$) as independent factors associated with the development of AMS at high altitude.
<table>
<thead>
<tr>
<th>Variables</th>
<th>Univariable</th>
<th>Multivariable</th>
<th>Multivariable</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OR (95% CI)</td>
<td>P value</td>
<td>OR (95% CI)</td>
</tr>
<tr>
<td>Age (years)</td>
<td>1.016 (0.942-1.096)</td>
<td>.69</td>
<td>N/A</td>
</tr>
<tr>
<td>Male (Y/N)</td>
<td>2.333 (0.684-7.960)</td>
<td>.18</td>
<td>N/A</td>
</tr>
<tr>
<td>BMI (kg/m²)</td>
<td>1.037 (0.852-1.262)</td>
<td>.72</td>
<td>N/A</td>
</tr>
<tr>
<td>Tobacco (Y/N)</td>
<td>1.636 (0.268-9.980)</td>
<td>.59</td>
<td>N/A</td>
</tr>
<tr>
<td>Alcohol (Y/N)</td>
<td>4.000 (0.744-21.496)</td>
<td>.11</td>
<td>N/A</td>
</tr>
<tr>
<td>HR (beats/min)</td>
<td>1.048 (0.982-1.118)</td>
<td>.16</td>
<td>N/A</td>
</tr>
<tr>
<td>SpO₂ (%)</td>
<td>0.907 (0.558-1.472)</td>
<td>.69</td>
<td>N/A</td>
</tr>
<tr>
<td>SBP (mm Hg)</td>
<td>1.002 (0.965-1.040)</td>
<td>.91</td>
<td>N/A</td>
</tr>
<tr>
<td>DBP (mm Hg)</td>
<td>0.983 (0.932-1.037)</td>
<td>.53</td>
<td>N/A</td>
</tr>
<tr>
<td>VO₂max-CPET (ml·kg⁻¹·min⁻¹)</td>
<td>0.807 (0.686-0.949)</td>
<td>.01</td>
<td>0.770 (0.640-0.926)</td>
</tr>
<tr>
<td>VO₂max-SWT (ml·kg⁻¹·min⁻¹)</td>
<td>0.765 (0.635-0.922)</td>
<td>.005</td>
<td>N/A</td>
</tr>
<tr>
<td>RBC (10⁻⁹/L)</td>
<td>0.711 (0.219-2.308)</td>
<td>.57</td>
<td>N/A</td>
</tr>
<tr>
<td>HGB (g/L)</td>
<td>0.949 (0.889-1.012)</td>
<td>.11</td>
<td>N/A</td>
</tr>
<tr>
<td>HCT (%)</td>
<td>0.923 (0.800-1.066)</td>
<td>.28</td>
<td>N/A</td>
</tr>
<tr>
<td>MCV (fl)</td>
<td>0.966 (0.876-1.064)</td>
<td>.48</td>
<td>N/A</td>
</tr>
<tr>
<td>MCH (pg)</td>
<td>0.892 (0.660-1.205)</td>
<td>.46</td>
<td>N/A</td>
</tr>
<tr>
<td>MCHC (g/L)</td>
<td>0.999 (0.961-1.038)</td>
<td>.95</td>
<td>N/A</td>
</tr>
<tr>
<td>RDW-CV (%)</td>
<td>1.177 (0.999-1.386)</td>
<td>.05</td>
<td>1.263 (1.028-1.553)</td>
</tr>
<tr>
<td>RDW-SD (%)</td>
<td>0.985 (0.850-1.141)</td>
<td>.84</td>
<td>N/A</td>
</tr>
</tbody>
</table>

aOR: odds ratio.
bDifferences were considered statistically significant if P<.05.
cN/A: not applicable.
dY/N: yes/no.
eHR: heart rate.
fSpO₂: oxygen saturation.
gSBP: systolic blood pressure.
hDBP: diastolic blood pressure.
iVO₂max-CPET: maximum oxygen consumption measured by cardiopulmonary exercise test.
jVO₂max-SWT: maximum oxygen consumption estimated by smartwatch test.
kRBC: red blood cell.
lHGB: hemoglobin.
mHCT: hematocrit.
nMCV: mean corpuscular volume.
oMCH: mean corpuscular hemoglobin.
pMCHC: mean corpuscular hemoglobin concentration.
qRDW-CV: red blood cell distribution width-coefficient of variation.
rRDW-SD: red blood cell distribution width-standard deviation.
VO_{2\text{max}}-Based Model for Predicting AMS

As both VO_{2\text{max}} and RDW-CV were closely related to AMS, we constructed the combined predictive models for AMS. Table 4 and Figure 5 show the area under the curve (AUC) of VO_{2\text{max}}-CPET (AUC 0.743, 95% CI 0.597-0.889), VO_{2\text{max}}-SWT (AUC 0.785, 95% CI 0.646-0.923), and RDW-CV (AUC 0.708, 95% CI 0.547-0.868).

Either the AUC of the VO_{2\text{max}}-CPET or VO_{2\text{max}}-SWT was higher than that of RDW-CV (both $P > .05$, Table 4). For the VO_{2\text{max}}-SWT, a sensitivity of 65% and a specificity of 88.46% were observed at the optimal cutoff value of 29.5 mL·kg\(^{-1}\)·min\(^{-1}\), with a higher positive predictive value of 81.25% and a negative predictive value of 76.67%. However, no significant difference was found in AUC when compared to the VO_{2\text{max}}-CPET (0.785 vs 0.743, respectively; $P = .25$). Although the independent indicators were effective and significant, this combined predictive model was more accurate when VO_{2\text{max}} and RDW-CV were combined. In other words, the combined model 2 enhanced the diagnostic power with modest AUC gains of 0.03-0.06, although not statistically different from model 1 (0.839 vs 0.804, respectively; $P = .27$) or VO_{2\text{max}}-SWT alone (0.839 vs 0.785, respectively; $P = .28$). The combined model 2 also improved the prediction of AMS by increasing sensitivity from 65% to 80% compared with VO_{2\text{max}}-SWT alone while attaining high specificity.

Table 4. Receiver operating characteristic curves to assess the performance of the maximum oxygen consumption measured by cardiopulmonary exercise test and the maximum oxygen consumption estimated by smartwatch test in predicting acute mountain sickness.\(^a\)

<table>
<thead>
<tr>
<th>Model</th>
<th>AUC(^b) (95% CI)</th>
<th>Optimal cutoff values (mL·kg(^{-1})·min(^{-1}) or fL)</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>PPV(^c) (%)</th>
<th>NPV(^d) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>VO_{2\text{max}}-CPET(^e)</td>
<td>0.743 (0.597-0.889)</td>
<td>26.50</td>
<td>45</td>
<td>96.15</td>
<td>90</td>
<td>69.44</td>
</tr>
<tr>
<td>VO_{2\text{max}}-SWT(^f)</td>
<td>0.785 (0.646-0.923)</td>
<td>29.50</td>
<td>65</td>
<td>88.46</td>
<td>81.25</td>
<td>76.67</td>
</tr>
<tr>
<td>RDW-CV(^g)</td>
<td>0.708 (0.547-0.868)</td>
<td>13.10</td>
<td>75</td>
<td>69.23</td>
<td>65.22</td>
<td>78.26</td>
</tr>
<tr>
<td>Model 1: VO_{2\text{max}}-CPET + RDW-CV</td>
<td>0.804 (0.675-0.933)</td>
<td>N/A(^b)</td>
<td>65</td>
<td>92.31</td>
<td>87.50</td>
<td>77.42</td>
</tr>
<tr>
<td>Model 2: VO_{2\text{max}}-SWT + RDW-CV</td>
<td>0.839 (0.720-0.959)</td>
<td>N/A(^b)</td>
<td>80</td>
<td>84.62</td>
<td>80</td>
<td>84.62</td>
</tr>
</tbody>
</table>

\(^a\)Comparison of area under the curve: maximum oxygen consumption measured by cardiopulmonary exercise test versus maximum oxygen consumption estimated by smartwatch test ($P = .25$); Model 1 versus maximum oxygen consumption measured by cardiopulmonary exercise test ($P = .22$); Model 2 versus maximum oxygen consumption estimated by smartwatch test ($P = .28$); Model 1 versus Model 2 ($P = .27$).

\(^b\)AUC: area under the curve.

\(^c\)PPV: positive predictive value.

\(^d\)NPV: negative predictive value.

\(^e\)VO_{2\text{max}}-CPET: maximum oxygen consumption measured by cardiopulmonary exercise test.

\(^f\)VO_{2\text{max}}-SWT: maximum oxygen consumption estimated by smartwatch test.

\(^g\)RDW-CV: red blood cell distribution width-coefficient of variation.

\(^h\)N/A: not applicable.
**Discussion**

**Principal Results**

Our study comparatively evaluated the VO\textsubscript{2max} (CPET vs SWT) of individuals at a low altitude and subsequently at a high altitude. We demonstrated that the smartwatch device was a feasible and accurate tool for assessing cardiorespiratory fitness at both altitudes. We also proposed a novel model based on smartwatch-derived VO\textsubscript{2max} with good performance in predicting AMS. Our easy-to-use approach for estimating VO\textsubscript{2max} can be more widely applied for screening individuals susceptible to AMS on a large scale.

Previous clinical trials [25-27] have shown that VO\textsubscript{2max} ranged from 20 mL·kg\textsuperscript{-1}·min\textsuperscript{-1} to 50 mL·kg\textsuperscript{-1}·min\textsuperscript{-1} according to the sex, age, or ethnicity of participants. In our study, the value of VO\textsubscript{2max} measured either in CPET (low altitude: 30.17 [SD 5.01] vs high altitude: 25.20 [SD 6.46]; P<.001) or SWT (low altitude: 31.28 [SD 5.17] vs high altitude: 26.17 [SD 6.71]; P<.001) was within a fair level range, reflecting the sedentary fitness of this cohort. The 10 pairs of participants’ VO\textsubscript{2max} at low altitude were nearly the same. The high overlap rate of our data may be because the measurement output from CPET and SWT are integers, which reduce the numerical difference. In other words, we consider that when the difference between the 2 measurements is less than 1, this difference may not show up. Such a high overlap rate outcome has been reported in a previous study [12]. Besides, repeated measures may help reduce the repetitive rate.

Similar to that shown in a previous report, VO\textsubscript{2max} was lower by approximately 16.5% at 3900 m evaluated by both CPET and SWT compared to that at low altitude in our trial, which can be attributed to the reduction of atmospheric PO\textsubscript{2} at high altitude [28]. Interestingly, the VO\textsubscript{2max}-SWT was slightly higher than the VO\textsubscript{2max} measured by the breath-to-breath method at both low and high altitudes. Therefore, we considered that the following issues may be associated with the differences: (1) the exercise mode in SWT was accelerative running, which requires a larger number of muscle groups, whereas the mode of CPET was a cycle ergometer, mostly relying on endurance, and (2) CPET required maximal performance; however, SWT only required submaximal exercise intensity. In addition, the overestimated VO\textsubscript{2max} of the SWT was more evident at high altitude, as highlighted by the higher MAPE (6.80% vs 6%, respectively) and wider 95% limits of agreement criterion. Interestingly, an increase in altitude did not significantly affect the $R^2$ and intraclass correlation coefficient values of VO\textsubscript{2max} assessed by the SWT, suggesting its high compatibility for...
hypobaric hypoxic conditions. To keep up with the exercise pattern used in the SWT, it is more rigorous to perform the CPET program on a treadmill than on a cycle ergometer to minimize the impact of the different muscular factors. However, there are several distinct differences between a treadmill and a bicycle ergometer (ie, space, safety, and costs)—all of which are conducive to a bicycle ergometer. It is only possible to change the slope and speed in the treadmill exercise. However, a cycle ergometer attains the linearity in workload increment well [29]. Thus, a cycle ergometer program should be preferred over a treadmill program at high altitudes. Hence, we finally opted to use a cycle ergometer for CPET. Nevertheless, the VO\(_{2}\)\(_{\text{max}}\) measured by the 2 methods has good correlation and consistency.

VO\(_{2}\)\(_{\text{max}}\) evaluation using CPET is inconvenient in practice. In the past few decades, several new methods for estimating VO\(_{2}\)\(_{\text{max}}\) have been investigated through a submaximal exercise protocol, including the Queen college step test [30], 20-m shuttle run test [31], and PWC170 [32,33]. Although they are easy to perform, the accuracy of the indirect method in estimating VO\(_{2}\)\(_{\text{max}}\) remains controversial. Thus, more variables such as basic parameters (age, sex, BMI) [34] and exercise indicators (maximal heart rate, speed, and covered distance) [35,36] were utilized in discrepant equations for more accuracy in subsequent studies. For instance, Marsh [37] found a 4-stage incremental running program estimating VO\(_{2}\)\(_{\text{max}}\) well (standard error of estimate=3.98-4.08 mL·kg\(^{-1}\)·min\(^{-1}\), r=0.642-0.646). However, this equation cannot be applied to the general population because correlation data were obtained for male athletes [37]. Instead of simply substituting variables into the equation, the smartwatch employed an algorithm called Firstbeat to evaluate VO\(_{2}\)\(_{\text{max}}\) in daily life. One of the key features of this patented technology is monitoring the running speed along with the heart rate continuously during each workout and automatically excluding the data without a linear relationship. A white paper of Firstbeat claimed that based on a database of 2690 freely performed runs by 79 individuals, its accuracy was up to 95% (MAPE<5%) and the error was below 3.5 mL·kg\(^{-1}\)·min\(^{-1}\) [14]. For perspective, it is superior to most other indirect submaximal tests (10%-15%) and approaches the direct laboratory test (approximately 5%). Thus, the FFT method can be commonly used to estimate VO\(_{2}\)\(_{\text{max}}\) when high-intensity exercise is limited or laboratory equipment is unavailable. Düring et al [38] found a coefficient of variation of 4% between Garmin watch and the criterion measure over the VO\(_{2}\) peak range from 38 mL·kg\(^{-1}\)·min\(^{-1}\) to 61 mL·kg\(^{-1}\)·min\(^{-1}\) through a small sample study. In this regard, the smartwatch with FFT is a portable device with satisfactory accuracy for estimating VO\(_{2}\)\(_{\text{max}}\) in the submaximal exercise protocol. Importantly, they also reported that the MAPE between the smartwatch and criterion measure was 7.1% when analyzing VO\(_{2}\) peak below 45 mL·kg\(^{-1}\)·min\(^{-1}\) whose discrepancy was less inaccurate in our study. The MAPE in this study was 6% and 6.8% at low and high altitudes, respectively. In [18], the 23 participants were of Caucasian origin, while in our study, the 46 participants were Chinese healthy adults. Hence, different race, gender, age, height, body weight and physical activity level of individuals may well explain differences in VO\(_{2}\)\(_{\text{max}}\), both between the other reports [39] and this study.

VO\(_{2}\)\(_{\text{max}}\) represents the maximum oxygen utilization capacity of an individual. In normoxic conditions, a higher VO\(_{2}\)\(_{\text{max}}\) indicates greater exercise capacity and better cardiorespiratory fitness [40-42]. However, due to PO\(_{2}\) decrease (approximately 63% of low altitude at 3700 m) at high altitude, arterial Sp\(_{\text{O}}\)\(_{2}\) and the amount of oxygen that eventually reaches the tissue and organ are reduced [43]. Thus, aerobic metabolic capacity and VO\(_{2}\)\(_{\text{max}}\) are significantly inhibited. To cope with hypoxia at high altitude, the body undergoes a series of physiological compensations in the cardiovascular and respiratory systems, such as increased heart rate [44,45], blood pressure [46], and respiratory rate [47]. Although these compensatory responses can compensate for oxygen insufficiency in a short period, long-term exposure may lead to irreversible changes such as pulmonary hypertension, chronic pulmonary disease, and heart failure [48,49]. VO\(_{2}\)\(_{\text{max}}\) has been an effective predictive indicator of mortality and rehospitalization in patients with chronic cardiovascular and respiratory diseases [50-52]. However, it has rarely been reported that VO\(_{2}\)\(_{\text{max}}\) contributes to the prognosis and rehabilitation of acute and chronic mountain illnesses [50]. In this study, we present the first evidence of VO\(_{2}\)\(_{\text{max}}\) as a predictor of AMS in a clinical trial.

It can be concluded from our results that individuals with a higher VO\(_{2}\)\(_{\text{max}}\) are unlikely to develop AMS. ROC analysis demonstrated that VO\(_{2}\)\(_{\text{max}}\)-CPET and VO\(_{2}\)\(_{\text{max}}\)-SWT showed a similar predictive value, particularly for VO\(_{2}\)\(_{\text{max}}\)-SWT, with a specificity up to 88.46% for a cutoff value of 29.5 mL·kg\(^{-1}\)·min\(^{-1}\). The high specificity ensures a low incidence of AMS when VO\(_{2}\)\(_{\text{max}}\) is below the cutoff value of lowlanders unsuitable for acute high-altitude exposure. In addition, we found that RDW-CV was more closely related to AMS when VO\(_{2}\)\(_{\text{max}}\) is below the criterion for AMS were young [39]. However, RDW-CV was an independent predictor for AMS and RDW-CV combined with VO\(_{2}\)\(_{\text{max}}\) showed a higher AUC, it is more convenient for individuals to obtain information on the potential suffering probability by using a smartwatch in daily life. Moreover, models 1 and 2 in Table 4 showed no statistical difference in AMS prediction compared to the single VO\(_{2}\)\(_{\text{max}}\) model. Therefore, SWT-based VO\(_{2}\)\(_{\text{max}}\) estimation can conveniently identify AMS-susceptible individuals and help evaluate the cardiorespiratory function and working capacity, which can benefit high-altitude travelers and workers and reduce the consumption of medical resources at high altitude. Although we cannot extend our validity claims to the entire population due to the small sample size and insufficiently diverse population characteristics, the conclusion that people with lower oxygen intake are more likely to develop AMS is well-founded and has been recently reported [55].

The VO\(_{2}\)\(_{\text{max}}\) estimated by SWT and measured by CPET has high consistency, indicating that smartwatches may replace the
CPET system to obtain VO\textsubscript{2}max accurately and objectively by monitoring the common physical activities with a portable, low-cost system. After each exercise, the smartwatch can measure and record the exercise information, integrate the calculation, and update the VO\textsubscript{2}max value. In addition, VO\textsubscript{2}max measured at low altitudes is highly correlated with the occurrence of AMS, with satisfactory prediction performance. Therefore, it is feasible to use a smartwatch to measure VO\textsubscript{2}max at low altitudes to evaluate the possibility of AMS. In the future, this will benefit tourists, temporary workers, and other individuals who plan to travel at high altitudes and will help in identifying participants susceptible to AMS before high-altitude exposure.

To advance this field, several measures are required. First, there is an urgent need for validation standards for smartwatch devices to enable standardized research. Second, the open disclosure of commercial validation studies can enable better resource usage, as studies will not have to be repeated unnecessarily. Third, further development of smartwatch devices will allow new possibilities in the field of VO\textsubscript{2}max monitoring. Finally, subsequent trials should continue to focus on validating these devices compared to conventional standards and broaden their use and demonstrate new possibilities for accurate VO\textsubscript{2}max monitoring.

**Limitations**

This study had some limitations. Notably, the Lake Louise consensus scoring system (2018 version) is subjective; therefore, we described each symptom as clearly as possible and provided necessary instructions before the participants completed the questionnaire to deal with the subjectivity. Second, running exercise instead of cycling should be implemented by CPET to minimize the inconsistencies in VO\textsubscript{2}max with SWT, which was not applied here due to the great safety risk at high altitude. Further studies and repeated measures are required to develop and investigate the predictive models of the SWT method based on submaximal running programs in terms of validity and reliability [11,56]. The present predictive models of the SWT method cannot be extended to the entire population. In the long term, conducting long-term validation research within a large and representative population is the scope of future studies, as the smartwatch will be extensively used by people. In addition, this study has insufficient reliability, as repeated measures analysis was not performed. It is contradictory to perform repeated measurements because measuring on the same day is limited by physical strength. Repeated measurements on different days also affect the assessment of AMS.

**Conclusions**

Our findings demonstrate that VO\textsubscript{2}max estimated by SWT and CPET have good accuracy and agreement at both low and high altitudes. Importantly, smartwatch-based VO\textsubscript{2}max at low altitudes was a convenient and effective approach to predict AMS and to identify susceptible individuals following acute high-altitude exposure, particularly by combining the RDW-CV at low altitudes.

**Acknowledgments**

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**Data Availability**

The data sets generated and analyzed during this study are available from the corresponding author on reasonable request.

**Conflicts of Interest**

None declared.

**Multimedia Appendix 1**

Original data of the cardiopulmonary exercise test and smartwatch test in this study.

[7Z File, 224520 KB - mhealth_v11i1e43340_app1.7z ]

**References**


Abbreviations
- AMS: acute mountain sickness
- AUC: area under the curve
- CPET: cardiopulmonary exercise test
- FFT: Firstbeat fitness test
- MAPE: mean absolute percentage error
- OR: odds ratio
- RBC: red blood cell
- RDW-CV: red blood cell distribution width-coefficient of variation
- ROC: receiver operating characteristic
- SpO2: oxygen saturation
- SWT: smartwatch test
- VO2max: maximum oxygen consumption

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Development and Validation of Multivariable Prediction Algorithms to Estimate Future Walking Behavior in Adults: Retrospective Cohort Study

Junghwan Park1,2,3,4, BSc; Gregory J Norman1,5, PhD; Predrag Klasnja6, PhD; Daniel E Rivera7, PhD; Eric Hekler1,2,3, PhD

1Herbert Wertheim School of Public Health and Human Longevity Science, University of California, San Diego, La Jolla, CA, United States
2Center for Wireless & Population Health Systems, Calit2’s Qualcomm Institute, University of California, San Diego, La Jolla, CA, United States
3The Design Lab, University of California, San Diego, La Jolla, CA, United States
4Ministry of Health and Welfare, Korean National Government, Sejong, Republic of Korea
5Department of Global Access and Evidence, Dexcom Inc., San Diego, CA, United States
6School of Information, University of Michigan, Ann Arbor, MI, United States
7Control Systems Engineering Laboratory, School for Engineering of Matter, Transport, and Energy, Arizona State University, Tempe, AZ, United States

Corresponding Author:
Junghwan Park, BSc
Herbert Wertheim School of Public Health and Human Longevity Science
University of California, San Diego
9500 Gilman Dr
La Jolla, CA, 92093
United States
Phone: 1 858 429 9370
Email: jup014@ucsd.edu

Abstract

Background: Physical inactivity is associated with numerous health risks, including cancer, cardiovascular disease, type 2 diabetes, increased health care expenditure, and preventable, premature deaths. The majority of Americans fall short of clinical guideline goals (ie, 8000-10,000 steps per day). Behavior prediction algorithms could enable efficacious interventions to promote physical activity by facilitating delivery of nudges at appropriate times.

Objective: The aim of this paper is to develop and validate algorithms that predict walking (ie, >5 min) within the next 3 hours, predicted from the participants’ previous 5 weeks’ steps-per-minute data.

Methods: We conducted a retrospective, closed cohort, secondary analysis of a 6-week microrandomized trial of the HeartSteps mobile health physical-activity intervention conducted in 2015. The prediction performance of 6 algorithms was evaluated, as follows: logistic regression, radial-basis function support vector machine, eXtreme Gradient Boosting (XGBoost), multilayered perceptron (MLP), decision tree, and random forest. For the MLP, 90 random layer architectures were tested for optimization. Prior 5-week hourly walking data, including missingness, were used for predictors. Whether the participant walked during the next 3 hours was used as the outcome. K-fold cross-validation (K=10) was used for the internal validation. The primary outcome measures are classification accuracy, the Mathew correlation coefficient, sensitivity, and specificity.

Results: The total sample size included 6 weeks of data among 44 participants. Of the 44 participants, 31 (71%) were female, 26 (59%) were White, 36 (82%) had a college degree or more, and 15 (34%) were married. The mean age was 35.9 (SD 14.7) years. Participants (n=3, 7%) who did not have enough data (number of days <10) were excluded, resulting in 41 (93%) participants. MLP with optimized layer architecture showed the best performance in accuracy (82.0%, SD 1.1), whereas XGBoost (76.3%, SD 1.5), random forest (69.5%, SD 1.0), support vector machine (69.3%, SD 1.0), and decision tree (63.6%, SD 1.5) algorithms showed lower performance than logistic regression (77.2%, SD 1.2). MLP also showed superior overall performance to all other tried algorithms in Mathew correlation coefficient (0.643, SD 0.021), sensitivity (86.1%, SD 3.0), and specificity (77.8%, SD 3.3).
Conclusions: Walking behavior prediction models were developed and validated. MLP showed the highest overall performance of all attempted algorithms. A random search for optimal layer structure is a promising approach for prediction engine development. Future studies can test the real-world application of this algorithm in a “smart” intervention for promoting physical activity.

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KEYWORDS
mobile health; mHealth; physical activity; walk; prediction; classification; multilayered perceptron; microrandomized trial; MRT; just-in-time adaptive intervention; JITAI; prevention; female; development; validation; application

Introduction
Physical inactivity is associated with numerous chronic diseases, including cancer, cardiovascular disease, type 2 diabetes [1-3], increased health care expenditure [4], and preventable, premature deaths [4]. Insufficient physical activity (PA) cost $53.8 billion worldwide in 2013. Clinical guidelines indicate 8000-10,000 steps per day [5]; nevertheless, the majority of Americans fall short of this goal [6].

In order to increase the level of PA, more than 300 commercial mobile apps have been developed [7]. The recent development of information technologies enabled mobile apps to deliver behavior change support when the users need this the most or when the utility (eg, how much the amount of PA was increased by the in-app notification) is predicted to be high. This new, promising type of intervention is called a just-in-time adaptive intervention (JITAI) [8].

JITAI are not widely used (eg, 2.2% in 2018 [7]) by commercially available apps. However, it has been shown that JITAI have the capacity to improve adherence and efficacy [9-11]. In addition, health behavior theories that commonly work as theoretical foundations for JITAI [9], including social cognitive theory [12] and goal setting theory [13], emphasize the importance of timely feedback and anticipatory intervention [12,14-16]. Adaptation to individual, time-varying needs is theorized to be an effective strategy [14] for implementing time-accurate feedback and anticipatory intervention [16]. Since the opportunity window to intervene depends on the individual’s environment, a fully automatic, predictive algorithm that can be run repeatedly is one of the key components of JITAI apps [14]. Thus, developing accurate algorithms to empower JITAI to promote PA is a central task in overall JITAI development.

Prior JITAI studies used pure randomizations [17], condition-triggered Boolean logic [18,19], a combination of manually designed logics [20], or models that reveal the mathematical relationships between input factors and the behavior (eg, system identification [21]) so that researchers could understand which factors are predictive of the behavior. In this study, the models were evaluated mainly focusing on predictive accuracy rather than explainability [22]. Time series data of walking behavior (ie, steps per minute) measured by a wearable sensor was used to predict future walking behavior. Multiple algorithms were compared using various metrics, including accuracy, Mathew correlation coefficient (MCC), sensitivity, and specificity. If these algorithms can be produced, it would be a critical step toward JITAI that are cost-efficient and fully autonomous (ie, without human couch interventions), and thus, it could be a valuable part of overall approaches for improving population health. To ensure the model’s cost-efficiency and real-time usage feasibility, the training computation time was measured in the standardized computing environment.

Methods
Source of Data
This study used the deidentified Jawbone walking data (ie, steps per minute) from the HeartSteps study [23], conducted in the United States from August 2015 to January 2016.

Ethical Considerations
The original study [23] was approved by the University of Michigan Social and Behavioral Sciences Institutional Review Board (HUM00092845) for data collection. As the data in this study were deidentified prior to being provided, the study was deemed as nonhuman subject research by the University of California, San Diego Institutional Review Board. This study adhered to the TRIPOD (Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis) statement on reporting development and validation of the multivariate predictive models [24] (Multimedia Appendix 1).

Study Design and Data Processing Protocol
Exclusion and Data Transformation
Minute-by-minute walking data (ie, number of steps per minute) were preprocessed in the following three steps: (1) excluded the participants who have the data of less than 10 days, (2) excluded the data if the participant was inactive (ie, 0 step per minute) or partially active (ie, less than 60 steps per minute) during the minute, and (3) excluded short walks lasted less than 5 minutes. Then, walk data were used to decide whether the participant was active or not during the hour. If there was one or more walks (ie, more than 5 consecutive walking minutes) during the hour, it was marked as an “active hour.” Then, the data were transformed to fit the machine learning algorithms (ie, from the time-series DataFrame objects of Pandas library to numerical array objects containing vector objects of NumPy library).

Training of Machine Learning Algorithms
The hourly walk data of the 5 prior weeks were used to predict the outcome (ie, whether the participant will walk or not during the next 3 hours). The following 6 sets of algorithms were used: logistic regression, radial basis function support vector machine [25], XGBoost [26], multilayered perceptron [27], decision tree,
and random forest [28] (Figure 1). We used the implementation of the open-source projects named “scikit-learn” [29], Keras [30], XGBoost [26,31], and “Sci-Keras” [32] for each algorithm.

Figure 1. Brief algorithm descriptions of classification models. RBF: radial basis function.

**Target Imbalance**

Due to sleeping hours and sedentary hours, nonactive hours usually outnumbered active hours. In machine learning algorithms, the phenomena are called “target imbalance” [33,34]. They usually critically reduce the performance of the prediction algorithm. Thus, in this study, we randomly sampled the nonactive hours to attain the same number as that of active hours.

**K-fold Validation**

After balancing the targets, the data were shuffled to perform K-fold validation [35] (Figure 2). We used K=10 in this study. We divide the shuffled data into 10 parts. Then, 1 part was separated to reduce the risk of overfitting the training data, and 1 part was separated for performance evaluation. In total, 8 out of 10 parts were used for machine learning algorithm training [35]. The process is iterated for 10 times, traversing each part for validation. The method allows us to internally validate the performance of the prediction engine. K (=10) sets of results were compared across the algorithms.

Figure 2. Brief description of K-fold validation method (eg, K=10).

**Outcomes**

Hourly data were generated during the preprocessing step. For the outcome variable, the activity data for 3 hours were merged. If the participant walked during the 3 hours, the outcome was assigned as “walked.”

**Predictor Variables**

In addition to 5 weeks’ hourly walking data, the variables noting the current date and time were used as predictors (Textbox 1). Each variable was encoded by the “One-hot-encoding” method [36]. It was a commonly used method to represent categorical (including ordinal or finite scale) variables in machine learning. The method converts the categorical variables (ie, N possible options) into an N-dimensional vector. Integers such as a current hour or current month were also converted into vectors. Each element of the vector can be ones or zeros. Each position in the vector denotes a particular value of options, and if a certain position was 1, the original value was mapped correspondingly. In a single vector, only one “1” was allowed. Since the encoding method enables the machine learning algorithm to train fast, it was commonly used. The discussion on the impact of the method on prediction performance was inconclusive [36].
Textbox 1. Variables used in classification algorithms.

<table>
<thead>
<tr>
<th>Predictor variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Current hour (24 dichotomous variables, one-hot-encoded)</td>
</tr>
<tr>
<td>• Today’s day of the week (7 dichotomous variables, one-hot-encoded)</td>
</tr>
<tr>
<td>• Current month (12 dichotomous variables, one-hot-encoded)</td>
</tr>
<tr>
<td>• Current day of the month (31 dichotomous variables, one-hot-encoded)</td>
</tr>
<tr>
<td>• Five Weeks’ hourly walking (Yes/No/Missing, 3 dichotomous variables, one-hot-encoded)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Outcome variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Whether the individual will walk during the next 3 hours (Yes/No, 1 dichotomous variable)</td>
</tr>
</tbody>
</table>

Random Search for Multilayered Perceptron Model Structure

Unlike other algorithms in this study, the multilayered perceptron (MLP) algorithm uses layer architectures as one of the critical performance factors. Optimization techniques such as evolutionary programming [37] or random search or grid search [38] may be used. A random search was used to minimize the implementation burden while not losing too much performance (Figure 3).

Figure 3. Pseudocode for searching optimal model structure.

```
K = 10, MAX_LAYER = 10, MIN_N = ~10, MAX_N = 1000

db = initialize_db()
For k = 1 to K:
    For n = 1 to MAX_LAYER:
        model = initialize_model()
        For i = 1 to n:
            n_neuron = random(MIN_N, MAX_N)
            model.add_layer(n_neuron)
            model.train(train_data)
            metric = model.test(test_data)
        # measure the performance
        db.insert(model, metric)
    # experiment K times
    # increase number of layers
    # initialize the model
    # for each layer
    # decide number of neurons
    # add a layer
    # train the model
```

Validation of the Models

The internal validation was performed by the K-fold validation methods. We used K=10. Individual test results were used to calculate the performance metrics such as accuracy, specificity, sensitivity, or MCCs. Data separation for the K-fold validation was conducted beforehand, which allows us to compare the metrics across the algorithms.

Mathew Correlation Coefficient

MCC [39] was defined as follows:

\[
MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}
\]

Where TP is true positive, TN is true negative, FP is false positive, and FN is false negative.

MCC was sometimes used as an optimization metric. In this study, we measured MCCs as a performance metric, not the optimization metric. Since we have balanced the output (see the Target Imbalance section), accuracy was used as the optimization metric.

Computation Time

To conduct fair comparisons for the computation time, each model was trained in an isolated, standardized computing environment so that the system clock could measure the time elapsed. The system was reset every time a single execution was completed to minimize the fallout of the previous execution to the upcoming execution. Elapsed times were averaged and analyzed per algorithm.

Results

Study Population and Baseline Characteristics

A total of 41 (93%) out of 44 participants were included in the analysis [23]. The population’s average age was 35.9 years. Of the 44 study participants, 31 (71%) were female, 26 (59%) were White, and 13 (30%) were Asian, with 36 (82%) having college degree or more. Moreover, 27% (n=12) of the participants had used a fitness app or activity tracker (Table 1).
Table 1. Baseline characteristics of participants at study entry.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>31 (71)</td>
</tr>
<tr>
<td>Male</td>
<td>13 (30)</td>
</tr>
<tr>
<td><strong>Race, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>26 (59)</td>
</tr>
<tr>
<td>Asian</td>
<td>13 (30)</td>
</tr>
<tr>
<td>Black or African American</td>
<td>2 (5)</td>
</tr>
<tr>
<td>Other</td>
<td>3 (7)</td>
</tr>
<tr>
<td><strong>Education, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Some college</td>
<td>8 (18)</td>
</tr>
<tr>
<td>College degree</td>
<td>13 (30)</td>
</tr>
<tr>
<td>Some graduate school or graduate degree</td>
<td>23 (52)</td>
</tr>
<tr>
<td><strong>Married or in a domestic partnership, n (%)</strong></td>
<td>15 (34)</td>
</tr>
<tr>
<td><strong>Have children, n (%)</strong></td>
<td>16 (36)</td>
</tr>
<tr>
<td><strong>Used fitness app before HeartSteps, n (%)</strong></td>
<td>12 (27)</td>
</tr>
<tr>
<td><strong>Used activity tracker before HeartSteps, n (%)</strong></td>
<td>10 (22)</td>
</tr>
<tr>
<td><strong>Phone used for study app, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Used personal phone</td>
<td>21 (48)</td>
</tr>
<tr>
<td>Used study-provided phone</td>
<td>23 (52)</td>
</tr>
<tr>
<td><strong>Age (years), mean (SD)</strong></td>
<td>35.9 (14.7)</td>
</tr>
</tbody>
</table>

Data Summary for Predictor and Outcome Variables

On average, participants had available walking data for 43.3 (SD 9.1) days and 145.7 (SD 44.6) minutes per day. The average number of walking minutes per participant per day was reduced to 53.3 (SD 26.1) minutes after filtering with the threshold of 60 steps per minute (Methods section). Participants had 2.6 (SD 1.7) walks (ie, 5 or more consecutive walking minutes) every day (Methods section). Average length of each walk was 10.3 (SD 8.0) minutes. In hourly view, the participants had 0.6 (SD 0.1) “walking hours” (ie, the hours in which the participant walked) per day (Figure 4). Missing data were also used as a predictor state (Methods section). There were 18.1 (SD 13.4) missed days on average per participant, equivalent to 36.9% (SD 26.3%) of total days per participant. In the matter of outcome variable, as training and validating data set, 8129 “walking hours” and 37,711 “non-walking hours” (eg, nighttime or sedentary hours) were prepared (Methods section). Across the data, 17.7% of the time included participant activity. Thus, inactive time is 4.64 times more common than active time. The target imbalance was handled by undersampling (Methods section).
Development of Prediction Algorithms

The calculation time vastly varied (Table 2). The radial basis function support vector machine algorithm and multilayered perceptron algorithm took the longest period to run. Tree-based algorithms such as decision tree and random forests were shorter than others. Random search to discover the optimal layer structure was tried. The optimization process improved the accuracy of the MLP algorithms from 49.8% to 82.1%. The process also improved all other metrics (Figure 5).

Table 2. Performance metrics of tried algorithms.

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Accuracy, mean (SD)</th>
<th>MCC a, mean (SD)</th>
<th>Sensitivity, mean (SD)</th>
<th>Specificity, mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic regression</td>
<td>0.772 (0.012)</td>
<td>0.545 (0.024)</td>
<td>0.795 (0.015)</td>
<td>0.749 (0.023)</td>
</tr>
<tr>
<td>RBF b SVM c</td>
<td>0.693 (0.010)</td>
<td>0.389 (0.020)</td>
<td>0.746 (0.022)</td>
<td>0.641 (0.017)</td>
</tr>
<tr>
<td>XGBoost</td>
<td>0.763 (0.015)</td>
<td>0.530 (0.030)</td>
<td>0.816 (0.010)</td>
<td>0.711 (0.030)</td>
</tr>
<tr>
<td>Multilayered perceptron</td>
<td>0.820 (0.011)</td>
<td>0.643 (0.021)</td>
<td>0.861 (0.030)</td>
<td>0.778 (0.033)</td>
</tr>
<tr>
<td>Decision tree</td>
<td>0.636 (0.015)</td>
<td>0.281 (0.026)</td>
<td>0.509 (0.075)</td>
<td>0.762 (0.049)</td>
</tr>
<tr>
<td>Random forest</td>
<td>0.695 (0.010)</td>
<td>0.396 (0.023)</td>
<td>0.776 (0.019)</td>
<td>0.614 (0.018)</td>
</tr>
</tbody>
</table>

aMCC: Mathew correlation coefficient.
bRBF: radial basis function.
cSVM: support vector machine.

Figure 4. Overall distribution of walking data (1 narrow cell=1 hour).
Validation and Model Performance

The reference algorithm (logistic regression) showed 77.2% (SD 1.2%) accuracy. XGBoost showed 76.3% (SD 1.5%), radial basis function support vector machine showed 69.3% (SD 1.0%), decision tree showed 63.6% (SD 1.5%), and random forest showed 69.5% (SD 1.0%), respectively. MLP performance largely varied from 49.8% (SD 1.7%) to 82.1% (SD 1.3%). Only 3 MLP architectures with the highest accuracies were included (Tables 2 and 3; Figure 6). Sensitivities, specificities, and MCC showed similar patterns to the accuracies. The decision tree algorithm generally showed the lowest performance overall, except on the dimension of specificity. MLP showed the highest performance across metrics (82.0% accuracy, 86.1% sensitivity, and 77.8% specificity).

Table 3. Average confusion matrix of each model of K-fold validation for the validation data set.

<table>
<thead>
<tr>
<th>Model</th>
<th>True positive, mean (SD)</th>
<th>True negative, mean (SD)</th>
<th>False positive, mean (SD)</th>
<th>False negative, mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic regression</td>
<td>646.3 (27.3)</td>
<td>609.0 (30.6)</td>
<td>203.5 (18.8)</td>
<td>166.2 (11.7)</td>
</tr>
<tr>
<td>RBF&lt;sup&gt;a&lt;/sup&gt; SVM&lt;sup&gt;b&lt;/sup&gt;</td>
<td>606.3 (25.4)</td>
<td>520.3 (18.3)</td>
<td>292.2 (19.4)</td>
<td>206.2 (19.5)</td>
</tr>
<tr>
<td>XGBoost</td>
<td>663.0 (18.3)</td>
<td>577.6 (33.3)</td>
<td>234.9 (24.7)</td>
<td>149.5 (12.3)</td>
</tr>
<tr>
<td>MLP&lt;sup&gt;c&lt;/sup&gt;</td>
<td>699.9 (35.2)</td>
<td>632.6 (34.7)</td>
<td>180.0 (27.5)</td>
<td>112.6 (24.2)</td>
</tr>
<tr>
<td>Decision tree</td>
<td>413.8 (65.4)</td>
<td>619.7 (52.5)</td>
<td>192.8 (39.1)</td>
<td>398.7 (56.5)</td>
</tr>
<tr>
<td>Random forest</td>
<td>630.3 (13.6)</td>
<td>499.0 (18.2)</td>
<td>313.5 (20.9)</td>
<td>182.2 (20.7)</td>
</tr>
</tbody>
</table>

<sup>a</sup>RBF: radial basis function.
<sup>b</sup>SVM: support vector machine.
<sup>c</sup>MLP: multilayered perceptron.
Compution Time

In all the tested performance indicators, the optimized MLP showed the best performance and showed the second-longest training time of 225 seconds on average (Table 4). If we add up the total training time of all 90 optimization experiments, it took 56 hours. It was feasible to consistently evaluate training speed, accuracy, MCC, sensitivity, and specificity within the standardized performance evaluation framework. Through 90 random experiments, multiple MLP algorithms with optimized performance were obtained. The development, validation, and evaluation protocols can be used for similar prediction or classification problems.

Python 3.7.3, Sci-Kit Learn 1.0.2, Numpy 1.21.6, and Pandas 1.3.5, Tensorflow 2.8.0, xgboost 0.90, keras 2.8.0 were used.

In the matter of computation cost-efficiency (ie, predictive performance vs computation time), each algorithm showed characteristic results. The logistic regression had reasonable prediction performance and relatively low average computation time cost, whereas MLP showed generally higher prediction performance but had the second highest average computation cost (Figure 7).

It was feasible to consistently evaluate training speed, accuracy, MCC, sensitivity, and specificity within the standardized performance evaluation framework. Through 90 random experiments, multiple MLP algorithms with optimized performance were obtained. The development, validation, and evaluation protocols can be used for similar prediction or classification problems (Figure 8).

Table 4. Computation time to reach optimally trained status (secondsa).

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean (SD)</th>
<th>CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic regression</td>
<td>20.73</td>
<td>24.89</td>
<td>22.37 (1.50)</td>
<td>19.43-25.31</td>
</tr>
<tr>
<td>RBFb SVMc</td>
<td>413.09</td>
<td>683.62</td>
<td>496.57 (94.58)</td>
<td>311.19-681.96</td>
</tr>
<tr>
<td>XGBoost</td>
<td>63.92</td>
<td>73.75</td>
<td>67.79 (4.33)</td>
<td>59.30-76.27</td>
</tr>
<tr>
<td>Multilayered perceptron</td>
<td>172.14</td>
<td>300.36</td>
<td>225.35 (38.83)</td>
<td>149.24-301.46</td>
</tr>
<tr>
<td>Decision tree</td>
<td>3.30</td>
<td>13.20</td>
<td>5.89 (2.68)</td>
<td>0.65-11.14</td>
</tr>
<tr>
<td>Random forest</td>
<td>4.32</td>
<td>13.42</td>
<td>6.63 (2.53)</td>
<td>1.68-11.57</td>
</tr>
</tbody>
</table>

aComputation was done in Google Colaboratory Pro+ (High-RAM mode with GPU hardware accelerator); 8 cores of Intel Xeon CPU 2.00 GHz, 53.4GB Memory, Tesla P100-PCIE-16GB.

bRBF: radial basis function.
cSVM: support vector machine.
Discussion

Key Implications

The high-level focus of our work is to develop approaches for using data from individuals themselves to create more individualized and adaptive support via digital technologies. In this paper, our goal was to test if predictive models could be generated that would be useful in terms of sensitive and specific probability estimates of the likelihood that someone will walk within an upcoming 3-hour window and that it could be done in a computationally efficient fashion. The latter part is important as computational efficiency is needed to enable the predictive models to be incorporated into future just-in-time adaptive interventions (JITAI) that could use these predictive models to guide future decision-making. To support robust, automated decision-making within a JITAI to increase walking, our goal was to test if it would be feasible to produce predictive models that are informative for individuals in terms of identifying moments when a person has some chance of walking as opposed to either times when a person will clearly walk and thus does not need support, or times when there was near-zero probability that, in a given 3-hour window, a person will walk. If a predictive model could be produced that would provide this information, it would enable a JITAI that could incorporate these individualized predictions as a signal that could be used for making decisions on whether a given moment would be a just-in-time moment to provide a suggestion to go for a walk, with the predictive model used to predict the likelihood that, within the next 3 hours, the person would have the opportunity to walk while also having a need for a suggestion (ie, a person would not need a suggestion to walk if they are very likely to walk anyway). Our results, overall, suggest it is possible to generate said models in a scalable fashion, which could then be incorporated into a future JITAI that incorporates these individualized predictive models. Central to this work, the models produced here are definitionally idiographic in nature and thus appropriate for each individual. Thus, the results from the model should not be generalized to other samples. Instead, the key transportable knowledge from this work is the overall approach used for selecting models to guide individualized decision-making in future JITAI (Figure 8).

Principal Findings

We developed 6 models (one of which was a group of models, and we chose the best 3 model architectures) for predicting future walking behavior within the subsequent 3-hour period using the previous 5 weeks’ hourly walking data. MLP algorithm
showed the best performance across all 4 metrics within this sample. A random search for MLP architecture produced an optimal model with the best performance. Using predictive engines to decide how to configure JITAI could enable the mobile physical activity app to deliver more timely, appropriate intervention components such as in-app notifications. To the best of our knowledge, interventions that use predictive models to adjust to participant’s behavior are still uncommon. Thus, our study makes a significant contribution by introducing the use of predictive algorithms for optimizing JITAI.

Methodological Considerations and Comparison With Prior Work
In this study, we designed a protocol to develop and validate a predictive model for walking behavior. While developing the model, we had a few common issues that should be handled as follows.

Small Data Sets and the Potential Risk for Low External Validity
Despite the effort to validate the model with the K-fold cross-validation, since we are using a small number of short time-series data, high levels of external validity are not assumed. However, since the model we developed in this study did not assume any prior knowledge or variability (ie, nonparametric), additional training data are theorized to harness better performance. The model also did not use the pretrained coefficients; we used randomized coefficients. This leaves room for better performance and higher computation efficiency when we use the pretrained model from this study to extend the training. Publicly available lifestyle data, including the All-of-Us project [40] and the ones available on the public data platforms [41], will be a good way to extend the data set.

Target Imbalance
Target imbalance is defined as a significantly unequal distribution between the classes [33]. In numerous clinical [42,43] and behavioral [33] data modeling studies, target imbalance is a common issue. Although a few oversampling methodologies to tackle unbalanced output data have been developed [44], this study used an undersampling approach due to potential concerns of exaggerated accuracy [34]. The separate analysis with oversampling of the same data and methodologies showed 5%-10% increases in the accuracy. It is suspected that the underlying individual behavior patterns in the training samples are partly included in the test and validation samples.

Performance Metrics
Accuracy is the most commonly used performance metric to evaluate classification algorithms. However, the accuracy metric is also known to have the inability to distinguish between type 1 and type 2 errors [45]. The metrics of sensitivity and specificity are also commonly used to overcome the limitation of accuracy. The information represented by both metrics is partial (ie, both are addressing either type of error). MCC [46] is used more commonly in recent publications due to its statistical robustness against target imbalance, which is a common issue of clinical and behavioral data. Considering the imbalance of the classification problem of interest, we included MCC as a performance metric.

Limitations of This Study
The original study was designed for the purpose of pilot-testing and demonstrating the potential of microrandomized trials. Thus, these analyses are all secondary in nature. Further, the initial study was a small study, with only a minimum amount of data (n=41) used. Additionally, since the participants were recruited in a homogeneous environment and demographic groups, the external validity of the algorithms may be limited. With that said, the overall approach for formulating predictive models and their selection could feasibly be used in the future and, thus, it is more of our protocol and approach that is likely to be generalizable and generally useful for JITAI compared to any specific insights from the models we ran. We contend that, for any targeted JITAI, a precondition for this type of approach is the appropriate data available, and that, for any JITAI, it is more valuable to build algorithms that match localized needs and contexts than seek to take insights from some previous samples that are different from a target population and assume they will readily translate. This, of course, can be done with careful tests of transportability using strategies such as directed acyclic graphs to guide the production of estimands [47] that would create formalized hypotheses of transportability. However, this is a much higher bar for transportability that, while valuable, can often be prohibitive for fostering progress in JITAI. Within our proposed approach, the strategy involves cleaning good enough data to enable a localized prediction algorithm appropriate for the targeted population to be produced, with subsequent deployment factoring in strategies and approaches for updating and improving the algorithms as new insights emerge.

Implication and Future Work
The results of our study show that prediction algorithms can be used to predict future walking behavior in a fashion that can be incorporated into a future walking JITAI. In this study, we modeled without contextual information other than the date, time, or day of the week. However, if the machine learning algorithm is trained using the other contextual information such as intervention data (eg, whether the in-app notification message is sent or not, which type of message is sent, and which sentiment is used to draw attention), the prediction engine would be capable of simulating how the intervention components might change the behavior in the multiple hypothetical scenarios. This capability would enable us to use the prediction algorithms uniquely, that is, comparing two or more possible scenarios to decide the optimal intervention mode of a JITAI. We could decide whether to send a message, which message should be sent, or what sentiment we could use to draw attention to our intervention. A pragmatic study that assesses the efficacy of such an approach is necessary.

The search methods for the optimal architectures of MLP could be improved. Evolutionary programming [48] and weight-agnostic neural network [37] are promising approaches. Such improvement could find the MLP architectures’ better performance in shorter computation time.
Conclusion
The protocol for developing and validating a prediction engine for health behavior was developed. As a case study, walking behavior classification models were developed and validated. MLP showed the highest overall performance of all tried algorithms, yet it needed relatively higher computation time. A random search for optimal layer structure was a promising approach for prediction engine development.

Acknowledgments
JP conceptualized the research question, analyzed the data, and wrote the manuscript. PK provided the data. DER provided the program code library to assist the analysis. EH provided guidance at each stage of study. All authors contributed to the writing of the manuscript. The National Library of Medicine (R01LM013107) funded JP’s stipend.

Conflicts of Interest
JP is an employee of Korean National Government, the Ministry of Health and Welfare. GJN is an employee of Dexcom, Inc.

Multimedia Appendix 1
TRIPOD (Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis) checklist: prediction model development and validation.

References


Abbreviations

- JITAI: just-in-time adaptive intervention
- MCC: Mathew correlation coefficient
- MLP: multilayered perceptron
- PA: physical activity
- TRIPOD: Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis

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Exploring the Feasibility and Usability of Smartphones for Monitoring Physical Activity in Orthopedic Patients: Prospective Observational Study

Arash Ghaffari¹, MD; Rikke Emilie Kildahl Lauritsen¹, MSc; Michael Christensen², MSc; Trine Rolighed Thomsen³,⁴, PhD; Harshit Mahapatra², MSc; Robert Heck³, PhD; Søren Kold¹, MD, PhD; Ole Rahbek¹, MD, PhD

¹Interdisciplinary Orthopaedics, Aalborg University Hospital, Aalborg, Denmark
²Alexandra Institute, Aarhus, Denmark
³Danish Technological Institute, Aarhus, Denmark
⁴Department of Chemistry and Bioscience, Aalborg University, Aalborg, Denmark

Corresponding Author:
Arash Ghaffari, MD
Interdisciplinary Orthopaedics
Aalborg University Hospital
Hobrovej 18 - 22
Aalborg, 9000
Denmark
Phone: 45 91483966
Email: a.ghaffari@rn.dk

Abstract

Background: Smartphones are often equipped with inertial sensors that measure individuals’ physical activity (PA). However, their role in remote monitoring of the patients’ PAs in telemedicine needs to be adequately explored.

Objective: This study aimed to explore the correlation between a participant’s actual daily step counts and the daily step counts reported by their smartphone. In addition, we inquired about the usability of smartphones for collecting PA data.

Methods: This prospective observational study was conducted among patients undergoing lower limb orthopedic surgery and a group of nonpatients as control. The data from the patients were collected from 2 weeks before surgery until 4 weeks after the surgery, whereas the data collection period for the nonpatients was 2 weeks. The participant’s daily step count was recorded by PA trackers worn 24/7. In addition, a smartphone app collected the number of daily steps registered by the participants’ smartphones. We compared the cross-correlation between the daily steps time series obtained from the smartphones and PA trackers in different groups of participants. We also used mixed modeling to estimate the total number of steps, using smartphone step counts and the characteristics of the patients as independent variables. The System Usability Scale was used to evaluate the participants’ experience with the smartphone app and the PA tracker.

Results: Overall, 1067 days of data were collected from 21 patients (n=11, 52% female patients) and 10 nonpatients (n=6, 60% female patients). The median cross-correlation coefficient on the same day was 0.70 (IQR 0.53-0.83). The correlation in the nonpatient group was slightly higher than that in the patient group (median 0.74, IQR 0.60-0.90 and median 0.69, IQR 0.52-0.81, respectively). The likelihood ratio tests on the models fitted by mixed effects methods demonstrated that the smartphone step count was positively correlated with the PA tracker’s total number of steps ($\chi^2=34.7, P<.001$). In addition, the median usability score for the smartphone app was 78 (IQR 73-88) compared with median 73 (IQR 68-80) for the PA tracker.

Conclusions: Considering the ubiquity, convenience, and practicality of smartphones, the high correlation between the smartphones and the total daily step count time series highlights the potential usefulness of smartphones in detecting changes in the number of steps in remote monitoring of a patient’s PA.

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KEYWORDS
remote monitoring; physical activity; step count; smartphone application; wearable sensors; mixed effects modeling; step count prediction; mobile phone
Introduction

Background
Daily physical activity (PA) is crucial for maintaining physical, mental, and social health [1]. For patients undergoing orthopedic surgery, resuming PA as soon as possible is vital to enhance recovery and prevent complications [2]. In addition, assessing PA after surgery can provide valuable information regarding a patient’s health condition, allowing for individualized rehabilitation based on the patient’s condition and demands [3-5]. However, some limitations and challenges exist regarding the measurement of PA. Current patient-reported outcome measures (PROMs) such as questionnaires and surveys might seem convenient for evaluating the level of PA; however, they have limitations such as low patient adherence, floor effects, and recall bias and are inefficient in measuring walking as an important PA [6]. In addition, PROMs are often obtained at specific and broad intervals. Therefore, the objective measurement of PA after discharge is of increasing interest [7].

Smartphones and other digital devices are currently equipped with sensors allowing the quantification of an object’s motion by converting inertial forces into measurable electrical signals [8]. This makes them valuable tools for remotely monitoring patients’ PA during recovery after surgery. Smartphones have also become increasingly prevalent across all age groups and are now ubiquitous [9]. For instance, in Denmark, 90% of the population has access to smartphones [10], making them a widespread technology with the potential for broad societal impact. Using smartphones in remote monitoring the patients also offers the possibility of applying supplementary PROMs. A recent study on patients undergoing hip replacement surgeries demonstrated the patients’ interest in using smartphone apps and learning how to use wearable sensors [11]. Collecting activity data and PROMs with a smartphone for this group of patients has proven feasible [12].

Given the increasing prevalence of smartphones in the general population and their growing application in telemedical methods, these devices can play a prominent role in collecting objective PA data. However, their capability has not been fully explored, especially in free-living settings and over extended periods, such as follow-up after surgeries. In addition, some uncertainties have been discussed regarding the validity of the measurements, as the patients usually do not carry their smartphones all the time [13]. Specifically, changing daily life routines during and immediately after surgery may cause the patients not to carry their devices as usual. Accordingly, the amount and the significance of the nonmeasured activity in the perioperative periods are unknown.

Objectives
In this study, we explored the utility of smartphones in measuring daily PA compared with wearable sensors in orthopedic patients during the perioperative period. The PA trackers were used to record step counts during regular continuous walking, sporadic walking, and slow continuous walking. The primary objective of this study was to determine the correlation between the daily step counts obtained from smartphones and the step counts registered by the PA trackers during these different types of walking. In addition, we investigated the ability of smartphones to predict the total number of daily steps taken during each type of walking. The secondary objective was to evaluate the usability of a smartphone app designed to collect health data.

Methods

Study Design and Setting
This prospective observational study was conducted at the Aalborg University Hospital, Denmark, between November 2021 and August 2022. The project was registered at North Jutland Research Database in Denmark (2021-119).

Ethics Approval
This study was approved by the Regional Committee on Health Research Ethics (reference 2021-000438). This study complies with the Strengthening the Reporting of Observational Studies in Epidemiology guidelines [14].

Participants

Overview
We included 2 groups of participants in this study to compare the results of the patients undergoing orthopedic surgeries with those of a control group. First, all participants were informed about the study process and were asked to sign informed consent forms. Subsequently, the participants were instructed to install and use the smartphone app and the PA trackers and transfer the data.

Patients
Patients undergoing lower limb orthopedic surgery were eligible for inclusion if they were smartphone users. No limitation was placed regarding the participant’s age or the type of surgery. However, older, frail patients who required a wheelchair for ambulation or who could not walk independently were not included.

Patients’ data were collected from at least 2 weeks before surgery until 4 weeks after surgery.

Nonpatients
We also included volunteers without orthopedic problems as the control group. Data regarding the step counts for at least 14 consecutive days were collected in this group.

Data Sources and Measurements

Participants’ Characteristics
The patients’ basic and demographic information, including their age, sex, BMI, comorbidities (history of medical illness), and previous orthopedic surgery on the lower limbs, were registered in a REDCap (Research Electronic Data Capture; Vanderbilt University) database hosted by the North Jutland Region, Denmark [15].

PA Tracker
SENS sensors (SENS Motion) were used to record the patients’ daily number of steps. SENS Motion is a wearable PA sensor worn as a patch on the lateral distal thigh and collects PA data...
by registering 3D linear acceleration data (Figure 1). Some studies have investigated the reliability and validity of the SENS PA trackers’ measurements [16,17] and demonstrated favorable results. As the sensors were attached 24/7 to the patients, we considered their measurements as the total daily step counts. To ensure that the patients wore the sensors for the entire duration, we observed the sensors’ relative temperature data in addition to the linear acceleration daily time series.

**Figure 1.** The photograph demonstrates the SENS Motion physical activity tracker at the lateral side of the distal thigh of 1 of the participants in the study.

The SENS Motion algorithm calculates the number of steps taken during sporadic and continuous walking, as well as training, in three different categories:

1. **Steps-1:** Summarized number of steps during continuous walking and training, based on analysis in the frequency domain.
2. **Steps-2:** Steps taken during sporadic and irregular walking where no continuous frequency can be recognized in the 5-second interval are summarized as 2 steps per 5-second interval.
3. **Steps-3:** Steps taken during slow walking where a continuous frequency can be recognized, but the intensity of the accelerations is lower than that in usual walking.

We calculated the total PA tracker steps as the sum of the 3 abovementioned variables.

**Smartphone App (OrtoApp)**

OrtoApp (Alexandra Institute) is a smartphone app developed to collect step counts and PA data from the Apple HealthKit application programming interface (API) on iOS and the Google Fit API on Android smartphones [18,19]. During the study, the app was installed on patients’ smartphones and automatically
recorded the steps registered by the Apple HealthKit and the Google Fit APIs. Furthermore, if a person also wears a smartwatch, the Apple HealthKit and Google Fit APIs will collect the data from both devices (the smartwatch and the smartphone), and the step counts will be calculated based on both inputs.

In addition, OrtoApp allows users to record their daily mood and pain levels on an 11-point visual analog scale (0-10). However, we did not use the data regarding the pain and mood scores in this study.

**Usability of the Smartphone App and PA Tracker**

We used the System Usability Scale (SUS) to evaluate participants’ experience with the smartphone app and the PA tracker. The SUS is developed as a survey scale that allows quick and easy assessment of the usability of a given product or service [20]. The original SUS instrument comprises 10 statements scored on a 5-point scale of the strength of agreement. Final SUS scores can range from 0 to 100, with higher scores indicating better usability [21]. In this study, we used the translated and validated Danish version of the SUS [22].

After the data collection period was over, we assessed the usability only in the patient group by distributing the SUS questionnaire via the REDCap web application.

**Steps Data Analysis**

We generated 5 time series for each participant, including 1 for the daily steps recorded by the smartphones and 4 for the daily PA trackers’ measurements (steps-1, steps-2, steps-3, and PA tracker total steps). These time series were then plotted for each participant, and we compared the smartphone data’s time series with the different variables of the PA trackers using cross-correlation. Before conducting the cross-correlation analysis, we differentiated the time series data to remove any trends or changes in the mean that may have affected the results. This was done by calculating the difference between consecutive time points (days). Next, we calculated the cross-correlation between the resulting time series using a standard method [23]. We specifically calculated the cross-correlation at 0 days lag (ie, the same day) to assess the immediate relationship between the variables. We used Fisher Z transformation to calculate the 95% CI for the correlation coefficients and to compare the correlation coefficients [24]. The comparisons were performed between various groups based on different criteria, including patient or nonpatient status, preoperative or postoperative status (for patients), age (≥60 years or <60 years), comorbidities, history of lower limb surgery, day of data collection (weekday—Monday through Friday—or weekend—Saturday and Sunday), content type of the smartphone used, and the use of a smartwatch.

In addition, we applied mixed effects models to investigate whether the smartphone’s step counts could predict the total number of steps. Only the data from the patient group were used for mixed effects modeling. To prepare the data for regression analysis, we applied the moving average method to calculate the average values for the 3 preceding days (trailing moving average with a window of 3 days). In time series data analysis, the moving average method helps discover certain traits by smoothing the variations and reducing the noise [23]. Subsequently, we scaled the data to have a mean 0 and a SD equal to 1.

We used different subjects as random intercepts in the models and by-subject PA tracker–smartphone steps slope variance as random slopes. We included the following variables and all possible interaction effects between the variables to fit the models:

1. Smartphone steps:
   - Scaled 3-days moving average as a continuous variable
2. Participants’ characteristics:
   - Age in years as a continuous variable
   - Sex as a categorical variable (male or female)
   - BMI in kg/m² as a continuous variable
   - Comorbidity as a categorical variable (yes or no)
   - History of lower limb surgery as a categorical variable (yes or no)
3. Characteristics of data collection day:
   - Preoperative versus postoperative as a categorical variable
4. Smartphone health app:
   - Apple HealthKit versus Google Fit as a categorical variable
5. Smartwatch:
   - Using a smartwatch as a categorical variable (yes or no).

The variables included in the best-performing models were selected by backward elimination, that is, if they did not improve the model, the variables were omitted.

Four models were created for the different variables from the PA tracker (steps-1, steps-2, steps-3, and PA tracker total steps). In the best-fitted models for the steps-2, steps-3, and PA tracker total steps, the selected variables were the period (preoperative or postoperative) and the presence of comorbidities in addition to smartphone steps. However, in the PA steps-1 model, the history of medical disease did not improve the model performance and hence was excluded.

The coefficients for the fixed and random effects variables in the best-fitted models and the performance metrics for the goodness of fit for the models (described in Statistical Methods section) were computed. The 95% prediction intervals for the models were created and plotted by bootstrapping techniques.

**Statistical Methods**

We used the R statistical package (version 4.1.0; R Foundation for Statistical Computing) for the statistical analyses and lme4 package [25] for the mixed effects models.

Descriptive statistics were used to describe participants’ basic information. The counts and percentages were used for the discrete variables, including the number and sex of the participants and the number of days for data collection. Means and SDs were used to describe the participants’ age and BMI.
We presented the cross-correlation coefficients between the time series as means and 95% CIs. The SUS values for the smartphone app and PA trackers were provided as median and IQR.

Mixed effects models were created using the restricted maximum likelihood approach. The repeated measures and covariance matrix were modeled as unstructured. No violation of the model assumptions regarding the linearity, homoscedasticity, and normality of residuals was detected. The goodness of fit of the models was assessed by calculating the deviance, Akaike information criterion, Bayesian information criterion [26], intraclass correlation coefficient, and conditional and marginal pseudo-$R^2$ [27]. Marginal pseudo-$R^2$ represents the variance explained by the fixed effects, whereas conditional pseudo-$R^2$ is interpreted as a variance explained by the entire model, that is, both fixed and random effects. The scaled step counts were back transformed into actual values in the plots. We compared the best-fitted models with and without the smartphone step counts by using likelihood ratio tests to calculate $P$ values. The significance level was set at $\alpha=0.05$.

**Results**

**Participants’ Characteristics**

Overall, 35 participants were included in the study; however, 4 participants were excluded, and data of 31 participants (n=21, 68% patients and n=10, 32% nonpatients) were analyzed. Table 1 presents the characteristics of the participants.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Patient (n=21)</th>
<th>Nonpatient (n=10)</th>
<th>Total (n=31)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years), mean (SD)</td>
<td>57.6 (16.4)</td>
<td>49.9 (10.2)</td>
<td>55.1 (14.9)</td>
</tr>
<tr>
<td>Sex (female), n (%)</td>
<td>11 (52)</td>
<td>6 (60)</td>
<td>17 (55)</td>
</tr>
<tr>
<td>History of lower limb surgery, n (%)</td>
<td>16 (76)</td>
<td>1 (10)</td>
<td>17 (55)</td>
</tr>
<tr>
<td>Comorbidities, n (%)</td>
<td>12 (57)</td>
<td>5 (50)</td>
<td>17 (55)</td>
</tr>
<tr>
<td>BMI (kg/m$^2$), mean (SD)</td>
<td>28.7 (5.2)</td>
<td>26.9 (5.3)</td>
<td>28.1 (5.3)</td>
</tr>
<tr>
<td>Smartphone health app, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Google Fit</td>
<td>17 (81)</td>
<td>8 (80)</td>
<td>25 (81)</td>
</tr>
<tr>
<td>Apple HealthKit</td>
<td>4 (19)</td>
<td>2 (20)</td>
<td>6 (19)</td>
</tr>
<tr>
<td>Smartwatch</td>
<td>4 (19)</td>
<td>2 (20)</td>
<td>6 (19)</td>
</tr>
</tbody>
</table>

Participants were excluded owing to surgery cancellation (2/4, 50%) and technical problems with the sensor (1/4, 25%) or the smartphone app (1/4, 25%). In addition, data from 3 patients only contained preoperative data because one of the patients discontinued collecting data after the surgery, the surgery was postponed in another patient, and the sensor was lost in the operating room in the third patient. The time series from patients who only had preoperative data were used for cross-correlation analysis and comparison, but they were not included in the regression analysis.

In the patient group, the surgical procedures performed included total hip arthroplasty (11/21, 52%), total knee arthroplasty (5/21, 24%), osteosynthesis (3/21, 14%), and high tibial osteotomy (2/21, 10%). The most common symptoms were pain (20/21, 95%), walking problems (18/21, 86%), and joint stiffness (7/21, 33%). In total, 17 participants had comorbidities, and 15 participants took daily medications for high blood pressure (8/21, 38%), heart disease (3/21, 14%), diabetes (2/21, 10%), high cholesterol (2/21, 10%), and other diseases (4/21, 19%). Regarding the history of lower limb surgeries, 7 patients had previous knee surgery, 3 had hip surgery, and 6 had other surgeries. In the nonpatient group, 1 person had previous knee surgery.

We collected 1067 days of data (915 days from the patients and 152 days from the nonpatients). The number of data collection days per patient was between 10 and 16 (mean 14) days in the nonpatient group and between 39 and 69 (mean 49) days in the patient group, except for 3 patients with only preoperative data (with 8-, 10-, and 13-day data).

**Step Count Analysis**

The median and IQR for the step counts from the PA tracker and the smartphone and the percentages of different step types (steps-1, steps-2, and steps-3) in the total PA tracker step counts in various groups of the participants are provided in Table 2.
Table 2. Median and IQR of step counts measured by smartphone and physical activity (PA) tracker by participant characteristics and distribution of step types (steps-1, steps-2, and steps-3) within PA tracker total steps.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Days, n</th>
<th>Smartphone steps, median (IQR)</th>
<th>PA tracker total steps, median (IQR)</th>
<th>PA tracker total steps composition, median (IQR)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Steps-1\textsuperscript{a}</td>
</tr>
<tr>
<td><strong>Group</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Patient</td>
<td>915</td>
<td>2000 (700-4800)</td>
<td>6500 (3800-10,800)</td>
<td>48 (35-57)</td>
</tr>
<tr>
<td>Nonpatient</td>
<td>152</td>
<td>4600 (2300-9400)</td>
<td>14,800 (10,600-18,300)</td>
<td>58 (52-65)</td>
</tr>
<tr>
<td><strong>Period</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Preoperative</td>
<td>394</td>
<td>2700 (1000-6300)</td>
<td>9600 (6000-13,600)</td>
<td>53 (47-60)</td>
</tr>
<tr>
<td>Postoperative</td>
<td>521</td>
<td>1400 (400-35,000)</td>
<td>5300 (2800-7700)</td>
<td>42 (22-51)</td>
</tr>
<tr>
<td><strong>Age (years)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≤60</td>
<td>560</td>
<td>3200 (900-6500)</td>
<td>8000 (4400-13,500)</td>
<td>54 (45-61)</td>
</tr>
<tr>
<td>&gt;60</td>
<td>507</td>
<td>1600 (600-3600)</td>
<td>6800 (4100-11,000)</td>
<td>44 (27-54)</td>
</tr>
<tr>
<td><strong>Sex</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>540</td>
<td>2600 (700-6400)</td>
<td>9300 (5000-14,500)</td>
<td>49 (36-58)</td>
</tr>
<tr>
<td>Male</td>
<td>527</td>
<td>2000 (800-4500)</td>
<td>6200 (4000-10,000)</td>
<td>50 (40-59)</td>
</tr>
<tr>
<td><strong>Comorbidity</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Negative</td>
<td>504</td>
<td>2100 (600-5300)</td>
<td>9500 (5200-14,300)</td>
<td>50 (40-59)</td>
</tr>
<tr>
<td>Positive</td>
<td>563</td>
<td>2400 (900-5900)</td>
<td>6200 (3900-10,000)</td>
<td>49 (37-58)</td>
</tr>
<tr>
<td><strong>Previous surgery</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Negative</td>
<td>394</td>
<td>3100 (1200-7300)</td>
<td>7800 (4900-13,800)</td>
<td>55 (47-61)</td>
</tr>
<tr>
<td>Positive</td>
<td>673</td>
<td>1900 (600-4500)</td>
<td>7100 (3900-11,500)</td>
<td>46 (30-55)</td>
</tr>
<tr>
<td><strong>Day of week</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weekday</td>
<td>755</td>
<td>2200 (800-5600)</td>
<td>7200 (4200-12,000)</td>
<td>50 (38-59)</td>
</tr>
<tr>
<td>Weekend</td>
<td>312</td>
<td>2200 (700-5100)</td>
<td>7900 (4300-12,800)</td>
<td>50 (38-58)</td>
</tr>
<tr>
<td><strong>Smartwatch</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>217</td>
<td>2900 (1500-5900)</td>
<td>6800 (4500-11,100)</td>
<td>42 (27-55)</td>
</tr>
<tr>
<td>No</td>
<td>850</td>
<td>2000 (600-5300)</td>
<td>7600 4200-12,600</td>
<td>51 (42-59)</td>
</tr>
<tr>
<td><strong>Smartphone health app</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Apple HealthKit</td>
<td>904</td>
<td>2200 (800-5600)</td>
<td>7300 (94,100-12,200)</td>
<td>49 (38-58)</td>
</tr>
<tr>
<td>Google Fit</td>
<td>163</td>
<td>2400 (800-4800)</td>
<td>8400 (94,800-12,400)</td>
<td>54 (39-60)</td>
</tr>
<tr>
<td>All participants</td>
<td>1067</td>
<td>2200 (800-5500)</td>
<td>7400 (4300-12,400)</td>
<td>50 (38-59)</td>
</tr>
</tbody>
</table>

\textsuperscript{a}Correspond to the proportions of total PA tracker steps in percentages.

In Figure 2, the time series data for each patient during the preoperative and postoperative periods and for the nonpatient group are presented for both the smartphone and PA trackers. Table 3 shows the cross-correlation coefficients ($r$) at lag 0 between the smartphone time series and the time series for different PA tracker step counts (steps-1, steps-2, steps-3, and total steps) for each participant in the study. Table 4 displays the median and IQR of the cross-correlation coefficients between the daily step count time series of smartphones and PA trackers for various variables (steps-1, steps-2, steps-3, and total steps).
Figure 2. The upper panel shows the time series for step counts recorded by the smartphone and physical activity tracker for each patient (P) before and after the surgery, whereas the lower panel displays the same for nonpatient participants (C). Each plot corresponds to 1 participant, and the bold black font indicates their ID, which matches the IDs in Table 3. In the patient group, each gray horizontal gridline represents 5000 steps, and each gray vertical gridline represents 5 days. In the nonpatient group, each gray horizontal gridline represents 5000 steps, and each gray vertical gridline represents 2 days.
Table 3. Cross-correlation at lag 0 between smartphone and physical activity (PA) tracker step count variables, with correlation coefficients (r) and P values for each participant.

<table>
<thead>
<tr>
<th>ID</th>
<th>Group</th>
<th>Steps-1 vs smartphone steps</th>
<th>Steps-2 vs smartphone steps</th>
<th>Steps-3 vs smartphone steps</th>
<th>PA tracker total steps vs smartphone steps</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>r</td>
<td>P value</td>
<td>r</td>
<td>P value</td>
</tr>
<tr>
<td>P1</td>
<td>Patient</td>
<td>0.70</td>
<td>&lt;.001</td>
<td>0.40</td>
<td>.001</td>
</tr>
<tr>
<td>P2</td>
<td>Patient</td>
<td>0.66</td>
<td>&lt;.001</td>
<td>0.19</td>
<td>.20</td>
</tr>
<tr>
<td>P3</td>
<td>Patient</td>
<td>0.92</td>
<td>&lt;.001</td>
<td>0.26</td>
<td>.009</td>
</tr>
<tr>
<td>P4</td>
<td>Patient</td>
<td>0.78</td>
<td>&lt;.001</td>
<td>0.57</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>P5</td>
<td>Patient</td>
<td>0.97</td>
<td>&lt;.001</td>
<td>0.77</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>P6</td>
<td>Patient</td>
<td>0.94</td>
<td>&lt;.001</td>
<td>0.45</td>
<td>.003</td>
</tr>
<tr>
<td>P7</td>
<td>Patient</td>
<td>0.72</td>
<td>&lt;.001</td>
<td>0.48</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>P8</td>
<td>Patient</td>
<td>0.88</td>
<td>&lt;.001</td>
<td>0.48</td>
<td>.001</td>
</tr>
<tr>
<td>P9</td>
<td>Patient</td>
<td>0.86</td>
<td>&lt;.001</td>
<td>0.44</td>
<td>.005</td>
</tr>
<tr>
<td>P10</td>
<td>Patient</td>
<td>0.78</td>
<td>&lt;.001</td>
<td>0.34</td>
<td>.01</td>
</tr>
<tr>
<td>P11</td>
<td>Patient</td>
<td>0.95</td>
<td>&lt;.001</td>
<td>0.32</td>
<td>.03</td>
</tr>
<tr>
<td>P12</td>
<td>Patient</td>
<td>0.78</td>
<td>&lt;.001</td>
<td>0.63</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>P13</td>
<td>Patient</td>
<td>0.30</td>
<td>.03</td>
<td>0.13</td>
<td>.40</td>
</tr>
<tr>
<td>P14</td>
<td>Patient</td>
<td>0.74</td>
<td>&lt;.001</td>
<td>0.28</td>
<td>.06</td>
</tr>
<tr>
<td>P15</td>
<td>Patient</td>
<td>0.55</td>
<td>&lt;.001</td>
<td>0.50</td>
<td>.002</td>
</tr>
<tr>
<td>P16</td>
<td>Patient</td>
<td>0.82</td>
<td>&lt;.001</td>
<td>0.27</td>
<td>.047</td>
</tr>
<tr>
<td>P17</td>
<td>Patient</td>
<td>0.96</td>
<td>&lt;.001</td>
<td>0.78</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>P18</td>
<td>Patient</td>
<td>0.92</td>
<td>&lt;.001</td>
<td>0.64</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>P19</td>
<td>Patient (only preoperative)</td>
<td>0.92</td>
<td>.01</td>
<td>0.44</td>
<td>.001</td>
</tr>
<tr>
<td>P20</td>
<td>Patient (only preoperative)</td>
<td>0.83</td>
<td>.08</td>
<td>0.20</td>
<td>.02</td>
</tr>
<tr>
<td>P21</td>
<td>Patient (only preoperative)</td>
<td>0.73</td>
<td>.02</td>
<td>0.49</td>
<td>.02</td>
</tr>
<tr>
<td>C1</td>
<td>Nonpatient</td>
<td>0.66</td>
<td>.005</td>
<td>0.29</td>
<td>.20</td>
</tr>
<tr>
<td>C2</td>
<td>Nonpatient</td>
<td>0.90</td>
<td>&lt;.001</td>
<td>0.15</td>
<td>.50</td>
</tr>
<tr>
<td>C3</td>
<td>Nonpatient</td>
<td>0.84</td>
<td>.01</td>
<td>0.06</td>
<td>.80</td>
</tr>
<tr>
<td>C4</td>
<td>Nonpatient</td>
<td>0.91</td>
<td>.002</td>
<td>0.69</td>
<td>.02</td>
</tr>
<tr>
<td>C5</td>
<td>Nonpatient</td>
<td>0.78</td>
<td>.007</td>
<td>0.15</td>
<td>.50</td>
</tr>
<tr>
<td>C6</td>
<td>Nonpatient</td>
<td>0.78</td>
<td>.01</td>
<td>0.26</td>
<td>.30</td>
</tr>
<tr>
<td>C7</td>
<td>Nonpatient</td>
<td>0.86</td>
<td>.003</td>
<td>0.76</td>
<td>.006</td>
</tr>
<tr>
<td>C8</td>
<td>Nonpatient</td>
<td>0.99</td>
<td>&lt;.001</td>
<td>0.52</td>
<td>.04</td>
</tr>
<tr>
<td>C9</td>
<td>Nonpatient</td>
<td>0.55</td>
<td>.10</td>
<td>0.09</td>
<td>.70</td>
</tr>
<tr>
<td>C10</td>
<td>Nonpatient</td>
<td>0.82</td>
<td>.01</td>
<td>0.24</td>
<td>.40</td>
</tr>
</tbody>
</table>

*The corresponding time series are demonstrated in Figure 2.*
Table 4. Cross-correlation coefficients and corresponding 95% CIs between daily smartphone step counts and different step counts from the physical activity (PA) tracker (steps-1, steps-2, steps-3, and total steps)\textsuperscript{a}.

<table>
<thead>
<tr>
<th>Group</th>
<th>Steps-1 vs smartphone steps, mean (95% CI)</th>
<th>Steps-2 vs smartphone steps, mean (95% CI)</th>
<th>Steps-3 vs smartphone steps, mean (95% CI)</th>
<th>PA tracker total steps vs smartphone steps, mean (95% CI)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient</td>
<td>0.79 (0.72-0.85)</td>
<td>0.35 (0.23-0.47)</td>
<td>0.48 (0.38-0.58)</td>
<td>0.70 (0.62-0.77)</td>
<td>.07</td>
</tr>
<tr>
<td>Nonpatient</td>
<td>0.88 (0.74-0.94)</td>
<td>0.33 (0.09-0.53)</td>
<td>0.41 (0.20-0.59)</td>
<td>0.77 (0.66-0.88)</td>
<td>.02</td>
</tr>
<tr>
<td>Period</td>
<td>.02</td>
<td>.06</td>
<td>.06</td>
<td>.02</td>
<td></td>
</tr>
<tr>
<td>Preoperative</td>
<td>0.82 (0.72-0.89)</td>
<td>0.41 (0.21-0.59)</td>
<td>0.53 (0.37-0.67)</td>
<td>0.74 (0.62-0.83)</td>
<td></td>
</tr>
<tr>
<td>Postoperative</td>
<td>0.75 (0.62-0.84)</td>
<td>0.28 (0.16-0.39)</td>
<td>0.42 (0.31-0.52)</td>
<td>0.64 (0.53-0.74)</td>
<td></td>
</tr>
<tr>
<td>Age (years)</td>
<td>.09</td>
<td>.10</td>
<td>.10</td>
<td>.10</td>
<td></td>
</tr>
<tr>
<td>≤60</td>
<td>0.83 (0.73-0.89)</td>
<td>0.39 (0.27-0.53)</td>
<td>0.46 (0.34-0.56)</td>
<td>0.75 (0.65-0.82)</td>
<td>.10</td>
</tr>
<tr>
<td>&gt;60</td>
<td>0.79 (0.70-0.86)</td>
<td>0.30 (0.15-0.44)</td>
<td>0.48 (0.33-0.61)</td>
<td>0.70 (0.58-0.79)</td>
<td></td>
</tr>
<tr>
<td>Sex</td>
<td>.40</td>
<td>.60</td>
<td>.30</td>
<td>.40</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>0.80 (0.69-0.88)</td>
<td>0.34 (0.18-0.48)</td>
<td>0.45 (0.30-0.57)</td>
<td>0.71 (0.58-0.81)</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>0.82 (0.75-0.87)</td>
<td>0.36 (0.21-0.50)</td>
<td>0.50 (0.39-0.59)</td>
<td>0.74 (0.67-0.79)</td>
<td></td>
</tr>
<tr>
<td>Smartwatch</td>
<td>.30</td>
<td>.60</td>
<td>.40</td>
<td>.97</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>0.84 (0.61-0.94)</td>
<td>0.31 (0.01-0.55)</td>
<td>0.40 (0.15-0.60)</td>
<td>0.73 (0.46-0.87)</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>0.80 (0.74-0.85)</td>
<td>0.36 (0.24-0.47)</td>
<td>0.49 (0.39-0.58)</td>
<td>0.72 (0.65-0.78)</td>
<td></td>
</tr>
<tr>
<td>Smartphone health app</td>
<td>.003</td>
<td>.40</td>
<td>.30</td>
<td>.01</td>
<td></td>
</tr>
<tr>
<td>Apple HealthKit</td>
<td>0.84 (0.77-0.90)</td>
<td>0.37 (0.24-0.48)</td>
<td>0.49 (0.39-0.58)</td>
<td>0.75 (0.68-0.81)</td>
<td></td>
</tr>
<tr>
<td>Google Fit</td>
<td>0.63 (0.49-0.73)</td>
<td>0.25 (0.06-0.42)</td>
<td>0.35 (0.26-0.44)</td>
<td>0.53 (0.42-0.62)</td>
<td></td>
</tr>
<tr>
<td>All participants</td>
<td>0.82 (0.64-0.90) b</td>
<td>0.30 (0.10-0.56)</td>
<td>—</td>
<td>0.45 (0.23-0.66)</td>
<td>.07</td>
</tr>
</tbody>
</table>

\textsuperscript{a} P values for group comparisons are provided.
\textsuperscript{b} Not available.

Regression Models for Step Counts

Tables 5-7 present the coefficients for the fixed and random effects for the regression models that best fit the data for steps-1, steps-2, steps-3, and the total steps recorded by the PA trackers, along with the goodness-of-fit metrics.

Table 5. Fixed effects for the best-fitted models estimating daily step counts using smartphone step counts\textsuperscript{a}.

<table>
<thead>
<tr>
<th>Variables\textsuperscript{a}</th>
<th>Models</th>
<th>Steps-1 P value</th>
<th>Steps-2 P value</th>
<th>Steps-3 P value</th>
<th>PA tracker total steps P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept, (\alpha) (95% CI)</td>
<td></td>
<td>0.33 (0.07 to 0.59)</td>
<td>&lt;.001</td>
<td>0.68 (0.14 to 1.23)</td>
<td>.01</td>
</tr>
<tr>
<td>Slope, (\beta) (95% CI)</td>
<td></td>
<td>0.82 (0.66 to 0.99)</td>
<td>&lt;.001</td>
<td>0.34 (0.15 to 0.52)</td>
<td>.001</td>
</tr>
<tr>
<td>Smartphone steps</td>
<td></td>
<td>-0.44 (-0.61 to -0.26)</td>
<td>&lt;.001</td>
<td>-0.30 (-0.53 to -0.06)</td>
<td>.02</td>
</tr>
<tr>
<td>Period (postoperative)</td>
<td></td>
<td>-0.84 (-1.55 to -0.13)</td>
<td>.02</td>
<td>-0.53 (-1.09 to 0.03)</td>
<td>.06</td>
</tr>
</tbody>
</table>

\textsuperscript{a} The values in this table regard the scaled step counts.
\textsuperscript{b} Not available.
Table 6. Random effects variances for the best-fitted models estimating daily step counts using smartphone step counts.

<table>
<thead>
<tr>
<th>Random effects</th>
<th>Models</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Steps-1</td>
</tr>
<tr>
<td>The variance between individuals’ intercepts</td>
<td>0.22</td>
</tr>
<tr>
<td>The variance of PA tracker—smartphone steps slope between individuals</td>
<td>0.08</td>
</tr>
<tr>
<td>The variance of the residuals</td>
<td>0.07</td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th>Model metrics</th>
<th>Models</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Steps-1</td>
</tr>
<tr>
<td>AIC(^a)</td>
<td>402</td>
</tr>
<tr>
<td>BIC(^b)</td>
<td>449</td>
</tr>
<tr>
<td>Deviance</td>
<td>38</td>
</tr>
<tr>
<td>ICC(^c)</td>
<td>0.83</td>
</tr>
<tr>
<td>Conditional pseudo-(R^2)</td>
<td>0.94</td>
</tr>
<tr>
<td>Marginal pseudo-(R^2)</td>
<td>0.65</td>
</tr>
</tbody>
</table>

\(^a\)AIC: Akaike information criterion.  
\(^b\)BIC: Bayesian information criterion.  
\(^c\)ICC: intraclass correlation coefficient.

Figure 3 displays the outcomes of various models, along with the 95% prediction intervals for all patients.

The models with the smartphone steps provided a better fit for the total step counts than the models without this variable. The likelihood ratio tests for comparing the selected models with and without smartphone steps demonstrated that the smartphone steps were positively correlated with PA tracker total steps \(\chi^2 = 34.7, P < .001\), steps-1 \(\chi^2 = 36.8, P < .001\), steps-2 \(\chi^2 = 11.4, P < .001\), and steps-3 \(\chi^2 = 22.1, P < .001\).
**Figure 3.** Results of the different models for estimating the daily step counts of the physical activity (PA) tracker, including the total steps, steps-1, steps-2, and steps-3. The mean values are depicted by solid lines, whereas the 95% prediction intervals are shown as light green shaded areas for each model.

**Questionnaires and SUS Scores**

Overall, 94% (17/18) of the patients filled out the questionnaires regarding SUS. The median scores were 78 (IQR 73-88) for the smartphone app and 73 (IQR 68-80) for the PA tracker, respectively. The scores were higher in female patients and in those aged <60 years (Table 8).

**Table 8.** The median and IQR of the System Usability Scale (SUS) scores for the smartphone app and the physical activity (PA) tracker for different age and sex groups.

<table>
<thead>
<tr>
<th>Variables</th>
<th>SUS, median (IQR)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Smartphone app</td>
</tr>
<tr>
<td>Age (years)</td>
<td></td>
</tr>
<tr>
<td>≤60</td>
<td>93 (83-96)</td>
</tr>
<tr>
<td>&gt;60</td>
<td>73 (65-76)</td>
</tr>
<tr>
<td>Sex</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>73 (65-80)</td>
</tr>
<tr>
<td>Female</td>
<td>83 (73-95)</td>
</tr>
<tr>
<td>Total</td>
<td>78 (73-88)</td>
</tr>
</tbody>
</table>

**Discussion**

**Principal Findings**

In this study, we explored the feasibility of using smartphones for remote monitoring of orthopedic patients’ PA. To achieve this, we analyzed the correlation between the step counts recorded by a smartphone and a 24/7 PA tracker. Our results indicated a high correlation ($r=0.70$) between the time series of daily smartphone steps and daily PA tracker total steps. In addition, we found that the number of steps recorded by the smartphone was a strong predictor of changes in total daily steps. However, the absolute number of daily steps predicted using smartphone data was neither precise nor reliable.

The role of smartphones in remote monitoring of patients’ PA has not yet been clearly defined because of 2 main reasons. First, concerns persist regarding the validity and reliability of PA data collected by smartphones, as conflicting results have
been reported in the literature [28]. For example, in a systematic review, the difference between smartphone measurements and a gold standard in a laboratory setting varied from 0.1% to 79.3%, and the reliability of smartphone measurements ranged from poor to excellent (intraclass correlation coefficient between 0.02 and 0.99) [13]. Second, the relationship between smartphone PA data and total PA data in different individuals is not fully understood and depends on various factors. The smartphone only records a variable proportion of the total daily PA, which is the time the person carries the device. Ignoring this point can lead to conflicting results, especially in studies with free-living settings. In this study, we investigated the relationship between the 2 variables and found that, despite considerable variability, a high correlation exists between smartphone step counts and total daily step counts.

The correlation between smartphone and total daily steps can vary significantly in a free-living setting, both between and within individuals. Several studies have found inferior results regarding the validity and reliability of smartphone measurements in free-living measurements compared with laboratory settings [29-31]. The variations may be even higher in orthopedic patients owing to pain and mobility issues during the early postoperative period, which could affect smartphone use and measurements. In a recent pilot study, Vorrink et al [32] found a mean correlation of 0.88 between smartphone and PA tracker measurements in a group of nonorthopedic patients, which was higher than the correlation we found in this study. However, we calculated the correlation between the time series after differentiating and detrending. Our analysis of different step count variables from the PA tracker revealed that the correlation with smartphone steps was the highest for steps-1 and the lowest for steps-2. We also found that the correlation between PA tracker’s steps-1 and PA data collected by smartphone was higher in the nonpatient group than in the patient group and during the preoperative period compared with the postoperative period. However, the correlation remained relatively high even during the postoperative period (r=0.75 for total steps and steps-1, respectively). This discrepancy in the correlation could be attributed to the possibility that patients do not carry their smartphones as frequently during the postoperative period as they would under normal circumstances, or it could be because of the lower measurement accuracy in lower walking velocities, which has been demonstrated in previous studies [33,34]. Regarding the PA tracker’s steps-2 and steps-3, we could not find a significant difference in the correlations between subject groups with different characteristics (the P values were between .06 and .80).

Most participants (>80%) in our study used iOS smartphones, and we observed a stronger correlation in PA tracker’s steps-1 and total steps with smartphones equipped with Apple HealthKit APIs. However, we were unable to compare different smartphone types owing to the small sample size of participants with Google Fit API in our study. Several studies have investigated the impact of smartphone type on the accuracy and precision of PA measurements [35-38]. For instance, Höchsmann et al [38] found lower accuracy in an Android smartphone during low-velocity gait when compared with other smartphones and PA trackers. Moreover, we did not observe a high correlation between smartwatch users and the total PA tracker steps. This finding can be attributed to the lower proportion of steps-1 in the total steps composition among smartwatch users (ie, smartwatch users took fewer continuous regular walking steps [steps-1] in this study), as shown in Table 2. As the highest correlation between the smartphone and PA tracker steps was observed for steps-1, we would not expect an increase in the correlation between the smartphone and the total PA tracker steps.

We applied mixed effects modeling to predict different step types (continuous regular walking, sporadic walking, and slow continuous walking) by using the smartphone step counts. Mixed effects models are a type of regression analysis and are especially useful in longitudinal studies with repeated measurements or when the measurements are made on cluster units [39]. Although we could fit mixed effects models with relatively high-performance metrics, the bootstrapping methods demonstrated wide prediction intervals. Therefore, estimating the daily number of steps by using the smartphone step counts without further recalibration would be imprecise and inaccurate. The best-fitted model was achieved for continuous regular walking (steps-1), which is consistent with the observation of the highest correlation between smartphone step counts and continuous regular walking (steps-1). On the basis of the models’ coefficients, we found that the postoperative period and a positive medical history were negatively associated with the total daily steps. The mixed effects models could also describe the variance in data between and within different individuals. We found that the variation between individuals in both the intercept and the slope of the PA tracker–smartphone steps was higher for sporadic walking (steps-2) and slow continuous walking (steps-3), which makes estimating these variables more difficult. In all 4 fitted models, the variance of the random effects intercept between individuals was more pronounced than that of the random effects slopes.

In this study, the PA tracker and the smartphone app obtained SUS score higher than the acceptable value, which was assumed to be 70 [21]. However, the SUS score cannot independently make absolute judgments about the goodness of a product. Factors such as success rate and the nature of the observed failures should play a prominent role in product usability [40]. During this study, we observed 1 smartphone app failure, which led to participant exclusion. This participant unintentionally removed the app from her smartphone and could not reinstall it because of technical issues. Furthermore, we found higher usability scores in patients aged <60 years and female patients. The effects of age and sex were analyzed in SUS applied for different products. A significant but not strong negative correlation has been demonstrated between SUS scores and age; however, no significant difference has been found in the mean SUS scores between female participants and male participants [21]. Some studies have also shown that the young adults and female participants were associated with higher PA tracker use [41,42].
Strengths and Weaknesses of the Study

This longitudinal study is the first of its kind to evaluate the correlation between the daily steps recorded by a smartphone with the total number of steps in patients undergoing orthopedic surgeries for several weeks before and after surgery and in a nonpatient group. We also analyzed different walking types (regular continuous, sporadic, and slow continuous walking) and demonstrated that smartphones are more competent in capturing the steps during regular continuous walking. Detecting different gait patterns by smartphones and PA trackers has recently received considerable attention [43-45]. Indisputably, we must acknowledge the limitation that the validity of the 3 categories of steps measured by the PA tracker in this study has not yet been fully explored and must be scrutinized. Furthermore, our study had other limitations, such as the inability to obtain information regarding the smartphone use habits of the participants, including how and where the user carries the smartphone. Nevertheless, we used mixed effects modeling and random effects variables to account for individual differences to increase the generalizability of the findings. Another limitation of the study was that owing to the setting of the study, we could not use direct observation as the gold standard for counting the steps. However, to reduce data collection bias, we used a previously validated PA tracker that measured PA continuously 24/7.

Implications and Future Research

In this study, we found a high correlation between the number of steps recorded by smartphones and the total number of daily steps. However, owing to the limitations and impact of participant dropouts and missing data, we recommend interpreting the findings with caution and conducting further investigations with larger sample sizes and more robust data collection methods. In addition, further investigations with larger sample sizes and more robust data collection methods are necessary to explore determining factors in the predictability of smartphone measurements and their role in remote patient monitoring. The study also demonstrated the predictive value of the postoperative period and positive medical history in estimating the total daily steps, but more homogenous samples may increase the precision of these prediction models. In future research, it would be valuable to compare the measurements of other well-known PA trackers with varying characteristics to smartphone measurements [46].

Conclusions

This study highlights the potential of smartphones for monitoring changes in PA, showing a strong correlation between daily steps recorded by smartphones and total daily steps, especially during continuous walking. This finding suggests that smartphones could be a valuable tool for remote patient activity monitoring. However, accurately predicting the precise daily step counts from smartphone data still requires further investigation, as our results suggest that the current methods may lack the necessary precision and accuracy.

Acknowledgments

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Conflicts of Interest

None declared.

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**Abbreviations**

- **API**: application programming interface
- **PA**: physical activity
- **PROM**: patient-reported outcome measure
- **REDCap**: Research Electronic Data Capture
- **SUS**: System Usability Scale
Exploring the Feasibility and Usability of Smartphones for Monitoring Physical Activity in Orthopedic Patients: Prospective Observational Study


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Augmented Reality in Real-time Telemedicine and Telementoring: Scoping Review

Alana Dinh¹, BA; Andrew Lukas Yin², MBA, MD; Deborah Estrin³, PhD; Peter Greenwald⁴, MS, MD; Alexander Fortenko⁴, MPH, MD

¹Medical College, Weill Cornell Medicine, New York, NY, United States
²Department of Internal Medicine, Weill Cornell Medicine, New York, NY, United States
³Department of Computer Science, Cornell Tech, New York, NY, United States
⁴Emergency Medicine, NewYork-Presbyterian Hospital, New York, NY, United States

Corresponding Author:
Alana Dinh, BA
Medical College
Weill Cornell Medicine
1300 York Ave
New York, NY, 10021
United States
Phone: 1 212 746 1067
Email: ald4006@med.cornell.edu

Abstract

Background: Over the last decade, augmented reality (AR) has emerged in health care as a tool for visualizing data and enhancing simulation learning. AR, which has largely been explored for communication and collaboration in nonhealth contexts, could play a role in shaping future remote medical services and training. This review summarized existing studies implementing AR in real-time telemedicine and telementoring to create a foundation for health care providers and technology developers to understand future opportunities in remote care and education.

Objective: This review described devices and platforms that use AR for real-time telemedicine and telementoring, the tasks for which AR was implemented, and the ways in which these implementations were evaluated to identify gaps in research that provide opportunities for further study.

Methods: We searched PubMed, Scopus, Embase, and MEDLINE to identify English-language studies published between January 1, 2012, and October 18, 2022, implementing AR technology in a real-time interaction related to telemedicine or telementoring. The search terms were “augmented reality” OR “AR” AND “remote” OR “telemedicine” OR “telehealth” OR “telementoring.” Systematic reviews, meta-analyses, and discussion-based articles were excluded from analysis.

Results: A total of 39 articles met the inclusion criteria and were categorized into themes of patient evaluation, medical intervention, and education. In total, 20 devices and platforms using AR were identified, with common features being the ability for remote users to annotate, display graphics, and display their hands or tools in the local user’s view. Common themes across the studies included consultation and procedural education, with surgery, emergency, and hospital medicine being the most represented specialties. Outcomes were most often measured using feedback surveys and interviews. The most common objective measures were time to task completion and performance. Long-term outcome and resource cost measurements were rare. Across the studies, user feedback was consistently positive for perceived efficacy, feasibility, and acceptability. Comparative trials demonstrated that AR-assisted conditions had noninferior reliability and performance and did not consistently extend procedure times compared with in-person controls.

Conclusions: Studies implementing AR in telemedicine and telementoring demonstrated the technology’s ability to enhance access to information and facilitate guidance in multiple health care settings. However, AR’s role as an alternative to current telecommunication platforms or even in-person interactions remains to be validated, with many disciplines and provider-to-nonprovider uses still lacking robust investigation. Additional studies comparing existing methods may offer more insight into this intersection, but the early stage of technical development and the lack of standardized tools and adoption have hindered the conduct of larger longitudinal and randomized controlled trials. Overall, AR has the potential to complement and...
Introduction

Background

Augmented reality (AR) is an emerging technology that can enhance how the real world is experienced by the user. Compared with virtual reality (VR), in which the user is immersed in a completely synthesized world, AR combines both the virtual and real by overlaying the external world with computer-generated sensory data such as audio, video, and graphics. AR technology, often accessed through head-mounted devices (HMDs) or software on personal devices, can be used to display information and virtual objects that facilitate learning and navigation through tasks in the real world [1,2].

In medicine, VR and AR have been explored in educational, diagnostic, and treatment settings, with an increasing number of publications in the last decade [3-6]. A 2012 to 2017 review of 338 original studies using AR in medicine, most related to surgery and simulation learning, estimated the technology readiness level of AR to be at the stage of a prototype that has yet to be completed and tested in its intended environment [7]. AR has since appeared in the literature across many specialized fields, with reviews since 2019 describing AR technology in emergency medicine (EM) [8], dermatology [9], radiology [10,11], orthopedics [12], nursing [13], and many more. A promising use of AR technology is in remote collaboration, an application seen in many industry- and engineering-related tasks over the last 2 decades [14,15]. As COVID-19 pushed health care to explore remote health solutions, providers, caregivers, and students have become increasingly aware of technology’s role in enabling access to care [16-18]. A cohort study of 36.5 million individuals in the United States found that 23.6% of ambulatory visits in 2020 were billed as telehealth visits compared with 0.3% in 2019 [19]. Although videoconferencing programs allow health care workers to remotely connect with each other, trainees, and patients, current systems limit the extent of care that can be delivered during such interactions [20]. Innovations using AR technology offer an opportunity to expand real-time remote health services such as consultation and telesurgery [21]. Recent literature on AR includes studies on caregiver perspectives on the technology [22], frameworks for AR-assisted remote medical communication [23], and remote health care delivery devices incorporating AR [24].

Objectives

Remote medical communication is a defining feature of telemedicine, a concept that first arose with the use of telephones to share information across hospital systems [25]. Since the conception of the internet and personal devices, remote health care visits and interventions have become possible, with the scope of care expanding as technological advances are introduced. Currently, there is no literature summarizing the applications of AR in 

Methods

Scoping Method

Scoping reviews entail a systematic selection of literature with the purpose of examining the extent and nature of an area of interest [29,30]. Compared with systematic reviews, scoping studies allow for the integration of a range of study designs, especially in fields with emerging evidence that may lack randomized controlled trials (RCTs). By mapping the existing evidence of AR in telemedicine, the scoping approach allows for the identification of gaps that may inform future studies and innovations.

Research Questions

Which devices and platforms using AR have been studied in the published literature in the context of real-time telemedicine and remote education? In which areas of medicine have these been integrated and for what purposes? How are outcomes evaluated and what variables have yet to be measured? What are the overall findings of existing studies?

Identifying Studies in the Literature

The literature was reviewed using PubMed, Scopus, Embase, and MEDLINE for articles or trials published from January 1, 2012, to October 18, 2022, with search queries submitted and articles accessed on October 18, 2022. The search terms were “augmented reality” OR “AR” AND “remote” OR “telemedicine” OR “telehealth” OR “telementoring.” The PubMed search was performed using article titles and abstracts. The Scopus search was performed using article titles, abstracts, and keywords, with articles and conference papers in the areas of “medicine,” “health professions,” and “nursing” included.
The Embase search was performed using article titles, abstracts, and keywords, with articles and conference papers included. The MEDLINE search was also performed using article titles, abstracts, and keywords. Only articles available in English were included.

Article Selection
Following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, the titles and abstracts of all articles were independently reviewed by 2 researchers (AD and AF) for relevance to AR and real-time communication between separated individuals. Articles were excluded if they were unrelated to medicine or were reviews or discussions. Any articles that were included by one reviewer but not the other were included in the full-text screening, which was also performed independently by the 2 researchers. As this review focused on the use of AR rather than the development of related equipment or software, articles were excluded if the technological design, rather than the implementation, was the focus or if the technology was not intended for remote interaction as described by the inclusion criteria. Articles that included both technological design and implementation data were included, with the review focusing on the latter. Articles that described mixed reality devices capable of both AR and VR were included if the implementation primarily used and studied AR features. Reviews, perspectives, discussion-based articles, and study proposals without results were excluded. Correspondence was sent to the authors of articles for which the full text was not available; a lack of response resulted in the exclusion of these articles. Any disagreements regarding an article’s inclusion were resolved through discussion between the 2 reviewers.

Data Charting
The articles were reviewed based on the context in which the AR was implemented. Articles describing mixed reality devices were analyzed for data relevant to AR use and not VR. Unique devices and platforms using AR across the articles were identified. The articles were later grouped into one of the 3 identified areas: patient evaluation, medical intervention, and education. “Patient evaluation” included articles that described the examination of patients and processes that obtained information for clinical decision-making. “Medical intervention” included articles that described procedures related to the initiation or provision of therapy. “Education” included articles that described the mentorship or training of a less experienced individual for a task or procedure. Subgroups for surgical versus nonsurgical tasks in the latter 2 groups were created. Articles that fell into more than one of the 3 identified areas were organized in the Results section of this paper based on which area was the primary focus. Finally, common objective and subjective end variables discussed in the articles were identified.

Collation and Summary
For this scoping review, we first provide an overview of the devices and platforms that use AR and the types of tasks in which they appear. We then summarize the implementation and measurement of these AR-capable tools within 3 areas: patient evaluation, medical intervention, and education. Finally, we review the common methodologies and end variables observed across the studies.

Results

Overview
The PubMed, Scopus, Embase, and MEDLINE searches yielded 298, 195, 187, and 274 articles, respectively. This totaled 954 articles, 558 (58.5%) of which were identified as duplicates. The abstracts and titles of the remaining 396 articles were reviewed, with 62 (15.7%) identified as meeting the inclusion criteria. In total, 5% (3/62) of the articles, for which the full text was not available, were excluded after no response was received from the original authors. A total of 39 articles were included following full-text screening. The selection process is depicted in Figure 1. The publication years of the selected articles spanned 2014 to 2022, with 64% (25/39) published in the last 3 years.

From the included articles, 20 unique devices and platforms with AR features were identified, with 10 (50%) being commercial HMDs in which AR features were projected before the wearer’s eyes and another 4 (20%) being “virtual presence”—type platforms in which a remote viewer can superimpose video of their hand or tools over the live stream of a local site or procedure; the hybrid video is accessed by both local and remote users via a smartphone, tablet, computer, or monitor. The remaining 30% (6/20) involved systems with no commercial HMDs or virtual presence—these included a smartphone app and systems built specifically for tele-ultrasonography, physical rehabilitation, and surgical telementoring. Overall, all the identified devices and platforms (20/20, 100%) allowed remote individuals to view the perspective or environment of the local user. Common AR features of these devices included annotation (12/20, 60%) and graphical overlay over the local user’s view, specifically 2D or 3D images (9/20, 45%) and the remote viewer’s hands or tools (8/20, 40%). The identified devices and platforms are listed in Table 1, with similar device models included in the same row.

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Figure 1. Selection process for the articles. AR: augmented reality.
Table 1. Overview of devices and features.

<table>
<thead>
<tr>
<th>Tool (year)</th>
<th>Communication features</th>
<th>Visual features</th>
<th>Relevant studies</th>
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<tbody>
<tr>
<td><strong>Commercial HMDs</strong></td>
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<tr>
<td>Vuzix Wrap 920AR (2010)</td>
<td>• Internet transmission of video data</td>
<td>• Camera-captured video feed of mentor’s hand gestures is overlaid on mentee’s HMD and vice versa</td>
<td>Chinthammit et al [31]</td>
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<tr>
<td>Vuzix Wrap 1200DX (2013)</td>
<td>• 2-way audio-video communication over Wi-Fi</td>
<td>• Camera-captured images of mentor’s hand gestures are transmitted to mentee’s HMD</td>
<td>Mather et al [32]</td>
</tr>
<tr>
<td>Recon Jet (2013)</td>
<td>• 2-way audio communication over phone or Wi-Fi</td>
<td>• Integration with custom Android-based triage app</td>
<td>Follmann et al [33]</td>
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<tr>
<td>Google Glass (2013-2017)</td>
<td>• Compatible with Google Hangouts for audio-video streaming on remote devices and 2-way audio communication</td>
<td>• Projects SMS text messages from remote viewers into local user’s view</td>
<td>Broach et al [34]</td>
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<td></td>
<td></td>
<td>• Remote viewer moves a mouse cursor in local user’s view</td>
<td>Ponce et al [35]</td>
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<td></td>
<td></td>
<td>• Remote viewer’s webcam captures image of their hands or tools that superimpose onto local user’s view</td>
<td>Armstrong et al [36]</td>
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<tr>
<td>Microsoft HoloLens (2016)</td>
<td>• Compatible with Skype or other Windows applications for audio-video streaming on remote devices and 2-way audio communication</td>
<td>• Displays instructions, patient data, and images</td>
<td>Kaylor et al [37]</td>
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<td></td>
<td></td>
<td>• Remote viewers annotate local user’s view</td>
<td>Cofano et al [38]</td>
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<td></td>
<td></td>
<td>• Remote viewers create and annotate screenshots to be displayed in local user’s view</td>
<td>Liu et al [39]</td>
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<td>Hanna et al [40]</td>
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<td>Wang et al [41]</td>
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<tr>
<td>Moverio BT-300 (2016) and Moverio BT-350 (2017)</td>
<td>• Compatible with TeamViewer app for audio-video streaming on remote devices and 2-way audio communication</td>
<td>• Remote viewers directly annotate local user’s view</td>
<td>Cofano et al [38]</td>
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<td></td>
<td></td>
<td>• Remote viewers create and annotate screenshots to be displayed in local user’s view</td>
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<tr>
<td>Vuzix Blade (2018)</td>
<td>• Compatible with TeamViewer app for audio-video streaming on remote devices and 2-way audio communication</td>
<td>• Remote viewers directly annotate local user’s view</td>
<td>Cofano et al [38]</td>
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<td></td>
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<td>• Remote viewers create and annotate screenshots to be displayed in the local user’s view</td>
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<td>Magic Leap One (2018)</td>
<td>• 2-way audio communication over Wi-Fi</td>
<td>• Displays holographic patients and monitors that can be modulated by remote viewers</td>
<td>Hess et al [42]</td>
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<td><strong>Virtual presence tools</strong></td>
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<tr>
<td>Original augmented reality telementoring platform (2014)</td>
<td>• Wired connection allows for the sharing of video feeds and audio communication</td>
<td>• Image of mentor’s laparoscopic instruments is superimposed onto mentee’s monitor; hybrid video seen at both sites</td>
<td>Vera et al [50]</td>
</tr>
<tr>
<td>Tool (year)</td>
<td>Communication features</td>
<td>Visual features</td>
<td>Relevant studies</td>
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<tr>
<td>Virtual interactive presence and augmented reality platform (2013)</td>
<td>• 2-way video streaming via internet</td>
<td>• Remote viewer’s hand or instrument is superimposed over local video feed</td>
<td>• Ponce et al [51]</td>
</tr>
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<td></td>
<td>• Can combine with Skype or other teleconferencing software</td>
<td>• Remote viewer can freeze screen or 2D annotate image using pen tool</td>
<td>• Ponce et al [35]</td>
</tr>
<tr>
<td>Help Lightning mobile app (2016)</td>
<td>• 2-way internet transmission of audio and video between phones</td>
<td>• Foreground of physician’s video (eg, physician’s hand) is superimposed over patient’s video for live gesturing</td>
<td>• Vyas et al [52]</td>
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<td></td>
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<td>• Physician annotates over patient’s live video</td>
<td>• Davis et al [53]</td>
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<td>Proximie (2016)</td>
<td>• Audio-video streaming from local site can be accessed by remote computers via internet</td>
<td>• Virtual hand pointer or pen to mark video feed from local site</td>
<td>• Ponce et al [54]</td>
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<td></td>
<td>• Viewers from different remote sites can access the same live stream and talk with each other and the local site</td>
<td>• Image of remote viewer’s hand is superimposed over video from local site</td>
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<td></td>
<td></td>
<td>• Overlaying video with 2D images and 3D models</td>
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<tr>
<td></td>
<td></td>
<td>• Computer vision algorithm allows for the anchoring of annotations</td>
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<tr>
<td>Other original systems</td>
<td></td>
<td>• 2-way internet transmission of audio and video between tablets or to HMD</td>
<td>• Hassan et al [55]</td>
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<tr>
<td>System for Telementoring with Augmented Reality platform (2015)</td>
<td>• 2-way internet transmission of audio and video between tablets or to HMD</td>
<td>• Remote viewer annotates over local site’s video</td>
<td>• El-Asmar et al [56]</td>
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<td></td>
<td></td>
<td>• Remote viewer places scalable instrument icons or labels over local site’s video</td>
<td>• Greenfield et al [57]</td>
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<td></td>
<td></td>
<td>• Local user can access prerecorded video clips to guide procedure in the event that the remote connection is unstable [59]</td>
<td>• Patel et al [58]</td>
</tr>
<tr>
<td>Vuforia Chalk mobile app (2017)</td>
<td>• 2-way internet transmission of audio between devices</td>
<td>• Remote viewer annotates over local user’s live video</td>
<td>• Rojas-Muñoz et al [60-62]</td>
</tr>
<tr>
<td></td>
<td>• Internet transmission of camera feed from local user to remote expert</td>
<td>• Annotations remain anchored to objects in the video even if local camera moves</td>
<td>• Andersen et al [59,63]</td>
</tr>
<tr>
<td>Original tele-ultrasound system (2018)</td>
<td>• Open-source software for communication between remote viewer and local user</td>
<td>• Remote viewer draws or writes directly on ultrasound images being streamed by local user; hybrid video seen at both sites</td>
<td>• Ramsingh et al [64]</td>
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<td></td>
<td>• Internet transmission of ultrasound video and live video of local user’s environment sent to remote viewer’s laptop</td>
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<tr>
<td>Augmented Reality–based Tele rehabilitation System with Haptics (2019)</td>
<td>• 2-way internet transmission of audio and visual data via computers</td>
<td>• Camera data used to generate image of remote and local users sitting across from each other in a virtual space seen on 3D televisions</td>
<td>• Borresen et al [66,67]</td>
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<td></td>
<td>• Haptic devices relay force feedback and motion to each other through networked computer</td>
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<tr>
<td>Telestration with coaxial projective imaging (2022)</td>
<td>• 2-way audio-video streaming over the internet</td>
<td>• Obtains images from local field that remote viewer can annotate</td>
<td>• Zhang et al [68]</td>
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<td></td>
<td></td>
<td>• System projects annotations onto local field directly</td>
<td></td>
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<tr>
<td>Original remote training platform (2022)</td>
<td>• 2-way audio-video streaming over the internet</td>
<td>• HMD optics has see-through transparency and enables display of instructional information and video</td>
<td>• Stone et al [69]</td>
</tr>
</tbody>
</table>

HMD: head-mounted device.
Of the 39 studies, 22 (56%) were related to surgery, 6 (15%) were related to EM, and 4 (10%) were related to hospital medicine. When looking at the setting and structure of the tasks from each study, 51% (20/39) involved an operation or technique used in the operating room, where a mentor figure used AR to remotely interact with a task performer. The remaining 19 studies involved nonoperative tasks, 11 (58%) of which also involved a mentor remotely interacting with a task performer, whereas 8 (42%) involved the mentor performing the task instead, with AR enhancing what their remote spectators saw.

The articles were divided into 3 sections based on the AR-assisted task performed: patient evaluation, medical intervention, and education (Multimedia Appendix 1-3). Medical intervention and education are further subdivided based on whether AR supported a nonsurgical or surgical task. Notably, some articles discussed in the medical intervention section were also relevant to education.

**AR in Remote Patient Evaluation**

The 26% (10/39) of articles included in this section (Multimedia Appendix 1 [33,34,37,43–45,54,65–67]) described implementations of AR in remote triage, wound assessment, musculoskeletal examination, sonography, and hospital rounding.

The potential of AR to perform fast-paced triage assessments remotely was explored in 20% (2/10) of the studies. Broach et al [34] investigated the use of Google Glass to relay what paramedics saw to other remote providers, with the intention of allowing the remote EM physicians to perform secondary triage before the patient’s arrival at a hospital. The remote physicians accessed the perspective of the paramedics at a simulated disaster scene and could send instructional SMS text messages projected onto the paramedics’ Glass. When comparing the remote assessments of physicians with the in-person assessments by different EM physicians, the study found high interrater agreement (0.923), which was not significantly different from the interrater agreement within the same assessment condition (0.976; \( P=.41 \)) [34]. Follmann et al [33] investigated how AR implementation could affect triage time and accuracy. The performance of non–AR-assisted first responders was compared with that of 2 groups using AR-capable glasses, one that displayed an interactive triage algorithm and the other that streamed footage to a remote EM physician who could verbally guide the on-site individual. The results revealed that AR assistance increased accuracy at the cost of time, with the accuracy of the 3 groups being 58%, 92% (\( P=.04 \)), and 90% (\( P=.01 \)), whereas the duration of triage was 16.6, 37.0 (\( P=.001 \)), and 35.0 (\( P=.01 \)) seconds, respectively [33].

Other studies focused on AR’s potential to enhance remote wound assessments. Ponce et al [54] demonstrated the use of AR with mobile devices to allow orthopedic surgeons and neurosurgeons to conduct remote postoperative visits. Using a virtual interactive presence (VIP) smartphone app, surgeons overlaid live camera footage of their hands over the camera footage of the patient’s postoperative wound. Surveys from users revealed that both patients and surgeons found utility (27 of 28 and 26 of 29 with positive responses) in the virtual experience [54]. Kaylor et al [37] and Hill [43] focused on the use of AR for consultations during inpatient wound assessments. Using Microsoft HoloLens, bedside nurses in the former study could send live video of a patient’s wound and communicate with a remote wound, ostomy, and continence (WOC) nurse. The remote WOC nurse could provide annotations or images to guide the local nurse during the assessment. When comparing remote assessments with in-person assessments performed by a different WOC nurse, the study found the interrater agreement of treatment plans to be 100% across 21 cases [37]. The bedside nurses in the study by Hill [43] used the Microsoft HoloLens 2 to consult for complications at night or over weekends for patients undergoing negative pressure wound therapy. Compared with a control group of previous cases that did not use AR, the study group underwent fewer unplanned surgical revisions (\( P=.002 \)) and admissions related to wound infection (\( P=.004 \)) [43].

Borresen et al [66,67] introduced the AR-based Telerehabilitation System with Haptics (ARTESH) to perform remote strength and range-of-motion examinations. Both the local and remote sites were equipped with a haptic device, a Kinect camera, and a 3D-capable television that allowed the physician and patient to view each other seated together at a virtual table. The 7-point Likert scale surveys from the pilot study showed positive ratings from 5 physicians on the ability to evaluate arm strength and visualize limb movement (6/7 and 5.87/7) [66]. A follow-up study measured interrater agreement between in-person examinations and remote evaluations using ARTESH for different components of the upper extremity examination. The highest levels of agreement were observed in strength testing of elbow flexion, shoulder abduction, and protraction (\( k=0.63 \), 95% CI 0-1.0), with the percentage of interrater agreement across evaluations for all 15 patients ranging from 30 to 100 [67].

Rigamonti et al [44] and Carbone et al [65] conducted studies that integrated AR technology to allow for supervision and consultation while performing ultrasound examinations. Rigamonti et al [44] interviewed engineering and sports science professionals across 6 countries after they accessed live video footage from a Microsoft HoloLens 2 worn by an ultrasound operator in Germany. Users were able to annotate the stream, overlay pictures and videos onto the display, and communicate in real time as they watched the examination from the operator’s perspective. Interview responses from the spectators revealed AR’s potential in both education and enhancing remote examinations with the supplementation of live data and feedback [44]. Carbone et al [65] developed a tele-ultrasound system that allowed rural hospital clinicians to contact a consultant. The remote consultant, who viewed live video of the user’s environment and ultrasound sequences, could provide audio feedback and overlay annotations or a cursor on the ultrasound imaging seen at the local site. Although the connected parties primarily used the platform to discuss the diagnosis, in 5 of 12 cases, the consultant directed the user on the device’s probe position [65].

The study by Martin et al [45] used an AR-capable Microsoft HoloLens 2 in multiple COVID-19 wards. The senior member
of a clinical team would wear the headset and personal protective equipment (PPE) while examining patients, allowing the remaining members of the team to watch and interact remotely. Viewers could remotely annotate objects as well as overlay patient imaging and data from the electronic health record onto the view of the headset user and the live video feed. In comparison with teams without the device, the AR-assisted teams saw less COVID-19 exposure time by 51.5% and decreased PPE use by 83.1% over a week (P=.002 and P=.02) [45].

**AR in Remote Medical Intervention**

The 41% (16/39) of articles included in this section (Multimedia Appendix 2 [31,35,38,39,46,52,53,55-57,59-61,63,64,68]) described AR in remote nonsurgical and surgical contexts. The latter included studies that focused on surgical efficiency, long-distance consultation, and differences between telesurgical systems.

**Nonsurgical**

Chinthammit et al [31] introduced the “Ghostman” system, in which a patient and a remote physical therapist are connected via AR-capable headsets (Vuzix Wrap 920AR). The hands and tools of the therapist were overlaid onto the patient’s headset, allowing the patient to obtain real-time feedback during the session. To test the system’s potential for telerehabilitation, an RCT was designed with 2 groups of volunteers receiving training on how to use chopsticks, one group with AR assistance and the other with face-to-face mentoring. Assessments performed immediately after, 1 day after, and 7 days after training found no significant difference in total skill errors or time to task completion between the 2 groups [31].

Ramsingh et al [64] described the use of a commercial smartphone app (Vuforia Chalk) to allow experts in Loma Linda, California, United States, to support an ultrasound-guided popliteal nerve block performed in Port-au-Prince, Haiti. The remote expert viewed the patient and ultrasound monitor through the local smartphone’s camera and created annotations that appeared on the local smartphone screen to guide the procedure. Both local and remote users rated the quality of the video communication as 5/5, whereas the local user rated the clarity of the AR annotations in guiding probe placement as 5/5 and the identification of relevant anatomy in ultrasound imaging as 4/5 [64].

**Surgical**

The efficacy of various AR-capable tools in the operative setting was tested in 25% (4/16) of the studies. Rojas-Muñoz et al [60] designed an RCT comparing audio-only telementoring against the System for Telementoring with AR (STAR) combined with an HMD (HMD-STAR) in the setting of emergency cricothyroidotomies by first responders. HMD-STAR use, in which a remote mentor placed helpful annotations and icons in the responder’s line of sight, increased performance scores when considering all-experience groups (P=.01) and those with low first-responder experience (P=.01) and low procedure experience (P=.03) [60]. Cofano et al [38] surveyed orthopedic surgeons who used various AR-capable HMDs for telementoring and visualization of 3D anatomical reconstructions. The surgeons reported positive feedback on the ergonomics of the headsets and perceived them as a beneficial tool that would shorten procedures and reduce postoperative complications [38]. Hassan et al [55] and El-Asmar et al [56] described neurointerventional and urological case series in which the telesurgery platform Proximie was used. Proximie allows a remote surgeon to overlay live video of their hands and tools onto a live stream of the operating field, thereby giving the consulting surgeon, who sees the hybrid video on a monitor in the operating room, real-time guidance. Hassan et al [55] observed no complications after 10 neurovascular procedures and noted no significant difference in contrast dye use or fluoroscopy times compared with similar on-site procedures (P=.38 and P=.85) [55]. El-Asmar et al [56] compared 21 AR-proctored aquablation procedures with 38 on-site guided cases and found no significant difference in length of stay, hospitalization, and 3-month adverse events [56].

Other studies (6/16, 38%) used AR in long-distance consultation and global surgery. Greenfield et al [57] described a case report in which a surgeon in Gaza, Palestine, connected with a specialist in Beirut, Lebanon, via Proximie for a hand reconstruction procedure. Ponce et al [35] described a case report that used VIP and AR (VIPAAR) to connect a remote consultant in Atlanta, Georgia, with a Google Glass–wearing orthopedic surgeon in Birmingham, Alabama, for a successful shoulder replacement. Similar to Proximie, VIPAAR allows the remote user, equipped with a computer and web camera, to create annotations and superimpose video of their hands or instruments over the local video of the operating field. However, instead of a hybrid video appearing on a monitor at the local site, the manipulations of the remote viewer would appear on the Glass worn by the local surgeon. Vyas et al [52] and Davis et al [53] focused on VIPAAR for telesurgery across continents. Vyas et al [52] described surgeons in Peru performing pediatric cleft lip repairs while using VIPAAR to connect with expert surgeons in California, United States. Davis et al [53] reported a pediatric neurosurgery case (endoscopic third ventriculostomy) in Ho Chi Minh City, Vietnam, with consultation from a specialist in Birmingham, Alabama, United States. Liu et al [39] described a case of cross-continental telesurgery while also introducing a 3D point-tracking module compatible with the Microsoft HoloLens to accurately track a scalpel’s location. During a skin grafting and faciotomy of a rabbit model, a surgical trainee wearing the headset in Anhui, China, was able to visualize surgical trajectories drawn by a surgeon in Columbus, Ohio, United States [39]. Van der Putten et al [46] featured the unplanned use of the Microsoft HoloLens 2 to allow a product manager to remotely guide a surgeon through the installation of an implant that would address a complication encountered during total knee arthroplasty. This study uniquely involved a nonsurgeon as the mentoring individual and described the minimal learning curve required for the remote consultant to instruct through the HMD [46].

Andersen et al [59,63], Rojas-Muñoz et al [61], and Zhang et al [68] developed trials to compare the procedural efficiencies of different AR tool setups during telesurgery. Andersen et al [63] compared conventional telestration, in which the hybrid video with the expert’s annotations is displayed on a separate monitor outside the surgical field, with the STAR platform, in
which the hybrid video is shown on a tablet directly above the field and the surgeon’s hands. Premedical and medical students were guided through a placement task for would-be laparoscopic ports, followed by abdominal incisions on a model. The STAR-assisted group saw lower placement errors ($P<.01$) and focus shifts away from the operating field ($P<.001$), with time to task completion being slower but not statistically significant ($P=.17$) [63]. A subsequent study by Andersen et al [59] focused on the addition of offline references during a cricothyroidotomy with network limitations. A control group using conventional telestration was compared with a STAR group with access to offline video references showing future steps. Less idle time ($P<.001$) and higher performance scores were observed ($P<.05$ for both raters) in the STAR group [59]. Rojas-Muñoz et al [61] later compared STAR with HMD-STAR, in which the remote viewer’s modifications were displayed on a headset instead of a tablet. The RCT used 2 groups of medical students performing a similar marking and incision task. Across the 2 tasks, the HMD-STAR group had fewer placement errors ($P<.001$ and $P=.01$) and focus shifts ($P<.001$ and $P=.004$) but took more time ($P<.001$ and $P<.02$) [61]. Zhang et al [68] implemented a system (coaxial projective imaging) that allowed a remote mentor’s annotation to directly project onto the local operating field. The study compared the performance of trainees using this system with that of a control group using conventional telestration during a skin cancer surgery simulation. The experimental group demonstrated higher accuracy, shorter operating times, and fewer focus shifts away from the operating field ($P<.05$ each) [68].

AR in Remote Education

The articles discussed in this section (Multimedia Appendix 3 [32,36,40-42,47-51,58,62,69]) are divided based on nonsurgical contexts, which include clinical skills, autopsy, and sonography, and surgical contexts, which include procedure observation, tool-specific training, simulations, and intraoperative learning. Of note, one-third (6/19, 32%) of the articles that involved education have been described in the previous section and will be briefly mentioned in this section.

Nonsurgical

In total, 16% (3/19) of the articles described proof-of-concept studies in which a clinician wore a Microsoft HoloLens 2 to live stream footage of patient examinations during general medicine rounds to remote students. The Microsoft HoloLens 2 allowed students to not only see through the clinician’s eyes using their personal devices but also simultaneously review overlaid 2D patient data and imaging. Rafi et al [47] featured a cardiovascular examination that was remotely spectated by final-year medical students. Using the Microsoft Teams application compatible with the HoloLens, the study measured student engagement in the form of written “chat” comments from students during the session [47]. Bala et al [48] conducted a similar study with remote fourth-year medical students observing a 1-hour session with a patient interview followed by a data interpretation and management planning session. Survey responses from the students found unanimous positive ratings regarding the tool’s impact on accessibility of education, whereas free-response feedback from students, staff, and patients revealed that the technology was a feasible and acceptable method for providing clinical education [48]. Mill et al [49] accommodated 53 fourth-year students split across 3 sessions that each featured a case discussion, bedside review, and debriefing. Survey responses from students and instructors found favorable feedback regarding the teaching quality of the sessions despite one-third of respondents reporting issues with audio and video quality [49].

A few studies (3/19, 16%) integrated AR tools with nonsurgical telementoring. Hanna et al [40] described the use of the Microsoft HoloLens by pathology staff to communicate with an attending pathologist during an autopsy. The headset allowed trainees to view holograms of tissue specimens and web-based procedure manuals, whereas the attending could provide guidance remotely during the procedure [40]. Wang et al [41] introduced the HoloLens to sonography training in a trial comparing an AR-assisted group with an audio-assisted group. Undergraduate and paramedic students were equipped with an AR headset to view the remote mentor’s hand gestures while being instructed on how to perform the right upper quadrant portion of the Focused Assessment with Sonography in Trauma examination. A control group of similar low-experience students wore headphones instead of the headset, with the mentor being able to view their progress through on-site cameras. The results revealed that performance scores were not significantly different between the 2 groups ($P=.53$), although the task completion time was longer for the AR group ($P=.008$) [41]. Mather et al [32] implemented 2 AR-capable HMDs (Vuzix Wrap 1200DX) to create an educational system called “Helping Hands.” A remote instructor’s HMD could capture their hand movements to be overlaid onto the display of a student’s HMD while the student’s hands could be visualized by the instructor. The pilot study involved guiding students through handwashing, with free-text survey responses from students showing favorable impressions of the system [32].

Hess et al [42] described a remote advanced cardiovascular life support simulation using Magic Leap One headsets distributed to second-year medical and physician assistant students. The HMDs used AR to display the holographic simulation apparatus (eg, patients, beds, and monitors) modulated by instructors, thereby allowing students to attend the simulation from their homes. Postsession interviews yielded positive feedback regarding experiential satisfaction and value in practicing communication skills [42].

Surgical

AR-capable HMDs also allowed surgical trainees to remotely observe a procedure from the operating surgeon’s perspective. Cofano et al [38], discussed in the previous section, described 2 spine surgeries in which surgical interns and medical students received live commentary from the operating surgeon while also viewing reference models and images.

Vera et al [50] and Patel et al [58] implemented AR for training on the use of surgical tools. Vera et al [50] conducted an RCT using portable laparoscopic training boxes with AR telementoring features to train medical students. An experimental group of students used the AR telementoring platform, in which the instructor’s laparoscopic instruments
were superimposed in real time on the student’s monitor during a training session. Compared with a control group that was mentored in person, the AR telementoring group had significantly faster skill acquisition ($P<.001$) and more completed attempts during a posttraining suturing task ($P=.02$) [50]. Patel et al [58] used Proximie to remotely teach medical students how to use robotic surgery tools (da Vinci Skills Simulator), with postexperience Likert surveys showing positive ratings for ease of use and quality of the audio-video feed. Other articles (4/19, 21%) discussed surgical education performed through simulated procedures. Andersen et al [63] and Rojas-Muñoz et al [61] both featured trials using medical students for abdominal incision tasks and have been discussed in the previous section. Another study by Rojas-Muñoz et al [62] compared HMD-STAR with textbook review for leg fasciotomies performed by medical students and surgical residents. The HMD-STAR group could receive verbal guidance and annotations from a remote mentor, whereas the control group performed the procedure with independent review of the procedure beforehand. When comparing both groups, the HMD-STAR group had a 10% higher weighted individual performance score ($P=.03$) with 67% fewer errors ($P=.04$) and no significant difference between task completion times [62]. Stone et al [69] introduced a novel training system that allowed for the remote instruction of a transperineal prostate biopsy and rectal spacer placement on an anatomical model. The system involved a pair of HMDs that allowed users to view ultrasound imaging and the procedural field simultaneously. The students observed the mentor perform the procedure before practicing on the model with remote guidance. Both learners and instructors reported that the displayed images were adequate for the procedures and that the HMDs did not affect performance negatively [69]. Education in the form of intraoperative telementoring was featured in 21% (4/19) of the studies. A study by Armstrong et al [36] entailed a case report in which a junior resident wore Google Glass while performing a delayed primary closure of a plantar defect under the supervision of a remote attending surgeon. Accessing the audio-video feed through Google Hangouts, the attending could provide verbal feedback and use a mouse on their computer to point to items seen by the Glass [36]. Ponce et al [51] implemented a VIP platform for a pilot study in which surgical residents performed arthroscopic shoulder procedures under the remote mentorship of an attending surgeon. The platform was similar to the VIPAAR platform described previously: video of the operating site was viewed by a remote mentor, allowing the mentor to create annotations or superimpose their own hand and instruments over the video feed. A monitor at the operating site showed the hybrid video to the residents to allow for real-time feedback. Survey responses from those involved showed positive ratings for ease and utility of the tool in anatomical learning, with all in agreement that the system did not compromise safety [51]. Vyas et al [52] and Davis et al [53] were described previously in the context of global surgery, but both demonstrated examples of long-distance surgical training. Mentoring surgeons in the overseas curriculum described by Vyas et al [52] evaluated the local mentees on various aspects of cleft lip repair following both in-person and telementored surgeries. In-person procedures preferentially improved intraoperative decision-making ($P<.001$) and repair principles ($P<.001$), whereas remote sessions preferentially improved understanding of anatomy ($P<.01$) and increased procedural efficiency ($P<.001$) [52].

**Evaluation of AR-Assisted Remote Tasks**

Of the 39 studies, 21 (54%) had a comparative design, with 6 (15%) being RCTs. Most studies (23/39, 59%) gathered data through user feedback surveys or interviews, 70% (16/23) of which used numerical Likert scales. Tables 2 and 3 summarize the variables measured and discussed across the articles in nonsurgical and surgical tasks, respectively.
Table 2. Range of variables studied in augmented reality–assisted nonsurgical tasks.

<table>
<thead>
<tr>
<th>Variable and subcategory</th>
<th>Study, year</th>
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<tr>
<td><strong>Objective</strong></td>
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| Performance score                             | ● Wang et al [41], 2017  
● Rigamonti et al [44], 2021 |
| Time for task                                 | ● Chinthammit et al [31], 2014  
● Wang et al [41], 2017 |
| Accuracy                                      | ● Chinthammit et al [31], 2014  
● Follmann et al [33], 2019 |
| Reliability across task performers            | ● Broach et al [34], 2018  
● Kaylor et al [37], 2019  
● Borresen et al [67], 2022 |
| Patient complications                         | ● Hill [43], 2022 |
| **Subjective efficacy**                       |             |
| Usefulness                                    | ● Chinthammit et al [31], 2014  
● Ponce et al [54], 2016  
● Wang et al [41], 2017  
● Broach et al [34], 2018  
● Carbone et al [65], 2018  
● Mather et al [32], 2018  
● Follmann et al [33], 2019  
● Ramsingh et al [64], 2022  
● Mill et al [49], 2021  
● Rigamonti et al [44], 2021  
● Hess et al [42], 2022 |
| Improved patient care                         | ● Martin et al [45], 2020 |
| Improved performance                          | ● Chinthammit et al [31], 2014  
● Wang et al [41], 2017 |
| Efficacy in communication                     | ● Wang et al [41], 2017  
● Borresen et al [66], 2019  
● Ramsingh et al [64], 2022  
● Martin et al [45], 2020  
● Bala et al [48], 2021  
● Mill et al [49], 2021  
● Hess et al [42], 2022 |
| Superiority to other communication methods    | ● Ponce et al [54], 2016  
● Wang et al [41], 2017 |
| **Feasibility**                               |             |
| Ease of use                                   | ● Wang et al [41], 2017  
● Broach et al [34], 2018  
● Carbone et al [65], 2018  
● Mather et al [32], 2018  
● Borresen et al [66], 2019  
● Martin et al [45], 2020  
● Mill et al [49], 2021  
● Rigamonti et al [44], 2021  
● Hess et al [42], 2022 |
| Interference in task                          | ● Broach et al [34], 2018  
● Carbone et al [65], 2018  
● Mill et al [49], 2021 |
The most common objective variable measured was time to task completion, with other common variables being task performance and procedure-related complications. Several studies (7/39, 18%) on the topics of telerehabilitation and telesurgery found no difference in task time compared with non–AR-assisted conditions, whereas Vera et al [50] found that less time was needed when using AR for laparoscopic training. In contrast, Follmann et al [33], Wang et al [41], and Ponce et al [35] found that AR increased the time needed compared with non-AR conditions for triage assessment, ultrasound examination, and shoulder replacement, respectively. Performance, measured using scoring systems or frequency of errors, was seen to improve with AR use in telesurgery tasks described by Vera et al [50], Rojas-Muñoz et al [60,62], and Andersen et al [63], whereas Wang et al [41] and Chinthammit et al [31] found no difference when comparing with non-AR groups in tele-ultrasonography and a telerehabilitation-related task, respectively. When comparing AR-assisted tools with each other, as done by Andersen et al [63] and Rojas-Muñoz et al [61], improved performance was observed as AR-enhanced displays were brought closer to the eyes of the user. AR’s impact on resource use was different based on context, with Martin et al [45] finding that AR-assisted rounding during COVID-19 saved PPE, whereas El-Asmar et al [56] and Hassan et al [55] found no significant increases in general anesthesia use in aquablation procedures or contrast use for neuroradiological interventions, respectively.

Subjective measures included in the studies were related to device efficacy, feasibility, and acceptability. All studies that examined feedback-related efficacy, such as the perceived “usefulness” of AR assistance, reported a majority of positive ratings. However, when comparing the ratings of AR-assisted conditions with those of non-AR conditions, Wang et al [41] and Chinthammit et al [31] notably found no differences. Studies that measured ratings for feasibility, such as ease or comfort of use, also found a majority of positive responses. The lowest percentage of positive Likert-scale ratings for ease was observed in first responders in the study by Broach et al [34] in the context of using Google Glass for triage assessments, with 64% (9/14) of users giving a rating of 4 out of 5 or higher. Studies that examined acceptability ratings, such as experience satisfaction or interest, similarly found a consistent majority of positive ratings from AR users. Further study into potential differences between patient and provider ratings may be warranted as Ponce et al [54] found that postoperative patients using a virtual presence–type mobile app were more likely to be satisfied with the overall experience (average rating of 4.6 vs 4.2 out of 5; \( P<.05 \)) and view the virtual interaction as superior to email and SMS text messaging (4.7 vs 4.4 out of 5; \( P<.05 \)) than surgeons.
Table 3. Range of variables studied in augmented reality–assisted surgical tasks.

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<th>Variable and subcategory</th>
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<td>Performance</td>
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<td>• Vyas et al [52], 2020</td>
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<td>• Zhang et al [68], 2022</td>
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<td>Procedural efficiency</td>
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<td>• Hassan et al [55], 2021</td>
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<td>Complications</td>
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<td>• El-Asmar et al [56], 2021</td>
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<td>• Van der Putten et al [46], 2022</td>
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<td>Patient length of stay and rehospitalization rates</td>
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<td>Skill acquisition</td>
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Although most survey- or interview-based studies measured user feedback about AR’s usefulness (15/23, 65%), far fewer studies (2/23, 9%) surveyed AR’s ability to substitute in-person methods in telemedicine. Borresen et al [66], who used the ARTESH system for motor and strength examinations, found an average Likert rating (4/7) from physicians when they were asked whether in-person examinations would have similar results. Surveyed patients similarly had a lower percentage of positive responses (9/15, 60%) compared with other feasibility and acceptability questions when asked about the device’s potential to substitute an in-person examination [66]. In telementoring, the literature shows that AR may have more potential. Patel et al [58], who used Proximie to remotely mentor students in using robotic surgery tools, observed average ratings above 4/5 for utility as an alternative to in-person mentoring. Across all 39 studies, there were gaps in the longitudinal measurements related to patient outcomes, such as costs, hospitalization course, and quality of life. Only the study by Davis et al [53] analyzed the finances of implementing an AR system, estimating a cost of US $14,900 per calendar year for a VIPAAR system used for telementoring pediatric neurosurgery in Vietnam. Meanwhile, only El-Asmar et al [56] measured postoperative length of stay and 3-month adverse events to find no significant difference between AR and non-AR conditions. Furthermore, there were few studies (2/39, 5%) that focused on the long-term benefits of AR-enabled remote education, such as retention of learned material and performance over an extended period. Chinthammit et al [31] measured the performance of trainees multiple times over a period of a week after training; however, studies that examined nonsurgical skills over longer periods are absent in this review. Vyas et al [52] described a 13-month overseas course in pediatric cleft lip repair; however, the curriculum combined both in-person and remote intraoperative learning sessions rather than comparing the methods.

**Discussion**

**Principal Findings**

In this scoping review, we discussed 39 studies that used AR in real-time telemedicine and telementoring. From these studies, 20 unique devices and platforms, most of which involved an HMD, were identified and found to have common features such as annotation, graphical references, and the ability to overlay a remote viewer’s hands or tools onto a local user’s screen. AR builds on the remote examinations of current audio- and videoconferencing tools by enhancing the remote acquisition and exchange of information. AR technology can supply users with visual aids, such as electronic health record data and guidelines, or facilitate communication with specialists trained to identify specific conditions or manipulate diagnostic equipment. Studies on AR-assisted remote patient evaluations...
took place in both outpatient and inpatient settings, including emergency triage, wound evaluation, and hospital rounding. Although the devices vary across settings, the comparative studies in this review found noninferior accuracy and reliability of AR-assisted remote conditions compared with in-person controls. Devices dedicated to remote musculoskeletal and sonographic examinations were also developed, with positive user ratings. As technology improves and becomes more accessible, the types of examinations that can be performed remotely will expand and allow for greater access to care, especially by patients and providers in low-resource areas.

The research on AR in the remote delivery of medical interventions predominantly focused on surgery, with other treatment modalities such as physical therapy being less studied [70]. Telesurgery implemented AR features such as virtual presence and annotation to facilitate procedural guidance, mentorship, and consultation. The distance of such connections was tested, with several case reports describing AR in the telementoring of operations across continents. Various types of surgical procedures were telementored using AR, including minimally invasive surgery, orthopedic surgery, and pediatric neurosurgery. The literature surrounding AR and telesurgery focused primarily on the technology’s potential to improve procedural efficiency and communication with experts, with the differences across systems for surgical telementoring studies being investigated in more recent articles. From the data available so far, the performance of AR-assisted procedures appears equivalent to other remotely mentored conditions, with limited research suggesting AR’s potential to substitute in-person mentorship without sacrificing resources or short-term outcomes. Although such findings require further validation, AR plays a promising role in enabling less experienced providers to perform more specialized treatments and avoid the unnecessary transfer of patients across hospital systems. Research on AR-assisted telerehabilitation and psychotherapy could offer insight into whether these nonsurgical treatments could also be effectively performed as remote visits.

Medical education emerged as a common theme underlying AR’s integration into telemedicine and telementoring. In addition to surgery, remote training using AR was studied for clinical skills that are important to inpatient wards and procedures related to pathology and EM. Both surgical and nonsurgical studies implemented AR tools in similar ways, including observational learning, real-time audiovisual feedback, and teaching by demonstration. When in-person mentorship was not possible or inconvenient, the studies showed how AR-enhanced communication allowed distant learners to not just observe but also engage with clinicians and surgeons. Distance learning of surgical and sonographic equipment could also be achieved with AR systems, with few controlled trials thus far indicating noninferior performance results compared with in-person mentoring and superior results compared with unassisted conditions, particularly for less experienced trainees. As the equipment for telecollaboration in medicine becomes readily available, AR technology is expected to advance the sharing of knowledge related to clinical skills, health care devices, and procedural techniques, which directly and indirectly improves patient care outcomes.

Given the early stage of platform development, many studies included in this review (25/39, 64%) used small cohorts of ≤15 patients or participants per study group; although approximately half (21/39, 54%) of the studies included comparative data, far fewer were RCTs. This finding is expected as AR is an emerging technology in medicine, and its use in telemedicine and telementoring is still developing. Existing comparative trials that measured time consumption and performance have so far found that AR-assisted conditions mostly have noninferior results compared with other remote and in-person methods. However, as these studies are heterogeneous in methodology and equipment, dedicated RCTs with standardized designs are needed to understand whether certain AR systems for specific tasks can effectively substitute current remote alternatives or in-person methods. Feedback surveys and interviews were the most common form of data collection observed in this review; subjective variables such as perceived efficacy and ease ratings were commonly measured with consistently positive findings despite the novelty of the technology, suggesting interest across user groups, including providers, trainees, and patients.

**Future Directions**

Overall, interventions and learning that require active patient or family caregiver participation (eg, physical therapy, psychotherapy, preventative medicine, chemotherapy, and dialysis) have yet to achieve a similar level of investigation in the space of AR and telemedicine or telementoring as surgery. From the nonsurgical studies included in this review, there is an interest in AR for tele-sonography, EM, and hospital medicine, with many nonsurgical fields yet to be represented. In the realm of patient evaluation, AR’s role is still being separately investigated for electromyography [71], diagnostic procedures related to endoscopy [72], biopsies [73], and urology [74], as well as specialty-specific examinations pertinent to dentistry [75], ophthalmology [76], and dermatology [9], to name a few.

Considering the diversity of medical fields and levels of experience across users, AR-enabled remote interactions are likely to appear in certain settings or users sooner than in others. In the interventional and educational space, studies so far have primarily implemented AR tools for remote consultation between current or future medical professionals. Few trials using untrained individuals for AR-assisted procedural, nonsurgical tasks exist; it would be reasonable to anticipate future research with AR facilitating remote provider-to-patient or provider-to-caregiver interactions in the therapeutic context [77]. To support innovations focused on remote interactions with home caregivers and patients, perspectives from and qualitative studies on these particular end users, rather than solely clinician users, are necessary [22,78].

Although more dedicated RCTs would be needed to assess the efficacy of AR-assisted communication in the treatment setting, AR’s impact on variables related to costs beyond procedure time and outcome measures beyond complication rates remains relatively unexplored. These include hospital-based measurements such as length of stay, equipment costs, and intra- and postoperative pain medication use but also patient-centered variables such as treatment cost, posttreatment functional status,
and quality of life. The literature in this review focused mainly on short-term variables, which reveals a lack of longitudinal research that could provide insights into both long-term outcomes of patients and system-wide effects on productivity and sustainability of AR use. Longitudinal studies with dedicated comparisons, which are likely to increase as devices improve in wearability, usability, and affordability, are also needed to fully understand whether AR could enhance knowledge and skill retention in the remote learning environment.

**Limitations**

This review was limited to studies from the last 10 years in 4 medical research databases. Many AR developments in telemedicine and telementoring that exist in the private sector have not been described in published articles and so cannot be systematically evaluated. Notably, a 2019 systematic review of AR in telementoring has also explored additional databases [28]; however, our review included “remote,” “telemedicine,” and “telehealth” as search terms to locate a wider variety of health care tasks that may not rely on equipment or procedures typically associated with “telementoring.” Furthermore, this scoping review placed more emphasis on the diversity of systems using AR and the nonsurgical specialties incorporating them. The small cohorts and predominant collection of subjective data were expected given the novel nature of this intersection and the technology.

Although the potential benefits of AR in telemedicine are promising, the challenges facing this technology are the early stage of research and prototype development for these application contexts and a lack of standardized devices. Outside the original and surgery-specific platforms, most of the hardware observed in this review is available to consumers but at costs that limit widespread use [79]. Furthermore, the adjunct programs and applications used with the hardware greatly varied across the studies. The diversity of tools and their availability could limit the design and generalizability of future trials, especially if the technology is custom-made and difficult to reproduce. Combined with low awareness and a lack of guidelines on how to evaluate AR technology, innovators face difficulty in developing appropriate tools and introducing them into current or even unexplored health care spaces. Future research focusing on the utility and feasibility of AR compared with current technology in the medical setting is paramount, but studies looking into the costs of implementation, user readiness, and user-friendly design are also necessary for successful adoption.

**Conclusions**

This scoping review discussed studies that combined AR with real-time telemedicine and telementoring, including patient evaluation, medical intervention, and education. Commonly explored applications for this novel intersection include consultation and procedural guidance, particularly in telesurgery. AR-assisted telecommunication was studied to complement or even improve the capability of remote visits, treatments, and training, but more RCTs are needed to validate task-specific benefits as well as understand the long-term effects for all users. As technology evolves and use at the consumer and industry levels becomes more widespread, research on AR in health care is expected to see larger cohorts, standardized equipment, and more rigorous methods of evaluation. Developing AR tools in medicine must balance user-friendly design with limited research and uptake; such challenges create an opportunity for institutional involvement and a need for perspectives from all those involved in health care, including but not limited to clinicians, caregivers, and patients.

**Acknowledgments**

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**Conflicts of Interest**

None declared.
References


Abbreviations

AR: augmented reality
ARTESH: Augmented Reality–based Telerehabilitation System with Haptics
EM: emergency medicine
HMD: head-mounted device
HMD-STAR: head-mounted device with System for Telementoring with Augmented Reality
PPE: personal protective equipment
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RCT: randomized controlled trial
STAR: System for Telementoring with Augmented Reality
VIP: virtual interactive presence
VIPAA: virtual interactive presence and augmented reality
VR: virtual reality
WOC: wound, ostomy, and continence

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Dinh et al

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Willingness to Use and Pay for Digital Health Care Services According to 4 Scenarios: Results from a National Survey

Junbok Lee1,2, MA; Yumi Oh3, PhD; Meelim Kim1,4, PhD; Belong Cho5, MD, PhD; Jaeyong Shin6,7,8, MD, MPH, PhD

1Health-IT Center, Yonsei University Health System, Seoul, Republic of Korea
2Department of Human Systems Medicine, Seoul National University College of Medicine, Seoul, Republic of Korea
3Korea Health Promotion Institute, Seoul, Republic of Korea
4Herbert Wertheim School of Public Health and Human Longevity Science, University of California San Diego, San Diego, CA, United States
5Department of Family Medicine, Seoul National University Hospital, Seoul, Republic of Korea
6Department of Preventive Medicine, Yonsei University College of Medicine, Seoul, Republic of Korea
7Institute of Health Services Research, Yonsei University, Seoul, Republic of Korea
8Institute for Innovation in Digital Healthcare, Yonsei University, Seoul, Republic of Korea

Corresponding Author:
Jaeyong Shin, MD, MPH, PhD
Department of Preventive Medicine
Yonsei University College of Medicine
50-1 Yonsei-Ro
Seodaemun-Gu
Seoul, 03722
Republic of Korea
Phone: 82 2 2228 1881
Email: DRSHIN@yuhs.ac

Abstract

Background: Smartphones and their associated technology have evolved to an extent where these devices can be used to provide digital health interventions. However, few studies have been conducted on the willingness to use (WTU) and willingness to pay (WTP) for digital health interventions.

Objective: The purpose of this study was to investigate how previous service experience, the content of the services, and individuals’ health status affect WTU and WTP.

Methods: We conducted a nationwide web-based survey in 3 groups: nonusers (n=506), public service users (n=368), and private service users (n=266). Participants read scenarios about an imagined health status (such as having a chronic illness) and the use of digital health intervention models (self-management, expert management, and medical management). They were then asked to respond to questions on WTU and WTP.

Results: Public service users had a greater intention to use digital health intervention services than nonusers and private service users: scenario A (health-risk situation and self-management), nonusers=odd ratio [OR] .239 (SE .076; P<.001) and private service users=OR .138 (SE .040; P<.001); scenario B (health-risk situation and expert management), nonusers=OR .175 (SE .044; P<.001) and private service users=OR .219 (SE .053; P<.001); scenario C (chronic disease situation and expert management), nonusers=OR .413 (SE .094; P<.001) and private service users=OR .401 (SE .098; P<.001); and scenario D (chronic disease situation and medical management), nonusers=OR .480 (SE .120; P=.003) and private service users=OR .345 (SE .089; P<.001). In terms of WTP, in scenarios A and B, those who used the public and private services had a higher WTP than those who did not (scenario A: β=.397, SE .091; P<.001; scenario B: β=.486, SE .098; P<.001). In scenario C, private service users had greater WTP than public service users (β=.264, SE .114; P=.02), whereas public service users had greater WTP than nonusers (β=.336, SE .096; P<.001). In scenario D, private service users were more WTP for the service than nonusers (β=.286, SE .092; P=.002).

Conclusions: We confirmed that the WTU and WTP for digital health interventions differed based on individuals’ prior experience with health care services, health status, and demographics. Recently, many discussions have been made to expand digital health care beyond the early adapters and fully into people’s daily lives. Thus, more understanding of people’s awareness and acceptance of digital health care is needed.
digital health intervention; service experience; willingness to pay; willingness to use; digital health; health technology

Introduction

Since their introduction, smartphones and their associated technology have evolved to an extent where these devices can be used to provide personal health care services through various mobile apps [1-4]. The number of such apps continues to increase [5,6].

Through such digital health interventions, people can manage their health anytime and anywhere [7,8]. Additionally, digital health interventions have the advantage of enabling health management through features that use objective, numerical, and health-related data, such as the step counter and heart rate tracker [9]. Digital health interventions aid in continuous health management, strengthening the potential to prevent chronic diseases by promoting constant individual health monitoring and to reduce medical expenses [10,11]. Interest in these interventions has further increased because of the COVID-19 pandemic and the consequent restrictions on outdoor activities and movements [12-15]. Given the growing preference for services that do not require physical contact, digital health interventions will only become more prevalent [16]. Digital health interventions are being developed for various medical conditions to complement traditional medical care and improve patient experience [17,18]. The US Food and Drug Administration approved several digital health apps, such as those for the management of diabetes (BlueStar) or the treatment of substance use disorder (reSET) [19]. In Germany, digital health apps approved by BfArM (Bundesamt für Arzneimittel und Medizinprodukte; the German Federal Institute for Drugs and Medical Devices) could be included in the DiGA (digitale Gesundheitsanwendung; digital health applications) directory for reimbursement [20].

Even with the convenience, usefulness, and potential for future development of digital health interventions, only some people manage their health using digital health care tools [21,22]. Additionally, the retention rate of digital health intervention services is low [23-25]. It is necessary to provide opportunities for more people to experience the service and make them use the service continuously. Thus, it is vital to identify factors that affect people’s willingness to use (WTU) and willingness to pay (WTP) for these services.

Only a few studies have been conducted on the WTU and WTP for digital health interventions [26-30]. Previous studies have identified demographic and health-related factors that affect the WTP for digital health interventions [26]. Research showed that the absolute WTP of those in the UK-representative cohort was £196 (US $258) and the marginal WTP was £160 (US $211), whereas those who availed the national digital health program had an absolute WTP of £162 (US $214) and a marginal WTP of £151 (US $199). Another study conducted an experimental vignette to identify factors affecting people’s use of and payment for mobile health care apps in the context of 4 different business models [27]. It showed that doctors’ recommendations helped increase both the WTU and WTP in Germany and the Netherlands.

This study intended to investigate how individuals’ previous service experience, the content of the services, and health status influence the WTU and WTP of digital health interventions. Referring to previous research [26], we surveyed not only those who availed public digital health intervention services but also those who had experience with private services in South Korea. We subdivided digital health interventions into self-management, expert (nonmedical) management, and medical personnel management to identify differences by service type.

Methods

Digital Health Interventions: Public and Private Service

Mobile Healthcare at public health centers is a free health care service program provided by the South Korean government. The service team at public health centers helps individuals manage their daily lives by setting health goals and counseling them via smartphones with activity trackers. As part of the program, they visit the public health centers for counseling and examinations after 3 and 6 months for check-ups.

Company N’s digital health intervention is a mobile-based app service whose users aim to lose weight and prevent diabetes through lifestyle changes. Based on behavioral science and psychology, health care coaches communicate with users to set health care goals and provide nutrition and exercise feedback, which help them achieve those goals. This service is used in the Centers for Disease Control and Prevention’s Diabetes Prevention Program in the United States.

Participants

For this study, a nationwide web-based and mobile survey of people aged 19 to 59 years was conducted. We recruited participants from 3 groups: nonusers (n=506), public service users (n=368), and private service users (n=266). Public service users were participants who took part in the Mobile Healthcare program at public health centers. Private service users were people who experienced Company N’s digital health intervention. In the case of public and private service users, recruitment notices were posted on the notice board of the mobile apps. People who expressed their intention to participate in the survey received a survey link. Nonusers were recruited via emails to a large-scale web-based panel of a research company. Based on the Mobile Healthcare project promoted by the Korean Ministry of Health and Welfare, samples of public service users were recruited using a proportional allocation of gender, age, and residence in 2020. Nonservice users were sampled using proportional rates based on gender, age, and residence as of 2020 in South Korea for national representation.
All participants responded through a web page developed by the research company, and the data were stored in the research company’s database. The participants received ₩1500 (South Korean won; US $1=₩1100) as a reward for the survey. Table 1 shows the demographic distribution of the study participants.

### Table 1. Demographic distribution of the participants.

<table>
<thead>
<tr>
<th>Demographics</th>
<th>Nonuser (n=506)</th>
<th>Public service user (n=368)</th>
<th>Private service user (n=266)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age range (years), n (%)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>19-29</td>
<td>121 (23.9)</td>
<td>23 (6.3)</td>
<td>64 (24.1)</td>
</tr>
<tr>
<td>30-39</td>
<td>113 (22.3)</td>
<td>92 (25)</td>
<td>78 (29.3)</td>
</tr>
<tr>
<td>40-49</td>
<td>136 (26.9)</td>
<td>160 (43.5)</td>
<td>72 (27.1)</td>
</tr>
<tr>
<td>≥50</td>
<td>136 (26.9)</td>
<td>93 (25.3)</td>
<td>52 (19.5)</td>
</tr>
<tr>
<td><strong>Gender, n (%)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Men</td>
<td>258 (51)</td>
<td>112 (30.4)</td>
<td>122 (45.9)</td>
</tr>
<tr>
<td>Women</td>
<td>248 (49)</td>
<td>256 (69.6)</td>
<td>144 (54.1)</td>
</tr>
<tr>
<td><strong>Residence, n (%)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Seoul Capital Area</td>
<td>268 (53)</td>
<td>76 (20.7)</td>
<td>80 (30.1)</td>
</tr>
<tr>
<td>Others</td>
<td>238 (47)</td>
<td>292 (79.3)</td>
<td>186 (69.9)</td>
</tr>
<tr>
<td><strong>Health status</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medication, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>160 (31.6)</td>
<td>45 (12.2)</td>
<td>57 (21.4)</td>
</tr>
<tr>
<td>No</td>
<td>346 (68.4)</td>
<td>323 (87.8)</td>
<td>209 (78.6)</td>
</tr>
<tr>
<td>Hypertension or diabetes, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>119 (23.5)</td>
<td>56 (15.2)</td>
<td>41 (15.4)</td>
</tr>
<tr>
<td>No</td>
<td>387 (76.5)</td>
<td>312 (84.8)</td>
<td>225 (84.6)</td>
</tr>
</tbody>
</table>

### Design and Procedure

People’s WTU and WTP may change according to the contents of digital health interventions, and several factors can influence them. Therefore, in this study, we created 3 digital health intervention models referring to the Evidence Standards Framework developed by The National Institute for Health and Care Excellence in the United Kingdom [31]. According to the functional aspect and potential risks, this framework classifies the level of digital health technology (DHT) into tier 1, tier 2, tier 3a, and tier 3b. Tier 1 includes DHT that provides systemic benefits but no direct benefits to the patient. Tier 2 includes DHT that cannot evaluate a patient’s health outcomes but can help them live a healthy life by providing information and offering simple monitoring services based on the patient’s health-related data. Tier 3a is a service for preventive behavioral modifications and management (which allows users to record and selectively exchange data with specialists) designed to modify health behaviors and eating habits using DHT. Tier 3b refers to DHT with measurable improvements, such as treatment and diagnosis devices. These include devices that provide treatment for diagnosed diseases, provide automated information records and data to experts, and perform calculations that affect clinical decisions. Tier 1 was excluded from this study because it does not directly serve patients.

All the study participants read the scenarios (Textbox 1) and responded to the questions (Table 2). They first read situation scenarios about their health status to imagine themselves as part of a high-risk group. Subsequently, they read the content of digital health interventions for self-management and then indicated their WTU and WTP. Thereafter, they read the scenario for digital health interventions administered by a health care professional (nonmedical person) and responded with their WTU and WTP in the same way.

Next, the participants read the chronic disease patient scenario to imagine themselves as patients with a chronic disease. They read the content of digital health interventions offered by a health care professional (nonmedical person; same as the previous service scenario) and responded with their WTU and WTP. Lastly, they responded with their WTU and WTP for the mobile app that verified the treatment effect and was managed by a doctor.
Textbox 1. Text of the scenarios.

**Health-risk situation**
- Imagine that a routine medical check-up reveals that you are at a high risk of becoming diabetic. The doctor advises you to come back for a check-up after three months of regular exercising and eating a healthy diet instead of prescribing medication.

**Self-management**
- A service that allows people to enter and monitor health-related data weekly or monthly, such as their food intake, steps walked, weight, blood pressure level, pulse rate, blood sugar level, and so on.

**Expert management**
- A service wherein a healthcare expert (non-medical person) sets up an exercise and diet plan based on the health-related information (diet, weight, etc.) provided, and sends messages via the application on a regular basis for counselling, or to share educational information and advice.

**Chronic disease situation**
- Imagine that you started taking diabetes medicine because your fasting blood sugar level did not drop, and the doctor recommended also utilizing the suggested service.

**Expert management**
- A service wherein a healthcare expert (non-medical person) sets up an exercise and diet plan based on the health-related information (diet, weight…) provided, and sends messages via the application on a regular basis for counselling, or to share educational information and advice.

**Medical management**
- A mobile application-based service that proves the effectiveness of diabetes treatment and a doctor checks the medical data entered by the patient undergoing treatment as well as provides a customized exercise and diet plan.

Table 2. Scenario design.

<table>
<thead>
<tr>
<th></th>
<th>Self-management (tier 2)</th>
<th>Expert management (tier 3a)</th>
<th>Medical management (tier 3b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Health-risk situation</td>
<td>Scenario A</td>
<td>Scenario B</td>
<td>N/A¹</td>
</tr>
<tr>
<td>Chronic disease situation</td>
<td>N/A</td>
<td>Scenario C</td>
<td>Scenario D</td>
</tr>
</tbody>
</table>

¹N/A: not applicable.

**Covariates**

**Sociodemographic and Health Status**
Before reading the scenarios, the participants provided information about their age, gender, and residence. After the survey ended, they provided information about their income and occupation. They also indicated their subjective health status, diagnosed disease (high blood pressure, diabetes, etc.), and whether they had taken medication for 3 months or longer within the last year for their disease.

**Dependent Variables, WTU, and WTP Questions**
The participants read 4 scenarios (A to D) and indicated their WTU the health care service app in each scenario on a 4-point scale (1=not at all, 2=not very much, 3=somewhat willing, and 4=highly willing). Participants who responded with “somewhat” and “a lot” were asked how much they were WTP per month for the service.

**Statistical Analysis**
In this study, logistic regression was used to identify factors affecting the WTU digital health interventions with completed questionnaires. Multiple linear regression analysis was conducted to confirm the WTP. Regarding the WTP, the analysis was performed by log transformation. We also conducted an ANOVA to find out the difference between participants’ WTU and WTP according to their service experience. STATA (version 16; StataCorp) software was used for the analysis.

**Ethics Approval**
This study was approved by the institutional review board of the Korea Health Promotion Institute (120160811107AN01-2020-HR-049-02). All participants agreed to participate in the study after reading the explanation page, including the purpose of this study, the number of participants, and the data storage period.

**Results**

**WTP**
In scenario A, the average WTP was ₩21,909 (SD ₩22,418) for private service users, ₩17,020 (SD ₩15,877) for public service users, and ₩11,913 (SD ₩11,090) for nonusers. In scenario B, the average WTP was ₩17,636 (SD ₩15,356) for private service users, ₩15,392 (SD ₩15,278) for public service users, and ₩10,279 (SD ₩10,428) for nonusers. In scenario C, the average WTP was ₩21,322 (SD ₩21,836) for private service users, ₩14,516 (SD ₩14,977) for public service users, and ₩11,906 (SD ₩12,268) for nonusers. In scenario D, the
average WTP was ₩23,520 (SD ₩25,277) for private service users, ₩15,500 (SD ₩16,035) for public service users, and ₩13,084 (SD ₩13,288) for nonusers. Table 3 shows the summary statistics of the WTP.

Table 3. Willingness to pay (₩; US $1=₩1100).

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Nonuser (n=506), ₩ (US $)</th>
<th>Public service user (n=368), ₩ (US $)</th>
<th>Private service user (n=266), ₩ (US $)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Scenario A</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>11,913 (10.8)</td>
<td>17,020 (15.5)</td>
<td>21,090 (19.9)</td>
</tr>
<tr>
<td>SD</td>
<td>11,090 (10.1)</td>
<td>15,877 (14.4)</td>
<td>22,418 (20.4)</td>
</tr>
<tr>
<td>Median</td>
<td>10,000 (9.1)</td>
<td>10,000 (9.1)</td>
<td>14,000 (12.7)</td>
</tr>
<tr>
<td>Range</td>
<td>0-65,000 (0-59.1)</td>
<td>0-100,000 (0-90.9)</td>
<td>0-109,000 (0-99.1)</td>
</tr>
<tr>
<td><strong>Scenario B</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>10,279 (9.3)</td>
<td>15,392 (14.0)</td>
<td>17,636 (16.0)</td>
</tr>
<tr>
<td>SD</td>
<td>10,428 (9.5)</td>
<td>15,278 (13.9)</td>
<td>15,356 (14.0)</td>
</tr>
<tr>
<td>Median</td>
<td>7000 (6.4)</td>
<td>10,000 (9.1)</td>
<td>10,000 (9.1)</td>
</tr>
<tr>
<td>Range</td>
<td>0-55,000 (0-50)</td>
<td>0-90,000 (0-81.8)</td>
<td>0-80,000 (72.7)</td>
</tr>
<tr>
<td><strong>Scenario C</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>11,906 (10.8)</td>
<td>14,516 (13.2)</td>
<td>21,322 (19.4)</td>
</tr>
<tr>
<td>SD</td>
<td>12,268 (11.2)</td>
<td>14,977 (13.6)</td>
<td>21,836 (19.9)</td>
</tr>
<tr>
<td>Median</td>
<td>8000 (7.3)</td>
<td>10,000 (9.1)</td>
<td>11,000 (10.0)</td>
</tr>
<tr>
<td>Range</td>
<td>0-70,000 (0-63.6)</td>
<td>0-90,000 (0-81.8)</td>
<td>0-100,000 (0-90.9)</td>
</tr>
<tr>
<td><strong>Scenario D</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>13,084 (11.9)</td>
<td>15,500 (14.1)</td>
<td>23,520 (21.4)</td>
</tr>
<tr>
<td>SD</td>
<td>13,288 (12.1)</td>
<td>16,035 (14.6)</td>
<td>25,277 (23.0)</td>
</tr>
<tr>
<td>Median</td>
<td>10,000 (9.1)</td>
<td>10,000 (9.1)</td>
<td>15,000 (13.6)</td>
</tr>
<tr>
<td>Range</td>
<td>0-80,000 (0-72.7)</td>
<td>0-100,000 (0-90.9)</td>
<td>0-150,000 (0-136.4)</td>
</tr>
</tbody>
</table>

WTU and WTP in Scenario A (Health-Risk Situation and Self-management)

We explored the WTU and WTP of those in the health-risk situation on the self-management service (see Multimedia Appendix 1). Linear regression analyses were conducted to identify the factors influencing the WTU digital health interventions. In scenario A, age, gender, income, type of service experience, medication use, and residence affected the WTU. Specifically, younger people (odds ratio [OR] .961, SE .010; \( P < .001 \)), women (OR .470, SE .099; \( P < .001 \)), people with high income (OR 1.364, SE .099; \( P < .001 \)), and people who lived in the metropolitan area (OR .629, SE .144; \( P = .04 \)) were more WTU the self-management service. In the case of service experience, public service users had a greater intention to use the self-management service than nonusers and private service users (nonusers: OR .239, SE .040; \( P < .001 \); private service users: OR .138, SE .044; \( P < .001 \)). People who were on medication for 1 year were more likely to use the self-management service (OR 1.773, SE .365; \( P = .005 \)). The explanatory power of the model with all predictors was 13.1%. We also conducted logistic regression analyses to examine the WTP. Private and public service users had higher WTP than nonusers (\( \beta = -.397, SE .091; P < .001 \)). The explanatory power of WTP was 5.2%.

WTU and WTP in Scenario B (Health-Risk Situation and Expert Management)

We investigated the WTU and WTP of those in the health-risk situation on the expert management service (see Multimedia Appendix 2). The type of service experience and medication use affected the WTU in scenario B. Specifically, public service users showed greater intention to use the service than private service users and nonusers (nonusers: OR .175, SE .040; \( P < .001 \); private service users: OR .219, SE .053; \( P < .001 \)). People who were on medication for 1 year were more WTU the expert management service (OR 1.773, SE .365; \( P = .005 \)). The explanatory power of the model with all predictors was 7.2%. We also performed logistic regression analyses to examine the WTP. Private and public service users had higher WTP than nonusers (\( \beta = -.486, SE .098; P < .001 \)). In terms of demographics, women had a greater WTP for the service than men (\( \beta = .233, SE .082; P = .03 \)). The explanatory power of WTP was 5.9%.

WTU and WTP in Scenario C (Chronic Patient Situation and Expert Management)

We conducted linear regression analyses to explore the WTU in scenario C (see Multimedia Appendix 3). Several factors influenced the WTU: age, gender, type of service experience, and having high blood pressure or diabetes. To be specific, younger people (\( \beta = .982, SE .008; P = .03 \)) and women (\( \beta = .705, SE .091; P < .001 \)) had higher WTP than those who did not (\( \beta = -.397, SE .091; P < .001 \)). The explanatory power of WTP was 5.2%.
SE .119; P=.04) were more WTU the service. In the case of service experience, public service users showed greater WTU the expert management service than nonusers and private service users (nonusers: OR .413, SE .094; P<.001; private service users: OR .401, SE .098; P<.001). Regarding health status, those with high blood pressure or diabetes showed more WTU the service (OR 1.751, SE .487; P=.04). The explanatory power of the model with all predictors was 3.4%. The result of logistic analyses of the WTP showed that private service users had greater intention to pay than public service users (β=.264, SE .114; P=.02), whereas public service users had greater WTP than nonusers (β=.336, SE .096; P<.001). Women were more WTU for the service than men (β=.250, SE .080; P=.002), similar to scenario B. The explanatory power of the WTP was 5.4%.

**WTU and WTP in Scenario D (Chronic Patient Situation and Medical Management)**

We performed linear regression analyses to investigate the WTU of those in the chronic disease situation on the medical management service (see Multimedia Appendix 4). Age, gender, type of service experience, and having high blood pressure or diabetes influenced the WTU in scenario D. Specifically, younger people (OR .967, SE .009; P<.001) and women (OR .569, SE .106; P=.002) were more WTU the service. Similar to the other scenarios, public service users showed greater WTU the medical management service (nonusers: OR .480, SE .120; P=.003; private service users: OR .345, SE .089; P<.001). Those with high blood pressure or diabetes had higher intention to use the service (OR 1.894, SE .596; P=.04). The explanatory power of the model with all predictors was 5.2%. The result of logistic analyses of the WTP revealed that private and public service users were more WTP for the service than nonusers (β=.286, SE .092; P=.002). Those who experienced private services had a marginally higher WTP than those who used public services (β=.193, SE .111; P=.08). Younger people (β=.010, SE .004; P=.007) and women (β=.177, SE .779; P=.02) had a higher likelihood of paying for the medical management service. The explanatory power of the model for WTP was 4.4%.

**Discussion**

**Principal Findings**

We conducted a web-based survey to investigate the WTU and WTP according to the type of digital health intervention, wherein the respondents were divided into 3 groups (nonusers, public service users, and private service users). We also aimed to identify the factors that affect the WTU and WTP for digital health interventions.

Participants’ WTU and WTP for digital health interventions differed significantly based on their prior experience with health care services. Public service users tended to use digital health intervention more than nonusers and private service users, whereas private service users were more WTP for digital health interventions than the others. This trend was true for all 4 scenarios. Private service users had an average WTP that is 1.5 to 2 times higher than nonusers. However, in this study, it is not clear whether those with high WTP used private services or whether their WTP increased because of positive experiences with the services. Public service users were 1.2 to 1.5 times more WTP than nonusers. In the health-risk situation, there was no difference in the WTP between public and private service users, but the WTP of private service users was much higher than that of public service users in the chronic disease situation.

At first, we expected that private service users would have a higher intention to use digital health interventions. Contrary to our expectations, public service users showed higher WTU such interventions. This might imply higher motivation and interest in terms of health care among public service users. They must have visited the public health center at least thrice to avail the service for additional examination and counseling and receive activity trackers. As the public service is linked to the national health examination, perhaps they realized how severe their health condition was and felt the need for health care. Hence, they showed high intention to use digital health interventions in our study.

An individual’s health status is one of the most critical aspects of the WTP for digital health interventions. Even when the same service was to be provided by a nonmedical person (scenarios B and C), participants were WTP more after reading scenario C (chronic disease situation) than in scenario B (health-risk situation). Additionally, in the health-risk situation scenarios (A and B), having high blood pressure and diabetes did not affect their WTU digital health interventions. Rather, participants with such ailments were more WTP digital health interventions than the others in the chronic disease situation scenarios (C and D).

The content of the services provided is a factor that affects people’s WTP and WTU. This scenario was developed based on The National Institute for Health and Care Excellence’s Evidence Standards Framework. Scenario A is a self-care service that allows people to manage their health. Services in scenarios B and C help people manage exercise and diet with health care experts. In contrast, scenario D is a service in which medical professionals manage diseases with services verified to be effective. Participants wanted to use and pay more for the service in scenario D than in scenarios B and C. This result shows that the more professional and advanced the service, the more willing people are to use and pay for the service.

In scenario D, the importance of validating effectiveness in digital health care services was confirmed. Compared to other scenarios, people were WTP and WTU more for the service that validated their effectiveness. The previous study showed that the effectiveness of digital health care services is an essential factor for British health professionals [32]. Our result also indicated that service users also recognized the importance of effectiveness by clinical evidence.

Another factor highlighted in this study is the percentage of people who are WTP for services. Similar previous studies, the proportion of people WTP for services was at the level of 50% to 60%, and the rest were unwilling to pay [26]. This result indicates that it is necessary to work on the maturation of DHT. Like previous research [26,27,29], this study showed that age, gender, and income affected the WTP for digital health
interventions. Younger individuals and men were more WTP for digital health intervention services. However, the results regarding the WTU somewhat differed from previous studies. Women were more WTU digital health interventions than men in scenarios A, C, and D.

Limitation
First, the participants responded to hypothetical scenarios, which means that they answered based on what they imagined about a given situation. Their response to a similar real-life situation may distinctly differ. Their reactions to similar situations in practice may be different because of the service's various features that determine the price, such as governmental regulatory approval with significant evidence or the existence of a physician guide. Additionally, this study cited diabetes as an example of a chronic disease. Patients with other serious diseases may want to pay more for services. Despite this limitation, this study might help provide a lot of insight into developing user-centered services. Second, different countries have different health insurance systems, so the WTU and WTP in other nations may differ from the result of this study. The WTP presented in this study is the general price average for hypothetical scenarios, and attention is needed to interpret it directly. Third, the WTP in scenario A was higher than those in other scenarios. This may be attributed to the question order bias. To reduce this bias, the order of scenarios A to D could have been presented at random. However, we did not do so because we had to consider the presence or absence of disease and services. Fourth, the explanatory power of the regression analysis was not high. However, even in a previous study [27], the explanatory power of the WTP was 3% to 8%, close to the WTP explanatory power of 4.4% to 5.9% for scenarios A to D in this study.

Conclusion
Digital health care technology has continued to develop and is expected to grow further. More people are WTU their smartphones to manage their health, creating various health care innovations. Recently, there have been many discussions about expanding digital health care for general people, not only early adopters. However, studies have yet to be conducted on the WTU and WTP for digital health care. It is necessary to develop a deeper understanding of people’s awareness and acceptance of digital health care. Digital health care companies should develop their product based on this understanding. Since digital health care needs to work within the health care system, it is essential to evaluate the effectiveness of the services with clinical evidence.

Acknowledgments
This research was supported by the National Health Promotion Fund, funded by the Ministry of Health and Welfare, Republic of Korea, and by the Technology Innovation Program (20018246, Promotion of Digital Therapeutics Industry for Global Expansion), funded by the Ministry of Trade, Industry & Energy (MOTIE; Republic of Korea). We thank the Korea Health Promotion Institute and Noom for helping to recruit participants.

Conflicts of Interest
None declared.

Multimedia Appendix 1
Willingness to use (WTU) and willingness to pay (WTP) in scenario A (health-risk situation and self-management).
[DOCX File, 31 KB - mhealth_v11i1e40834_app1.docx]

Multimedia Appendix 2
Willingness to use (WTU) and willingness to pay (WTP) in scenario B (health-risk situation and expert management).
[DOCX File, 31 KB - mhealth_v11i1e40834_app2.docx]

Multimedia Appendix 3
Willingness to use (WTU) and willingness to pay (WTP) in scenario C (chronic disease situation and expert management).
[DOCX File, 32 KB - mhealth_v11i1e40834_app3.docx]

Multimedia Appendix 4
Willingness to use (WTU) and willingness to pay (WTP) in scenario D (chronic disease situation and medical management).
[DOCX File, 32 KB - mhealth_v11i1e40834_app4.docx]

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32. Leigh S, Ashall-Payne L, Andrews T. Barriers and facilitators to the adoption of mobile health among health care professionals from the United Kingdom: discrete choice experiment. JMIR mHealth uHealth 2020 Jul 06;8(7):e17704 [FREE Full text] [doi: 10.2196/17704] [Medline: 32628118]

Abbreviations

BfArM: Bundesamt für Arzneimittel und Medizinprodukte (German Federal Institute for Drugs and Medical Devices)

DiGA: digitale Gesundheitsanwendung (digital health applications)

DHT: digital health technology

OR: odds ratio

WTP: willingness to pay

WTU: willingness to use

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Economic Evaluation of Digital Therapeutic Care Apps for Unsupervised Treatment of Low Back Pain: Monte Carlo Simulation

Daniel Lewkowicz¹, MSc; Erwin Bottinger¹, Prof Dr; Martin Siegel², Prof Dr

¹Digital Health Center, Hasso Plattner Institute, University of Potsdam, Potsdam, Germany
²Department of Empirical Health Economics, Technische Universität Berlin, Berlin, Germany

Corresponding Author:
Daniel Lewkowicz, MSc
Digital Health Center
Hasso Plattner Institute
University of Potsdam
Prof.-Dr.-Helmert-Straße 2-3
Potsdam, 14482
Germany
Phone: 49 331 55094
Email: daniel.lewkowicz@hpi.de

Abstract

Background: Digital therapeutic care (DTC) programs are unsupervised app-based treatments that provide video exercises and educational material to patients with nonspecific low back pain during episodes of pain and functional disability. German statutory health insurance can reimburse DTC programs since 2019, but evidence on efficacy and reasonable pricing remains scarce. This paper presents a probabilistic sensitivity analysis (PSA) to evaluate the efficacy and cost-utility of a DTC app against treatment as usual (TAU) in Germany.

Objective: The aim of this study was to perform a PSA in the form of a Monte Carlo simulation based on the deterministic base case analysis to account for model assumptions and parameter uncertainty. We also intend to explore to what extent the results in this probabilistic analysis differ from the results in the base case analysis and to what extent a shortage of outcome data concerning quality-of-life (QoL) metrics impacts the overall results.

Methods: The PSA builds upon a state-transition Markov chain with a 4-week cycle length over a model time horizon of 3 years from a recently published deterministic cost-utility analysis. A Monte Carlo simulation with 10,000 iterations and a cohort size of 10,000 was employed to evaluate the cost-utility from a societal perspective. Quality-adjusted life years (QALYs) were derived from Veterans RAND 6-Dimension (VR-6D) and Short-Form 6-Dimension (SF-6D) single utility scores. Finally, we also simulated reducing the price for a 3-month app prescription to analyze at which price threshold DTC would result in being the dominant strategy over TAU in Germany.

Results: The Monte Carlo simulation yielded on average a €135.97 (a currency exchange rate of EUR €1=US $1.069 is applicable) incremental cost and 0.004 incremental QALYs per person and year for the unsupervised DTC app strategy compared to in-person physiotherapy in Germany. The corresponding incremental cost-utility ratio (ICUR) amounts to an additional €34,315.19 per additional QALY. DTC yielded more QALYs in 54.96% of the iterations. DTC dominates TAU in 24.04% of the iterations for QALYs. Reducing the app price in the simulation from currently €239.96 to €164.61 for a 3-month prescription could yield a negative ICUR and thus make DTC the dominant strategy, even though the estimated probability of DTC being more effective than TAU is only 54.96%.

Conclusions: Decision-makers should be cautious when considering the reimbursement of DTC apps since no significant treatment effect was found, and the probability of cost-effectiveness remains below 60% even for an infinite willingness-to-pay threshold. More app-based studies involving the utilization of QoL outcome parameters are urgently needed to account for the low and limited precision of the available QoL input parameters, which are crucial to making profound recommendations concerning the cost-utility of novel apps.

(JMIR Mhealth Uhealth 2023;11:e44585) doi:10.2196/44585
Introduction

Background

Low back pain (LBP) poses a tremendous health burden for patients and health care systems worldwide, with a lifetime prevalence of up to 85% [1,2]. For patients with nonspecific and nonacute LBP, current clinical guidelines recommend conservative treatment with physiotherapy at regular intervals and increased physical activity [3,4]. Smartphone or web-based digital therapeutic care (DTC) apps offer a novel unsupervised treatment modality for patients with nonspecific LBP [5]. Although DTC apps are now offered by numerous providers, they all follow the same treatment approach, in that video-based exercises aim to replace face-to-face physiotherapy and the provided educational material aims to reinforce patients' coping abilities for everyday life [5]. A major strength of DTC apps lies in their potential inclusion of decision support interventions, which include tailored push notifications and personalized exercise recommendations that guide subscribed patients through the treatment program [5-7]. These decision support interventions may stimulate persistent engagement and thereby enhance coping abilities and support long-term treatment compliance [8,9].

In Germany, the Digital Health Care Act allows statutory health insurance providers to reimburse DTC apps since December 2019, if sound scientific evidence indicates that they are an effective treatment alternative [10]. At present, there are 2 companies, namely ViViRa and HelloBetter, which have developed apps that can provide digital therapeutic via the smartphone or PC and that are now listed in the Digital Health Applications (DiGA) directory to be prescribed for patients with LBP via International Classification of Diseases-10 (ICD-10) code M54 [10]. This paper explores potential trade-offs between higher chances of achieving better long-term health outcomes through lasting behavioral changes, as well as the risk of reimbursing the cost without any benefit for the patients because of higher attrition rates for unsupervised DTC programs as compared to the treatment as usual (TAU; ie, physiotherapy and medication for temporary pain relief [11]).

Objectives

We applied a probabilistic sensitivity analysis (PSA) to address uncertainties in the transition probabilities, attrition rates, cost components, and health-related quality of life (QoL) scores, which were beyond the scope of the deterministic analysis recently published by Lewkowicz et al [11]. Amending the recently published deterministic analysis offers a relevant contribution to the literature because decision-making based on Markov chains, or other at least moderately complex or nonlinear models, should not be based solely on deterministic models but should include parameter uncertainty as well [12]. Moreover, we intended to explore to what extent the results in this probabilistic analysis differ from the results in the base case analysis and to what extent a shortage of outcome data concerning QoL metrics impacts the overall results. Hence, this underlying PSA intends to reveal the incapacity of a deterministic sensitivity analysis to overcome the challenges of a small patient cohort to simulate the long-term uncertain utility of an intervention. Accordingly, this study aims to inform researchers and decision-makers equally—both to underline the importance of a large data set of QoL data gathered from a large patient cohort and for future approvals of DTC apps for LBP regarding a potential price range, for which such apps may be expected to be a cost-effective alternative to the TAU.

Methods

Ethical Considerations

Because this was a simulation study with no human participants, ethics approval was not sought.

Model Framework

This paper builds on a recent analysis of the cost-utility of a DTC program for patients with nonacute LBP in Germany from a societal perspective [11]. The adopted state-transition model in Figure 1 comprises seven distinct health states: (1) low impact of LBP, (2) high impact of LBP, (3) treatment weeks 1 to 4, (4) treatment weeks 5 to 8, (5) treatment weeks 9 to 12, (6) remission, and (7) healthy. States 3, 4, and 5 represent different phases of the treatment progress. State 6 is a state of only temporary improvement, which allows for reoccurring phases with higher or lower pain intensities in the simulation, and state 7 is the final healthy state where no recrudescence can occur.

Like Lewkowicz et al [11], we covered a model time horizon of 3 years and used a cycle length of 4 weeks to allow the inclusion of different treatment states and for patients to drop out before finishing the 3-month course of treatment. Since no published evaluation studies for the ViViRa or HelloBetter DTC apps were available, Lewkowicz et al [11] employed outcome data from an evaluation of the Kaia Health app against 6 face-to-face physiotherapy sessions over a period of 12 weeks [13], arguing that the Kaia Health app is sufficiently similar to the 2 apps currently listed in the DiGA directory.

The transition probabilities for states 3, 4, and 5 were derived from the attrition rates reported in the Kaia Health app study [13]. Patients undergoing app-based treatment continued the program with a chance of 87.5% after each month. In the TAU group, 93.5% of the patients continued the recommended treatment program after the first month, and 95.7% continued after the second month. A recent systematic review on the effects of DTC apps for patients with LBP confirmed this pattern and found that attrition rates can even peak up to 80% in noncontrolled retrospective studies [5].
Lewkowicz et al [11] incorporated several assumptions in their model to be able to specify transition probabilities for their Markov chain. First, the probability of LBP patients visiting a general practitioner, and thus entering treatment, was set to 75% for low-impact LBP and to 80% for high-impact LBP. Second, 50% of the dropout patients were assumed to experience health improvements and thus move to the temporary remission state (state 6). The other 50% of the dropout patients were assumed to have stopped because of coping issues, lack of motivation, or time constraints. Of these, 82.5% fell back into the low-impact LBP state (state 1) and 17.8% fell back into the high-impact LBP state (state 2). Finally, the decision support interventions integrated into the DTC app were assumed to yield a 5% higher chance to transfer to the healthy state (state 7) [8,9,11] than in the TAU strategy [13]. We use the same figures here and display the resulting transition matrices for DTC and TAU in Table 1.

Lewkowicz et al [11] utilized the Veterans RAND 6-Dimension (VR-6D) preference single-utility index [14] derived from the Kaia Health study data [13] for QoL in states 1, 3, 4, and 5. For the remaining states, utility scores based on the Short-Form 6-Dimension (SF-6D) scale were retrieved from other lower back pain (LBP) studies [15,16]. The cost components taken from [11] include direct costs for general practitioner and orthopedic consultations, diagnostic procedures, medication, and indirect costs through nonproductive time due to LBP. The price for the DTC app is the current reimbursement price of the ViViRa app of €239.96 for a 3-month prescription (a currency exchange rate of EUR €1=US $1.069 is applicable throughout this paper) [17]. The cost of face-to-face physiotherapy was set to €21.11 per session according to the binding German medical fee schedule [18]. The included utility scores and cost data were discounted with a discount factor of 3% [11].
### Table 1. Transition matrix of the Markov chain.

<table>
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<tr>
<th>To and from</th>
<th>Low impact (state 1)</th>
<th>High impact (state 2)</th>
<th>Treatment weeks 1-4 (state 3)</th>
<th>Treatment weeks 5-8 (state 4)</th>
<th>Treatment weeks 9-12 (state 5)</th>
<th>Remission (state 6)</th>
<th>Healthy (state 7)</th>
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<td></td>
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<td>0.75&lt;sup&gt;b&lt;/sup&gt;</td>
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<td>0.0375</td>
<td>0</td>
</tr>
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<td>0.75&lt;sup&gt;b&lt;/sup&gt;</td>
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<td>0</td>
<td>0.0375</td>
<td>0</td>
</tr>
<tr>
<td><strong>High impact (state 2)</strong></td>
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<tr>
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<td>0</td>
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<td>0</td>
</tr>
<tr>
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<td>0</td>
<td>0</td>
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<tr>
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<tr>
<td>DTC</td>
<td>0.5047</td>
<td>0.1092</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.386</td>
<td>0</td>
</tr>
<tr>
<td>TAU</td>
<td>0.5047</td>
<td>0.1092</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.386</td>
<td>0</td>
</tr>
<tr>
<td><strong>Healthy (state 7)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DTC</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>TAU</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

<sup>a</sup>DTC: digital therapeutic care.

<sup>b</sup>Transition probabilities taken from the literature. All other transition probabilities in the respective rows are calculated from conditional probabilities given the respective event based on [11].

<sup>c</sup>TAU: treatment as usual.

### PSA Measure

For the PSA, which is a robust method to evaluate the impact of parameter uncertainties [12], we employed the aforementioned model and performed a Monte Carlo simulation with 10,000 iterations. In each iteration, the input parameters were randomly drawn from a priori–defined probability distributions for an entire cohort of 10,000 hypothetical patients. The model time horizon was 3 years with a state length of 4 weeks. We employed a beta distribution to simulate transition probabilities and QoL parameters and a gamma distribution to simulate costs.

We considered the input parameters for transition probabilities and QoL outcomes from the literature as “most likely” values and applied the Program Evaluation and Review Technique (PERT) approximation [19-21] to transform them into estimates for our mean and SD calculations [22] (Multimedia Appendix 1A). We then obtained the shape parameters $\alpha$ and $\beta$ for the beta distribution through the method of moments [18,21]:

$$\alpha = \frac{\text{Mean}}{\text{SD}} \quad \beta = \frac{\text{Mean}}{\text{Mean}^2 - \text{SD}^2}$$

We applied the gamma distribution for all cost components, which requires the mean and SD of the cost components as input parameters. We used the results for direct and indirect cost components of chronic LBP over a 6-month period reported in a large German cost-of-illness study [23] to obtain cost estimates for health states 1, 2, 3, 4, and 5. We assumed costs to be distributed evenly over time and rescale the reported mean costs and the upper and lower limit of the 95% CIs to monthly costs. We derive the SD from the rescaled 95% CIs by dividing the range between the upper and lower limit by twice the 97.5% quantile of the normal distribution [24]:

$$SD = \frac{\text{Upper Limit} - \text{Lower Limit}}{2 \times 1.96}$$

where $n=51$ [23].

We deviated from the assumption in [11] that all physiotherapy costs occur in the first treatment cycle and allocated costs for weekly physiotherapy sessions to states 3 and 4 because they...
can only be paid if patients continue their treatment. Costs for 4 of the 6 physiotherapy sessions were allocated to state 3, and the remainder was allocated to state 4. The adapted input parameters, including the corresponding distribution parameters, are shown in Tables 2, 3, and 4. Multimedia Appendix 1B contains a full list of all parameters and probability density functions, and Multimedia Appendices 2-5 contain histograms of the parameters and matrices.

We derived cost-effectiveness acceptability curves (CEACs) to illustrate the probability of DTC apps being a cost-effective measure given a certain willingness-to-pay (WTP) threshold. The CEAC indicated the fraction of iterations considered to be cost-effective given a specific WTP. Graphically, the WTP threshold was a line through the origin with a slope equal to the respective WTP, and the outcome of an iteration in the Monte Carlo simulation was considered to be cost-effective if it lies below the WTP threshold in the cost-utility plane [22].

Some health care systems may only adopt novel technologies which are more effective than TAU, (ie, if its incremental effect is nonnegative). We derived an additional CEAC where we included only outcomes that lay in the southeast quadrant or in the northeast quadrant under the WTP threshold in the cost-utility plane to account for this constraint. Moreover, we computed the number of iterations where DTC strictly dominates TAU (ie, where cost_DTC<cost_TAU and effect_DTC>effect_TAU, and vice-versa).
Table 2. Transition probabilities and beta parameters for simulation after PERT\textsuperscript{4} transformation.

<table>
<thead>
<tr>
<th>Transition probability</th>
<th>Expected value(b)</th>
<th>SD(c)</th>
<th>(\alpha^d)</th>
<th>(\beta^d)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Temporary health states</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low impact (state 1) to</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low impact (state 1)</td>
<td>0.30000</td>
<td>0.16667</td>
<td>1.96800</td>
<td>4.59200</td>
</tr>
<tr>
<td>High impact (state 2)</td>
<td>0.02439</td>
<td>0.01234</td>
<td>3.78404</td>
<td>151.36171</td>
</tr>
<tr>
<td>Treatment weeks 1-4 (state 3)</td>
<td>0.66667</td>
<td>0.16667</td>
<td>4.66667</td>
<td>2.33333</td>
</tr>
<tr>
<td>Remission (state 6)</td>
<td>0.06977</td>
<td>0.03612</td>
<td>3.40097</td>
<td>45.34629</td>
</tr>
<tr>
<td>High Impact (state 2) to</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low Impact (state 1)</td>
<td>0.07749</td>
<td>0.04027</td>
<td>3.33817</td>
<td>39.74008</td>
</tr>
<tr>
<td>High Impact (state 2)</td>
<td>0.27200</td>
<td>0.16667</td>
<td>1.66970</td>
<td>4.46160</td>
</tr>
<tr>
<td>Treatment weeks 1-4 (state 3)</td>
<td>0.70000</td>
<td>0.16667</td>
<td>4.59200</td>
<td>1.96800</td>
</tr>
<tr>
<td>Remission (state 6)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low impact (state 1)</td>
<td>0.50314</td>
<td>0.16667</td>
<td>4.02493</td>
<td>3.97471</td>
</tr>
<tr>
<td>High impact (state 2)</td>
<td>0.17938</td>
<td>0.09793</td>
<td>2.57361</td>
<td>11.77401</td>
</tr>
<tr>
<td>Remission (state 6)</td>
<td>0.42400</td>
<td>0.16667</td>
<td>3.30384</td>
<td>4.48823</td>
</tr>
<tr>
<td><strong>DTC(e)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment weeks 1-4 (state 3) to</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low impact (state 1)</td>
<td>0.09318</td>
<td>0.04880</td>
<td>3.21274</td>
<td>31.26755</td>
</tr>
<tr>
<td>High impact (state 2)</td>
<td>0.02177</td>
<td>0.01100</td>
<td>3.80694</td>
<td>171.09847</td>
</tr>
<tr>
<td>Treatment weeks 5-8 (state 4)</td>
<td>0.80000</td>
<td>0.11024</td>
<td>9.73257</td>
<td>2.43314</td>
</tr>
<tr>
<td>Remission (state 6)</td>
<td>0.11111</td>
<td>0.05871</td>
<td>3.07279</td>
<td>24.58235</td>
</tr>
<tr>
<td>Treatment weeks 5-8 (state 4) to</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low impact (state 1)</td>
<td>0.09318</td>
<td>0.04880</td>
<td>3.21274</td>
<td>31.26755</td>
</tr>
<tr>
<td>High impact (state 2)</td>
<td>0.02177</td>
<td>0.01100</td>
<td>3.80694</td>
<td>171.09847</td>
</tr>
<tr>
<td>Treatment weeks 9-12 (state 5)</td>
<td>0.80000</td>
<td>0.11024</td>
<td>9.73257</td>
<td>2.43314</td>
</tr>
<tr>
<td>Remission (state 6)</td>
<td>0.11111</td>
<td>0.05871</td>
<td>3.07279</td>
<td>24.58235</td>
</tr>
<tr>
<td>Treatment weeks 9-12 (state 5) to</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low impact (state 1)</td>
<td>0.32339</td>
<td>0.16667</td>
<td>2.22404</td>
<td>4.65314</td>
</tr>
<tr>
<td>High impact (state 2)</td>
<td>0.09241</td>
<td>0.04838</td>
<td>3.21882</td>
<td>31.61410</td>
</tr>
<tr>
<td>Remission (state 6)</td>
<td>0.57600</td>
<td>0.16667</td>
<td>4.48823</td>
<td>3.30384</td>
</tr>
<tr>
<td>Healthy (state 7)</td>
<td>0.16667</td>
<td>0.09045</td>
<td>2.66255</td>
<td>13.31276</td>
</tr>
<tr>
<td><strong>TAU(f)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment weeks 1-4 (state 3) to</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low impact (state 1)</td>
<td>0.05072</td>
<td>0.02601</td>
<td>3.55883</td>
<td>66.60730</td>
</tr>
<tr>
<td>High impact (state 2)</td>
<td>0.01144</td>
<td>0.00575</td>
<td>3.89784</td>
<td>336.89235</td>
</tr>
<tr>
<td>Treatment weeks 5-8</td>
<td>0.88496</td>
<td>0.06090</td>
<td>23.40459</td>
<td>3.04260</td>
</tr>
<tr>
<td>Remission</td>
<td>0.06103</td>
<td>0.03146</td>
<td>3.47283</td>
<td>53.42822</td>
</tr>
<tr>
<td>Treatment weeks 5-8 (state 4) to</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low impact (state 1)</td>
<td>0.03414</td>
<td>0.01736</td>
<td>3.69970</td>
<td>104.67097</td>
</tr>
<tr>
<td>High impact (state 2)</td>
<td>0.00760</td>
<td>0.00381</td>
<td>3.93198</td>
<td>513.71610</td>
</tr>
<tr>
<td>Treatment weeks 9-12</td>
<td>0.92081</td>
<td>0.04119</td>
<td>38.65633</td>
<td>3.32444</td>
</tr>
<tr>
<td>Remission</td>
<td>0.04123</td>
<td>0.02104</td>
<td>3.63908</td>
<td>84.62987</td>
</tr>
<tr>
<td>Transition probability</td>
<td>Expected value^b</td>
<td>SD^c</td>
<td>α^d</td>
<td>β^d</td>
</tr>
<tr>
<td>------------------------</td>
<td>------------------</td>
<td>------</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td><strong>Treatment weeks 9-12 (state 5) to</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low impact (state 1)</td>
<td>0.35079</td>
<td>0.16667</td>
<td>2.52522</td>
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</tr>
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<td>High impact (state 2)</td>
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<td>0.05633</td>
<td>3.10581</td>
<td>25.96486</td>
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<td>Remission (state 6)</td>
<td>0.57600</td>
<td>0.16667</td>
<td>4.48823</td>
<td>3.30384</td>
</tr>
<tr>
<td>Healthy (state 7)</td>
<td>0.09091</td>
<td>0.04756</td>
<td>3.23069</td>
<td>32.30693</td>
</tr>
</tbody>
</table>

^aPERT: Program Evaluation and Review Technique.
^bFirst moment: “Most likely” (expected) value taken from [11].
^cSD for calculation of the second moment taken from [11].
^dShape parameters α and β for beta distribution were calculated using the method of moments.
^eDTC: digital therapeutic care.
^fTAU: treatment as usual.

Table 3. Cost components.

<table>
<thead>
<tr>
<th>Cost components (health state)</th>
<th>Mean^a (SD^b)</th>
<th>α^c</th>
<th>β^c</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low impact (state 1)</td>
<td>441.74 (476.74)</td>
<td>0.8584</td>
<td>514.5364</td>
</tr>
<tr>
<td>High impact (state 2)</td>
<td>588.96 (476.74)</td>
<td>1.5261</td>
<td>385.9023</td>
</tr>
<tr>
<td><strong>Treatment weeks 1-4 (state 3)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GP^d consultation</td>
<td>20.47 (43.93)</td>
<td>0.2171</td>
<td>94.2767</td>
</tr>
<tr>
<td>Medication</td>
<td>16.81 (35.36)</td>
<td>0.226</td>
<td>74.3801</td>
</tr>
<tr>
<td>Diagnostic procedure</td>
<td>29.24 (53.72)</td>
<td>0.2962</td>
<td>98.6948</td>
</tr>
<tr>
<td>Indirect cost</td>
<td>147.47 (476.74)</td>
<td>0.0953</td>
<td>1543.6092</td>
</tr>
<tr>
<td>App price (only DTC^e)</td>
<td>239.96 (N/A^f)</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>4 × physiotherapy (only TAU^g)</td>
<td>102.88 (44.4266)</td>
<td>5.363</td>
<td>19.184</td>
</tr>
<tr>
<td><strong>Treatment weeks 5-8 (state 4)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medication</td>
<td>16.81 (35.36)</td>
<td>0.226</td>
<td>74.3801</td>
</tr>
<tr>
<td>2 × physiotherapy (only TAU)</td>
<td>46.44 (22.2133)</td>
<td>4.3711</td>
<td>10.6249</td>
</tr>
<tr>
<td><strong>Treatment weeks 9-12 (state 5)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medication</td>
<td>16.81 (35.36)</td>
<td>0.226</td>
<td>74.3801</td>
</tr>
</tbody>
</table>

^aMean values taken from [11].
^bSD calculated from 95% CIs reported in [23].
^cParameters α and β for Gamma distribution calculated from mean and SD values.
^dGP: general practitioner.
^eDTC: digital therapeutic care.
^fN/A: not applicable.
^gTAU: treatment as usual.
Table 4. Health-related QoL utility scores after PERT transformation.

<table>
<thead>
<tr>
<th>Health states</th>
<th>Expected value</th>
<th>SD</th>
<th>α</th>
<th>β</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low impact (state 1)</td>
<td>0.655</td>
<td>0.0743</td>
<td>26.1445</td>
<td>13.7708</td>
</tr>
<tr>
<td>High impact (state 2)</td>
<td>0.61</td>
<td>0.1248</td>
<td>8.7032</td>
<td>5.5643</td>
</tr>
<tr>
<td>Remission (state 6)</td>
<td>0.806</td>
<td>0.0713</td>
<td>23.9639</td>
<td>5.7679</td>
</tr>
<tr>
<td>Healthy (state 7)</td>
<td>0.806</td>
<td>0.0713</td>
<td>23.9639</td>
<td>5.7679</td>
</tr>
<tr>
<td>Treatment weeks 1-4 (state 3)</td>
<td>0.655</td>
<td>0.0766</td>
<td>24.5159</td>
<td>12.9129</td>
</tr>
<tr>
<td>Treatment weeks 5-8 (4)</td>
<td>0.699</td>
<td>0.0695</td>
<td>29.6712</td>
<td>12.7768</td>
</tr>
<tr>
<td>Treatment weeks 9-12 (5)</td>
<td>0.748</td>
<td>0.0699</td>
<td>28.1058</td>
<td>9.4687</td>
</tr>
<tr>
<td>Treatment weeks 1-4 (3)</td>
<td>0.655</td>
<td>0.0691</td>
<td>30.2894</td>
<td>15.954</td>
</tr>
<tr>
<td>Treatment weeks 5-8 (4)</td>
<td>0.717</td>
<td>0.0834</td>
<td>20.1705</td>
<td>7.9613</td>
</tr>
<tr>
<td>Treatment weeks 9-12 (5)</td>
<td>0.729</td>
<td>0.0862</td>
<td>18.6139</td>
<td>6.9196</td>
</tr>
</tbody>
</table>

aQoL: quality of life.
bPERT: Program Evaluation and Review Technique.
cQALY: quality-adjusted life year.
dFirst moment: “most likely” (expected) value taken from [11].
eShape parameters α and β for beta distribution were calculated using the method of moments.
fSD calculated from [13].
gSD calculated from [15].
hDTC: digital therapeutic care.
iTAU: treatment as usual.

**Results**

The 10,000 iterations of the Monte Carlo simulation yielded average costs of €2263.96 with an average of 0.6941 QALYs per person and year for DTC and an average cost of €2127.99 with an average of 0.6902 QALYs per person and year for TAU. Thus, the mean incremental cost is €135.97, and the mean incremental QALYs are 0.004 per person and year for the DTC app. The corresponding incremental cost-utility ratio (ICUR) amounts to an additional €34,315.19 per additional QALY. 

Table 5 shows the summary statistics of the relevant cost and effectiveness outcomes.

Figure 2 shows the simulation results per person and year in the cost-utility plane, where each of the dots reflects 1 outcome of one of the 10,000 Monte Carlo simulations. The histograms on the axes confirm the numbers from the table, which indicate that the mean and median incremental effect, as well as the mean and median incremental cost, are positive. The diagonal line visualizes the estimated average ICUR of 34,315.19.
Table 5. Summary statistics of the relevant cost and effectiveness outcomes\textsuperscript{a}.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mean (SD)</th>
<th>Median</th>
<th>Min\textsuperscript{b}</th>
<th>Max\textsuperscript{c}</th>
</tr>
</thead>
<tbody>
<tr>
<td>DTC\textsuperscript{d} cost (€)</td>
<td>2263.96 (1467.69)</td>
<td>1853.92</td>
<td>413.53</td>
<td>22108.91</td>
</tr>
<tr>
<td>DTC cost (€) (hypothetical if app price is € 0)</td>
<td>1830.94 (1456.95)</td>
<td>1420.13</td>
<td>99.77</td>
<td>21544.24</td>
</tr>
<tr>
<td>DTC QALYs\textsuperscript{e}</td>
<td>0.6941 (0.0321)</td>
<td>0.6944</td>
<td>0.5608</td>
<td>0.8223</td>
</tr>
<tr>
<td>TAU\textsuperscript{f} cost (€)</td>
<td>2127.99 (1459.20)</td>
<td>1736.76</td>
<td>251.55</td>
<td>21033.72</td>
</tr>
<tr>
<td>TAU QALYs</td>
<td>0.6902 (0.0309)</td>
<td>0.6909</td>
<td>0.5711</td>
<td>0.7997</td>
</tr>
<tr>
<td>Incremental cost (€)</td>
<td>135.97 (484.54)</td>
<td>149.88</td>
<td>-4748.22</td>
<td>4551.22</td>
</tr>
<tr>
<td>Incremental cost (€) (hypothetical, if app price is 0)</td>
<td>1830.9 (1456.9)</td>
<td>1420.1</td>
<td>99.77</td>
<td>21544.2</td>
</tr>
<tr>
<td>Incremental QALYs</td>
<td>0.0040 (0.0296)</td>
<td>0.0038</td>
<td>-0.0950</td>
<td>0.1484</td>
</tr>
</tbody>
</table>

\textsuperscript{a}Table shows summary statistics of the simulation results for the regular app price of €239 (a currency exchange rate of EUR €1=US $1.069 is applicable) and the hypothetical scenario with an app price of €0 per person and year.

\textsuperscript{b}Min: minimum.

\textsuperscript{c}Max: maximum.

\textsuperscript{d}DTC: digital therapeutic care.

\textsuperscript{e}QALY: quality-adjusted life year.

\textsuperscript{f}TAU: treatment as usual.

Figure 2. Monte Carlo simulation results per person and year in the cost-utility plane. Each dot represents incremental quality-adjusted life years (QALYs) and incremental costs for one simulated outcome in the cost-utility-plane. Histograms on axes visualize the marginal distributions of incremental costs and incremental QALYs.

DTC was costlier than TAU in 66.53% of the iterations but also yielded more QALYs in 54.96% of the iterations. DTC dominated TAU in 24.04% of the iterations, whereas TAU dominated DTC in 35.61% of the iterations. Table 6 gives an overview of the number of iterations, which indicate the different findings.

The CEAC in Figure 3 illustrates the probability of cost-effectiveness for given WTP thresholds. The solid black line depicts the probability of the DTC strategy being cost-effective given a certain WTP when taking all potential health outcomes into account. The dashed line indicates the probability of DTC being cost-effective at a given WTP under the additional condition that DTC is only acceptable if it produces better health outcomes than TAU. The solid gray line at 54.96% indicates the highest probability of cost-effectiveness at an infinite WTP. Since only 54.96% of the iterations yielded a positive incremental effect and negative incremental effects are unacceptable at an infinite WTP even without the additional condition, both CEACs approximate this threshold.
Table 6. Overview of the numbers of iterations, which indicate the different outcomes.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Current app price (€239), %</th>
<th>Hypothetical app price (€0), %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive incremental treatment outcome</td>
<td>54.96</td>
<td>54.96</td>
</tr>
<tr>
<td>Negative incremental treatment outcome</td>
<td>45.04</td>
<td>45.04</td>
</tr>
<tr>
<td>Positive incremental cost</td>
<td>66.53</td>
<td>17.64</td>
</tr>
<tr>
<td>Negative incremental cost</td>
<td>33.47</td>
<td>82.36</td>
</tr>
<tr>
<td>DTC(^a) dominant</td>
<td>24.04</td>
<td>48.85</td>
</tr>
<tr>
<td>TAU(^b) dominant</td>
<td>35.61</td>
<td>11.53</td>
</tr>
</tbody>
</table>

\(^a\)DTC: digital therapeutic care.
\(^b\)TAU: treatment as usual.

Figure 3. Cost-effectiveness acceptability curve (CEAC) for quality-adjusted life years (QALYs).

When including iterations with negative incremental effects, the minimum probability of DTC being effective was 33.47%, corresponding to the fraction of iterations with negative incremental costs. The CEAC reached 50% at a WTP of approximately €41,000, flattened at a WTP of around €80,000, and approximated the maximum possible probability of cost-effectiveness of 54.96% when the WTP tended to infinity. When excluding outcomes with negative incremental effects, DTC was only considered to be cost-effective with a probability of 24.04% for a WTP of €0, corresponding to the fraction of iterations in which DTC strictly dominated TAU. The restricted CEAC reached a probability of cost-effectiveness of 50% only at a WTP of approximately €60,000. Like the unrestricted CEAC, the restricted CEAC flattened around a WTP of €80,000 and approximated the maximum possible probability of cost-effectiveness of 54.96% when WTP tended to infinity.

We reran the Monte Carlo simulation using the same aforementioned figures but with the app cost set to €0 to assess the cost-effectiveness of DTC if the app was available free of charge. Decreasing the app price to €0 yielded a decrease in the incremental cost to €−297.04 and thus a decrease in the ICUR to €−74,964.87. Note that using the same random seed in both simulations assured that the effects and simulated courses of treatment and compliance remained unchanged. Comparing the ICUR with app prices of €239 and €0 allowed us to determine the association between app price and ICUR, which amounts to an increase in the ICUR of €455.41 for each additional Euro charged for a 3-month period. Although the ICUR would be negative for an app price below €164.61, the estimated probability of DTC being more effective than TAU was only 54.96%.

Discussion

Principal Findings

This paper presents a PSA to evaluate the potential benefits of an app-based DTC program for patients with LBP in comparison to the TAU in Germany. We found the resulting ICUR to be substantially higher compared to the ICUR in the deterministic base case analysis, indicating that DTC apps are not clearly cost-effective at the current app price of €239 compared to TAU in Germany. The PSA yielded incremental costs of €135.97 and 0.004 incremental QALYs per patient and year for the DTC app. The resulting ICUR was €34,315.19 per QALY gained, as compared to €5,486 reported in [11]. The highest probability of cost-effectiveness for DTC in the PSA was 54.96% at an
infinite WTP. Reducing the app price in the simulation from €239.96 to €164.61 for a 3-month prescription could yield a negative ICUR and thus make DTC the dominant strategy, even though the estimated probability of DTC being more effective than TAU is only 54.96%.

The large difference between the ICUR of 34,315.19 found in the PSA and the ICUR of 5,486 reported in [11] can be attributed to the differences in the incremental effects: DTC yielded 0.6941 QALYs per patient and year in the PSA, whereas Lewkowicz et al [11] found 0.697 QALYs per year for DTC. The PSA yielded 0.6902 QALYs per year for TAU, which is similar to the 0.689 QALYs per year reported for TAU in [9].

Overall, the stark difference between the outcome from the PSA and from [11] may be explained by the infinitesimally small incremental effect, indicating that DTC and TAU were similarly effective both in the PSA and in [11]. Since the incremental QALYs appear in the denominator and are close to 0, even small differences may produce drastically different ICURs. With this outcome, a high measurement precision would be required to allow reliable inference from the results, but the available QoL estimate is a single-study outcome derived from 42 participants of the Kaia Health App trial [13], which found no significant difference between DTC and TAU. By including additional states for temporary (state 6) and lasting (state 7) health improvements and simulating a 3-year period, our PSA goes beyond the information available in [13] but still produces similar findings in terms of QoL.

Although a recent review found 12 studies on 6 different DTC apps with implemented decision support interventions, the control groups in those studies received no specific treatment [5]. To the best of our knowledge, the only existing relevant study comparing a DTC app with physiotherapy for our evaluation is the Kaia Health App trial [13], which offered only imprecise estimates for the treatment effect. The limited precision of the available QoL input parameters is reflected in the rather flat histogram of incremental QALYs in Figure 2, which clearly calls for further studies to explore the effects of DTC and decision support interventions on compliance and QoL outcomes for patients with LBP. Particularly, considering that the underlying randomized controlled trial (RCT) [13] only involved a small patient cohort in the app-based intervention group, studies with greater patient cohorts are needed to achieve more precise estimates and to outweigh outlier potentials.

The incremental costs of €135.97 found in the PSA are fairly similar to the €121.59 reported in [11]. The primary cost driver in the DTC strategy is the fixed app prescription cost, which occurs every time a patient starts a new treatment program, entering state 3 in the model. These high initial fees may backfire for such highly scalable and easily available app programs, especially if patients’ compliance is unobservable, and there is a high risk for early discontinuation of the DTC. In our simulation, we allowed that the DTC could be prescribed multiple times for 1 patient, which we considered realistic. The higher attrition rate in DTC than in TAU reinforces this major cost driver since the cost of DTC in health state 3 is €239.96 and thus substantially higher than the cost of 4 physiotherapy sessions of €102.88 in the first month. However, it is unclear how often a physician will prescribe the DTC app for the same patient in real life if that patient repeatedly aborts treatment.

Our scenario analysis focused on the effects of the app cost and investigated how the reimbursement price could be updated to render app-based treatment as a cost-effective alternative. The results suggest that an adjusted app reimbursement price less than €164.61, which would be slightly higher than the presumed costs for physiotherapy in the TAU, could lead to negative incremental costs, thus yielding a negative ICUR for the DTC app. Therefore, according to our model, a reimbursement price below €54.87 per month could make DTC somewhat less costly than face-to-face physiotherapy, while the health outcomes cannot be considered to differ significantly between TAU and DTC.

Different DTC programs with different app components and divergently progressed decision support interventions are associated with different overall cost-utility outcomes. While the core components and the core method of health care delivery are similar among these apps, further implementations such as virtual reality guidance during exercises or personalized feedback interventions through push notifications may improve the efficacy of DTC programs and generate increased effects on the QoL of LBP patients. Extended capabilities of decision support interventions may have a significantly positive impact on the long-term outcome [5,9].

To the best of our knowledge, along with [11], this is the first cost-effectiveness analysis for a DTC app based on a RCT for patients with LBP. While we found no clear evidence for a positive incremental effect on health-related QoL but a noticeable increase in cost for the DTC app for LBP, recent studies found DTC apps to be a cost-effective and promising approach for the treatment of unipolar depression [25] and essential hypertension [24].

Limitations

The shortage of data may involve potential biases in the parameters of the distributions. We applied the PERT approach to derive probability density functions for the transition probabilities and considered the base-case values from [11] as “most likely” values. However, even though most of the probabilities represent reasonable scenarios in the treatment of LBP, not all parameter values could be derived from clinical findings.

For the gamma distribution, the input values for the standard deviation parameter were derived from a German cost-of-illness study and adopted for the cost components in the PSA. Since we found no information in the literature on potential correlations between different cost components, we sampled each cost component independently in the PSA. The cost outcome may thus be biased either upward or downward, depending on whether higher costs in 1 component increase (eg, if more physician visits trigger more prescriptions) or decrease (eg, if seeing the physician more often avoids costs in other components) the costs in other components. However, since indirect costs make up the largest part of total cost and all cost parameters except for the app reimbursement price and cost of face-to-face physiotherapy are equally included in both
strategies, we argue that the missing correlations may have only a relatively small impact on our overall findings.

Our model focused on the direct comparison between the cost of unsupervised DTC and personal physiotherapy, and we excluded inpatient and rehabilitation care, as well as minor ambulatory treatment modalities. Overall, only 81% of total LBP-related health care expenditures were considered in our simulation [23]. It remains unclear what effect an increased use of DTC would have on the utilization of, for instance, injection therapy or surgery. However, we argue that the exclusion of such treatment options does not influence the incremental cost outcome, especially since injection therapy and surgery are usually applied in acute and highly severe cases.

Finally, measuring QoL through 2 different metrics (ie, the SF-6D and VR-6D) is another potential limitation. We acknowledge that using different outcome metrics for 1 simulation is not recommended but argue that SF-6D and VR-6D tend to be highly correlated and yield comparable outcomes, so they may be used interchangeably [14]. Since for both strategies each metric was used similarly for a respective health state, we argue that this methodological choice does not have an impact on the overall results. In addition, probing the results by rerunning the simulation as a cost-effectiveness analysis with pain reduction on a numerical rating scale yielded a similar distribution of the incremental treatment effect (results are available from the authors on request).

Conclusion
Allowing for parameter uncertainty yielded a significantly higher ICUR than the previously published deterministic approach. The CEACs indicate that the DTC approach is not very likely to be cost-effective, as the probability of cost-effectiveness remains below 55% even for an infinite WTP. One reason for the inconclusive result for QoL may be the high uncertainty, especially in health outcomes. At present, decision-makers should be cautious when considering the reimbursement of DTC apps, since no significant incremental effect on health was found. However, future developments of DTC apps may involve further decision support interventions, which may improve compliance, decrease attrition, and eventually yield better health outcomes. Future evaluations of DTC programs should strive to improve the precision of QoL outcome data and preferably aim to evaluate DTC apps with decision support interventions in a real-life environment.

Acknowledgments
This work has received funding from the European Union’s Horizon 2020 research and innovation program Smart4Health (grant 826117). It was also funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – Projektnummer 491466077

Data Availability
All data generated or analyzed during this study are included in this published paper and its Multimedia Appendix files.

Authors’ Contributions
DL and MS conceptualized the study. DL and MS were in charge of the Monte Carlo simulation and analyses, interpretation of the results, and writing of the manuscript. DL, MS, and EB contributed to refining all sections and critically editing the manuscript. All authors approved the submitted manuscript.

Conflicts of Interest
None declared.

Multimedia Appendix 1
A. Applying Program Evaluation and Review Technique (PERT) and Method of Moments (MoM) methods. B. Summary of probabilistic sensitivity analysis (PSA) input parameters and probability density functions. [PDF File (Adobe PDF File), 905 KB - mhealth_v11i1e44585_app1.pdf ]

Multimedia Appendix 2
Histogram: cost parameter. [PDF File (Adobe PDF File), 322 KB - mhealth_v11i1e44585_app2.pdf ]

Multimedia Appendix 3
Histogram: quality of life (QoL) parameter. [PDF File (Adobe PDF File), 391 KB - mhealth_v11i1e44585_app3.pdf ]

Multimedia Appendix 4
Histogram: digital therapeutic care (DTC) transition matrix.
Multimedia Appendix 5
Histogram: treatment-as-usual (TAU) transition matrix.

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Abbreviations

CEAC: cost-effectiveness acceptability curve
DIGA: Digital Health Applications
DTC: digital therapeutic care
ICD-10: International Classification of Diseases 10th revision
ICUR: incremental cost-utility ratio
LBP: low back pain
PERT: Program Evaluation and Review Technique
PSA: probabilistic sensitivity analysis
QALY: quality-adjusted life year
QoL: quality of life
RCT: randomized controlled trial
SF-6D: Short-Form 6-Dimension
TAU: treatment as usual
VR-12D: Veterans RAND 12-Item Health Survey
VR-6D: Veterans RAND 6-Dimension
WTP: willingness to pay

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The Impact of a Digital Weight Loss Intervention on Health Care Resource Utilization and Costs Compared Between Users and Nonusers With Overweight and Obesity: Retrospective Analysis Study

Ellen Siobhan Mitchell1, PhD; Alexander Fabry1, MPhil; Annabell Suh Ho1, PhD; Christine N May1, PhD; Matthew Baldwin1, PhD; Paige Blanco1, MPH; Kyle Smith1, BSBA; Andreas Michaelides1, PhD; Mostafa Shokoohi2, PhD; Michael West3, MSc; Kim Gotera2, MSc; Omnya El Massad2, MSc; Anna Zhou2, MSc

1Academic Research, Noom, Inc, New York City, NY, United States
2Eversana, Burlington, ON, Canada
3Eversana, Sydney, NS, Canada

Corresponding Author:
Christine N May, PhD
Academic Research
Noom, Inc
450 W 33rd St
New York City, NY, 10001
United States
Phone: 1 8882665071
Email: christinem@noom.com

Abstract

Background: The Noom Weight program is a smartphone-based weight management program that uses cognitive behavioral therapy techniques to motivate users to achieve weight loss through a comprehensive lifestyle intervention.

Objective: This retrospective database analysis aimed to evaluate the impact of Noom Weight use on health care resource utilization (HRU) and health care costs among individuals with overweight and obesity.

Methods: Electronic health record data, insurance claims data, and Noom Weight program data were used to conduct the analysis. The study included 43,047 Noom Weight users and 14,555 non–Noom Weight users aged between 18 and 80 years with a BMI of ≥25 kg/m² and residing in the United States. The index date was defined as the first day of a 3-month treatment window during which Noom Weight was used at least once per week on average. Inverse probability treatment weighting was used to balance sociodemographic covariates between the 2 cohorts. HRU and costs for inpatient visits, outpatient visits, telehealth visits, surgeries, and prescriptions were analyzed.

Results: Within 12 months after the index date, Noom Weight users had less inpatient costs (mean difference [MD] −US $20.10, 95% CI −US $30.08 to −US $10.12), less outpatient costs (MD −US $124.33, 95% CI −US $159.76 to −US $88.89), less overall prescription costs (MD −US $313.82, 95% CI −US $565.42 to −US $88.89), and less overall health care costs (MD −US $450.39, 95% CI −US $706.28 to −US $62.21) per user than non–Noom Weight users. In terms of HRU, Noom Weight users had fewer inpatient visits (MD −0.03, 95% CI −0.04 to −0.03), fewer outpatient visits (MD −0.78, 95% CI −0.93 to −0.62), fewer surgeries (MD −0.01, 95% CI −0.01 to 0.00), and fewer prescriptions (MD −1.39, 95% CI −1.76 to −1.03) per user than non–Noom Weight users. Among a subset of individuals with 24-month follow-up data, Noom Weight users incurred lower overall prescription costs (MD −US $1139.52, 95% CI −US $1972.21 to −US $306.83) and lower overall health care costs (MD −US $1219.06, 95% CI −US $2061.56 to −US $376.55) per user than non–Noom Weight users. The key differences were associated with reduced prescription use.

Conclusions: Noom Weight use is associated with lower HRU and costs than non–Noom Weight use, with potential cost savings of up to US $1219.06 per user at 24 months after the index date. These findings suggest that Noom Weight could be a cost-effective weight management program for individuals with overweight and obesity. This study provides valuable evidence for health care providers and payers in evaluating the potential benefits of digital weight loss interventions such as Noom Weight.
Introduction

Background

Rising rates of obesity globally [1] have led to substantial increases in related health care expenditures. From 2000 to 2018, the age-adjusted rate of obesity in the United States increased from 30.5% to 42.4%, with 76.5% of the adult population classified as either overweight or obese in 2018 [2]. Between 1998 and 2016, obesity-related health care spending in the United States increased from US $111.7 to US $170.3 billion [3] to US $182 to US $288 billion (2021 US dollars) [4,5]. Obesity is associated with an increase in direct annual medical costs ranging from US $1961 [5] to US $3423 [4] per individual (2021 US dollars). Furthermore, obesity-related comorbidities are among the greatest contributors to total US annual medical expenditures, including US $126 billion for diabetes, US $101.2 billion for ischemic heart disease, US $89.5 billion for hypertension, and US $29.9 billion for hyperlipidemia (2021 US dollars) [6].

There is a pressing need for effective strategies to address these rising costs and the growing prevalence of obesity [7]. Standard dietary interventions that maintain an energy deficit typically produce an average maximal weight loss of 4 to 12 kg after 6 months, with smaller sustained losses of 4 to 10 kg after 1 year and only 3 to 4 kg after 2 years [8]. Lifestyle changes are typically required to sustain weight losses, and, as such, a lifestyle intervention is an effective approach [9-11].

In-person interventions, although effective, can be time-consuming, expensive, and thus unappealing to many potential participants [12,13]. In addition to these barriers, limited program availability and potential lack of reimbursement [14,15] further limit widespread participation. Remote interventions using mobile health (mHealth) technologies such as telephone calls, SMS text messages, and smartphone apps have been effective in the treatment of obesity [16-19] and can address many of the limitations associated with in-person treatment [20]. By maintaining regular interaction with health care providers and directly receiving educational content, support, and motivation in a widely accessible, convenient, and affordable format, patient engagement and adherence are improved [17,21]. Although the evidence for clinical effectiveness continues to grow, the literature lacks sufficient data on health care cost savings from mHealth programs [22].

Noom (Noom Inc) is an mHealth program that delivers a comprehensive lifestyle intervention through educational articles, coaching, support groups, diet and exercise tracking, and techniques based on the principles of cognitive behavioral therapy. Noom has 2 health programs: Noom Weight for weight management and Noom Mood for stress management. Previous work has shown that 56% of Noom Weight starters achieve weight loss of ≥5% of initial body weight after 6 months [23], a threshold shown to produce clinically meaningful improvements in health by improving lipid profiles and reducing the risks of developing diabetes and hypertension [8,24]. A retrospective analysis of >11,000 users who opened the program at least once after week 8 showed that the majority achieved ≥5% weight loss at 32 weeks (79%) and 52 weeks (82%), with the proportion of users losing ≥10% body weight increasing from 30% to 40% over the same period [25]. The degree of weight loss achieved has also been demonstrated to be strongly associated with user engagement levels [16,25-29]. Although the clinical benefit of Noom Weight has been established, its economic impact, such as that on health care resource utilization (HRU) and associated costs, has not been thoroughly evaluated or reported in the literature to date.

Objectives

We conducted a retrospective study using real-world data from the Noom Weight user database, electronic health records (EHRs), and a commercial insurance claims database to assess the impact of Noom Weight on HRU and health care costs for Noom Weight users in the United States. Using propensity score analyses, HRU and costs among Noom Weight users with overweight and obesity were compared with those of demographically similar non–Noom Weight users at 12 and 24 months of follow-up. We hypothesized that Noom Weight users would demonstrate lower HRU and health care costs than individuals who did not use Noom Weight. A secondary aim was to explore the potential correlation of observed impacts on HRU and costs with changes in obesity-related clinical outcomes.

Methods

Study Design

This retrospective longitudinal cohort study used a data set based on new Noom Weight registrants between July 31, 2018, and July 31, 2020, including self-reported demographic data recorded at the time of registration (eg, age, sex, height, and weight) and activity data (eg, body weight measurements, food intake, and physical activity) recorded longitudinally thereafter. This data set was linked with a cohort of patients across Eversana EHR and open insurance claims data, which included anonymized patient identifiers, vital signs, and health care provider visits with associated diagnoses and procedures for American patients, including those with commercial insurance, Medicare, and Medicaid coverage. Eversana’s EHR data set is an aggregation and standardization of EHR data into a common data model for >120 million American patients. The data are derived from >2000 outpatient or ambulatory health centers, >500 hospitals, >30 health systems (including academic medical centers), and >50 unique electronic medical record platform providers across all 50 states in the United States. All database records are statistically deidentified and certified to be fully...
compliant with the patient confidentiality requirements set forth in the Health Insurance Portability and Accountability Act of 1996. A Health Insurance Portability and Accountability Act–compliant health data privacy service (Datavant) was used to create anonymized encrypted codes, which allowed for data sets to be linked together without the use or exchange of identifiable information [30]. All linked data were deidentified, and an expert determination was completed before data were received for analysis. No identifiable Noom Weight user information was used or exchanged in this study. HRU, health care costs, and obesity-related clinical outcomes were compared between Noom Weight users and demographically similar non–Noom Weight users with overweight or obesity.

**Ethics Approval**

Noom Weight user data were collected from the Noom Weight database with prior approval from the Advarra Institutional Review Board (Pro00017565).

**Cohorts**

**Noom Weight Users**

Noom Weight users were required to have an initial treatment window of continuous Noom Weight use lasting at least 3 months. Continuous use was defined as opening the Noom Weight program at least once per week on average. Each user’s unique index date was defined as the first day of Noom Weight use in the treatment window. If users recorded multiple eligible 3-month treatment windows, the earliest eligible window was used. Users were required to be US residents aged between 18 and 80 years and have a baseline BMI of ≥25 kg/m². A minimum of 12 months of medical records before and after the index date, as well as a minimum documented insurance claims activity of at least 1 claim in the 12-month pre–index date period and at least 1 claim in the 12-month post–index date period, were required. In addition, users included in the 24-month post–index date analysis were required to have a second claim in the 12- to 24-month window.

Users were excluded if they had a history of medical conditions that would significantly affect body weight or the ability to fully engage in a comprehensive lifestyle intervention during the study period, including AIDS, cancer (all types), end-stage organ failure, hemiplegia, paraplegia, uncontrolled HIV infection, pregnancy, or wasting syndrome. Patients were also excluded if they had surgeries or acute-onset conditions affecting body weight, including bariatric surgery and cerebrovascular disease, at any time before the study up until before the end of the initial 3-month treatment window. Comorbidities were identified in the EHR using International Classification of Diseases, Ninth Revision, Clinical Modification and International Classification of Diseases, Tenth Revision, Clinical Modification codes.

**Non–Noom Weight Users**

A control cohort of non–Noom Weight users otherwise meeting the aforementioned inclusion and exclusion criteria defined for Noom Weight users were also identified using EHR and insurance claims data. The index date for non–Noom Weight users was defined as the date of the first qualifying BMI (≥25 kg/m²) entry recorded in the EHR between July 31, 2018, and July 31, 2020.

**Inverse Probability of Treatment Weighting Analysis**

**Baseline Covariates**

Baseline covariates, including BMI, sex, age, and US census region were derived from Noom data for Noom Weight users and from EHR data for non–Noom Weight users. The type of insurance coverage was derived from insurance claims data for both cohorts. Covariates were balanced between the cohorts using inverse probability of treatment weighting (IPTW) before analyses.

**HRU Determination**

HRU was determined from all submitted insurance claims for any service. Claims were categorized based on the recorded place of service and type of claim, including inpatient visits, length of inpatient stay (in days), outpatient visits (including the number of clinic, office, and outpatient hospital visits), telehealth visits, other or unknown visits, surgeries, total prescriptions, and obesity-specific prescriptions. Unique visits were counted as single events regardless of the extent of services rendered during the visit, and total prescriptions included the total count of all prescribed medications. For each service type, the number of uses per patient, as well as the number of uses per patient among only those patients with ≥1 use, were determined at 12 and 24 months after the index date.

**Health Care Costs**

Health care costs were determined based on remitted insurance claims and included all unique entries with valid Current Procedural Terminology codes, Healthcare Common Procedure Coding System codes, or the National Drug Code. In cases where remitted amounts were not available, costs were imputed using the median remitted amount for similarly coded claims, aggregated on the claimant’s insurance type, age group, sex, and state of residence. Prescription costs included only paid claims; submitted claims that were not reimbursed were excluded. Obesity-specific prescription costs included all medications approved for short-term or chronic weight management or those commonly prescribed off-label. Costs per patient were calculated at 12 and 24 months for each service type among all patients, as well as among only those patients with ≥1 use of each service type. All costs were reported in US dollars and adjusted for inflation to 2021 US dollars using the medical consumer price index inflation factors from the Federal Reserve Economic Data repository [31].

**Statistical Analysis**

Propensity score matching was conducted with IPTW to balance the Noom Weight and non–Noom Weight cohorts with respect to age, sex, geographic region, insurance plan, and BMI. Stabilized weights for reweighting were generated with the average treatment effect as the estimand. Summary statistics were expressed as mean and SD for continuous variables and frequency and percentage for categorical variables. Standardized mean differences (SMDs) were used to confirm covariate balance, with absolute SMDs <0.10 indicating potential balance. Mean differences (MDs) between the cohorts at 12 and 24
months were reported for HRU and costs. Generalized linear models were used to report incidence rate ratios (IRRs) for each HRU service (using a Poisson distribution with a log link) and cost ratios (CRs) for the overall costs (using a gamma distribution with a log link). All analyses were conducted using R statistical software (version 3.6.1; R Foundation for Statistical Computing).

**Subgroup Analysis**

Subgroup analyses were conducted by stratifying cohorts according to the diagnosis of type 2 diabetes (T2D; yes vs no), the diagnosis of hypertension (yes vs no), index date BMI (≥35 kg/m² vs <35 kg/m²), Noom Weight use duration (≥6 mo vs <6 mo), and Noom Weight engagement level (high vs low). Engagement was classified as high if the Noom Weight program was opened ≥6 days per week on average and classified as low if opened <6 days per week during the initial 3-month treatment period.

**Results**

**Patient Demographics**

A total of 114,691 Noom Weight users were represented in all 3 linked data sources, of whom 78,375 (68.34%) had valid index dates. After exclusions for comorbidities and inclusion criteria for index date BMI, index date age, Noom Weight use, and insurance claims activity were applied, of the 78,375 Noom Weight users, 43,047 (54.92%) were included for the 12-month analyses and 14,141 (18.04%) for the 24-month analyses. A total of 107,519 non–Noom Weight users were identified in both EHR and insurance claims data, of whom 95,005 (88.36%) had valid index dates. All inclusion and exclusion criteria were met by non–Noom Weight users for the 12-month (14,587/95,005, 15.35%) and 24-month (6487/95,005, 6.83%) analyses.

The baseline demographics of the study population are shown in Table 1 before and after IPTW. Before IPTW, the unweighted mean ages at baseline were 51.6 (SD 12.0) years for Noom Weight users and 52.7 (SD 14.3) years for non–Noom Weight users (SMD −0.077), and 82.75% (35,622/43,047) of the Noom Weight users and 54.67% (7975/14,587) of the non–Noom Weight users were female (SMD −0.635). After IPTW (ie, the sample analyzed for the study), the mean ages were equivalent between the cohorts (Noom Weight users: 51.9, SD 12.1 years; non–Noom Weight users: 51.9, SD 13.8 years; SMD 0.001), and the proportions of female users were identical at 75.6% (proportion after weighting) for both Noom Weight users and non–Noom Weight users (SMD 0.000). All other covariates were also well balanced after IPTW, with the proportion of balanced covariates (absolute SMDs <0.10) increasing from 23% to 100%. Relevant comorbid conditions before weighting are presented in Table 1.

Table 1. Baseline demographics before and after inverse probability of treatment weighting.

<table>
<thead>
<tr>
<th>Category</th>
<th>Before weighting</th>
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<th>After weighting</th>
<th>SMD</th>
</tr>
</thead>
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<td></td>
<td>Noom Weight users (n=43,047)</td>
<td></td>
<td>Noom Weight users (n=40,334b)</td>
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<td>Age (years), mean (SD)</td>
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<td>51.9 (12.1)</td>
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</tr>
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<td>Sex, n (%)</td>
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<tr>
<td></td>
<td>35,622 (82.8)</td>
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<td></td>
<td>7425 (17.2)</td>
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<td></td>
<td>West</td>
<td>−0.013</td>
<td>N/A (20.1)</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Northeast</td>
<td>0.213</td>
<td>N/A (12.2)</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Unknown</td>
<td>0.160</td>
<td>N/A (0)</td>
<td>N/A</td>
</tr>
<tr>
<td>Insurance type, n (%)</td>
<td>Commercial</td>
<td>0.103</td>
<td>N/A (71.9)</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Medicare</td>
<td>−0.218</td>
<td>N/A (21.6)</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Medicaid</td>
<td>−0.260</td>
<td>N/A (6)</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Others</td>
<td>0.125</td>
<td>N/A (0.6)</td>
<td>N/A</td>
</tr>
<tr>
<td>BMI (kg/m²), mean (SD)</td>
<td>33.1 (6.2)</td>
<td>0.100</td>
<td>33 (6.1)</td>
<td>0.024</td>
</tr>
</tbody>
</table>

aSMD: standardized mean difference.

bExcept for BMI and age, only percentages are reported for categorical variables after weighting to show the balance in distributions across the 2 cohorts.

cEffective sample sizes after weighting.

dN/A: not applicable.
**HRU Assessment**

Noom Weight users had statistically significantly lower HRU than non–Noom Weight users in the majority of places of service in both the 12-month (Table 2) and 24-month (Table 3) follow-up periods. Most notably, at 12 months after the index date, the average number of outpatient visits per person was 3.83 (SD 6.76) among Noom Weight users compared with 4.61 (SD 7.26) among non–Noom Weight users (MD −0.78, 95% CI −0.93 to −0.62; IRR 0.83, 95% CI 0.80-0.86; P<.001) and at 24 months after the index date was 8.16 (SD 11.77) visits among Noom Weight users compared with 8.74 (SD 12.04) visits among non–Noom Weight users (MD −0.04, 95% CI −0.06 to −0.02; IRR 0.93, 95% CI 0.89-0.98; P<.001). Fewer inpatient visits were recorded for Noom Weight users at 12 months (MD −0.03, 95% CI −0.04 to −0.03; IRR 0.53, 95% CI 0.47-0.60; P<.001) and 24 months (MD −0.04, 95% CI −0.06 to −0.02; IRR 0.68, 95% CI 0.58-0.79; P<.001) after the index date, and fewer surgeries were recorded at 12 months (MD −0.01, 95% CI −0.00 to −0.01; IRR 0.44, 95% CI 0.34-0.56; P<0.001) and 24 months (MD −0.01, 95% CI −0.01 to 0.00; IRR 0.67, 95% CI 0.51-0.86; P=.004) after the index date. Noom Weight users also had fewer prescriptions than non–Noom Weight users at 12 months (MD −1.39, 95% CI −1.76 to −1.03; IRR 0.92, 95% CI 0.90-0.94; P<.001) and 24 months (MD −3.13, 95% CI −4.25 to −2.00; IRR 0.92, 95% CI 0.89-0.95; P<.001) after the index date. The number of obesity-specific prescriptions was slightly higher among Noom Weight users than among non–Noom Weight users at 12 months after the index date (MD 0.08, 95% CI 0.01-0.16; IRR 1.07, 95% CI 1.01-1.16; P=.03), as was the number of telehealth visits (MD 0.02, 95% CI 0.01-0.04; IRR 1.50, 95% CI 1.15-1.97; P=.003), although significant differences did not persist at 24 months after the index date (P=.53 and P=.51, respectively). Additional analyses limited to patients with at least 1 encounter of each service type showed lower outpatient service use at 12 months after the index date as well as fewer prescriptions at 12 and 24 months after the index date for Noom Weight users compared with non–Noom Weight users (Table S1 in Multimedia Appendix 1).

**Table 2.** Health care resource utilization rates by service type at 12 months after the index date.

<table>
<thead>
<tr>
<th>Service type</th>
<th>Noom Weight users (n=40,334), mean (SD)</th>
<th>Non–Noom Weight users (n=10,549), mean (SD)</th>
<th>Comparison between cohorts</th>
<th>Mean difference (95% CI)</th>
<th>P value</th>
<th>Incidence rate ratio (95% CI)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Inpatient visits</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inpatient visits</td>
<td>0.04 (0.27)</td>
<td>0.07 (0.40)</td>
<td>−0.03 (−0.04 to −0.03)</td>
<td>&lt;.001</td>
<td>0.53 (0.47 to 0.60)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>Inpatient days</td>
<td>0.08 (0.76)</td>
<td>0.15 (1.09)</td>
<td>−0.07 (−0.09 to −0.05)</td>
<td>&lt;.001</td>
<td>0.52 (0.45 to 0.61)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>Telehealth visits</td>
<td>0.07 (0.81)</td>
<td>0.05 (0.56)</td>
<td>0.02 (0.01 to 0.04)</td>
<td>&lt;.001</td>
<td>1.50 (1.15 to 1.97)</td>
<td>.003</td>
<td></td>
</tr>
<tr>
<td><strong>Outpatient visits</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>3.83 (6.76)</td>
<td>4.61 (7.26)</td>
<td>−0.78 (−0.93 to −0.62)</td>
<td>&lt;.001</td>
<td>0.83 (0.80 to 0.86)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>Clinic</td>
<td>0.17 (1.86)</td>
<td>0.18 (1.99)</td>
<td>−0.01 (−0.05 to 0.03)</td>
<td>.57</td>
<td>0.94 (0.77 to 1.15)</td>
<td>.57</td>
<td></td>
</tr>
<tr>
<td>Office</td>
<td>2.76 (5.55)</td>
<td>3.25 (5.75)</td>
<td>−0.49 (−0.61 to −0.37)</td>
<td>&lt;.001</td>
<td>0.85 (0.82 to 0.88)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>Hospital</td>
<td>0.90 (2.58)</td>
<td>1.17 (3.02)</td>
<td>−0.28 (−0.34 to −0.21)</td>
<td>&lt;.001</td>
<td>0.77 (0.72 to 0.81)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>Other visits</td>
<td>0.86 (2.72)</td>
<td>0.95 (3.67)</td>
<td>−0.09 (−0.16 to −0.01)</td>
<td>&lt;.001</td>
<td>0.91 (0.84 to 0.98)</td>
<td>.02</td>
<td></td>
</tr>
<tr>
<td>Surgeries</td>
<td>0.01 (0.09)</td>
<td>0.01 (0.14)</td>
<td>−0.01 (−0.01 to 0.00)</td>
<td>&lt;.001</td>
<td>0.44 (0.34 to 0.56)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td><strong>Prescriptions</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>16.63 (15.73)</td>
<td>18.02 (17.23)</td>
<td>−1.39 (−1.76 to −1.03)</td>
<td>&lt;.001</td>
<td>0.92 (0.90 to 0.94)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>Obesity specific</td>
<td>1.21 (3.38)</td>
<td>1.12 (3.34)</td>
<td>0.08 (0.01 to 0.16)</td>
<td>.03</td>
<td>1.07 (1.01 to 1.14)</td>
<td>.03</td>
<td></td>
</tr>
</tbody>
</table>

aEffective sample size.

bIncludes visits of unlisted or unknown types.
HRU: Subgroup Analysis
When comparing Noom Weight users and non–Noom Weight users, subgroups without T2D or hypertension and with BMI <35 kg/m² had lower use of more service types than subgroups with T2D or hypertension and with BMI ≥35 kg/m², respectively (Tables S2-S4 in Multimedia Appendix 1); for example, although fewer outpatient visits were recorded among Noom Weight users than among non–Noom Weight users in both subgroups with and without T2D at 12 months after the index date, significant differences (reductions) were also observed for Noom Weight users compared with non–Noom Weight users in inpatient visits, inpatient days, surgeries, prescriptions, and obesity-specific prescriptions only in the subgroup without T2D (all P<.05; Table S2 in Multimedia Appendix 1). Similarly, relatively fewer significant differences between Noom Weight and non–Noom Weight users were observed for the subgroup with hypertension (all P<.05; Table S3 in Multimedia Appendix 1) and with BMI ≥35 kg/m² (all P<.05; Table S4 in Multimedia Appendix 1) in the respective subgroup analyses. The differences between the subgroups were more pronounced at 24 months after the index date.

More than three-quarters (33,810/44,416, 76.12%) of the Noom Weight users were categorized as high engaged, with the remaining users (10,606/44,416, 23.88%) categorized as low engaged. High-engaged Noom Weight users had significantly fewer prescriptions (overall and obesity specific) than low-engaged users at 12 months (overall MD −0.50, 95% CI −0.64 to −0.36; obesity-specific MD −0.16, 95% CI −0.26 to −0.06) and at 24 months (overall MD −2.79, 95% CI −4.41 to −1.17; obesity-specific MD −0.52, 95% CI −0.86 to −0.18) after the index date, and both engagement levels had significantly fewer inpatient visits, inpatient days, outpatient visits, and prescriptions than non–Noom Weight users at 12 months after the index date (Table S5 in Multimedia Appendix 1). These differences remained significant at 24 months after the index date for high-engaged Noom Weight users; for low-engaged Noom Weight users, only the differences in inpatient visits and outpatient visits remained significant at 24 months after the index date, and increases in obesity-specific prescriptions among low-engaged Noom Weight users compared with non–Noom Weight users were also noted at 12 and 24 months after the index date.

The mean duration of Noom Weight use was 8.67 (SD 5.70) months among all Noom Weight users, with 46.22% (20,530/44,416) using Noom Weight for <6 months and 53.78% (23,888/44,416) using Noom Weight for ≥6 months. Noom Weight users with ≥6 months of use had fewer prescriptions than users with <6 months of use at 12 months after the index date (MD −0.64, 95% CI −1.04 to −0.24), but a significant difference did not persist at 24 months (Table S6 in Multimedia Appendix 1). The pattern of significant differences for Noom Weight users of both durations was similar to that for Noom Weight engagement level at 12 months after the index date, with fewer inpatient visits, inpatient days, outpatient visits, surgeries, and prescriptions than for non–Noom Weight users. This pattern of significant differences was unchanged at 24 months after the index date for Noom Weight users with ≥6 months of use; for Noom Weight users with <6 months of use, only inpatient visits, inpatient days, a subset of outpatient visits (outpatient hospital visits only), and prescriptions were significantly lower than those for non–Noom Weight users.

### Table 3. Health care resource utilization rates by service type at 24 months after the index date.

<table>
<thead>
<tr>
<th>Service type</th>
<th>Noom Weight users (n=11,438a), mean (SD)</th>
<th>Non–Noom Weight users (n=4485b), mean (SD)</th>
<th>Comparison between cohorts</th>
<th>Mean difference (95% CI)</th>
<th>P value</th>
<th>Incidence rate ratio (95% CI)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inpatient visits</td>
<td>0.09 (0.51)</td>
<td>0.13 (0.55)</td>
<td>−0.04 (−0.06 to −0.02)</td>
<td>&lt;.001</td>
<td>0.68 (0.58 to 0.79)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>Inpatient days</td>
<td>0.20 (1.52)</td>
<td>0.29 (1.43)</td>
<td>−0.08 (−0.13 to −0.04)</td>
<td>&lt;.001</td>
<td>0.71 (0.59 to 0.85)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>Telehealth visits</td>
<td>0.14 (1.53)</td>
<td>0.13 (1.42)</td>
<td>0.00 (−0.04 to 0.07)</td>
<td>.51</td>
<td>1.15 (0.76 to 1.74)</td>
<td>.52</td>
<td></td>
</tr>
<tr>
<td>Outpatient visits</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>8.16 (11.77)</td>
<td>8.74 (12.04)</td>
<td>−0.58 (−1.00 to −0.17)</td>
<td>.006</td>
<td>0.93 (0.89 to 0.98)</td>
<td>.005</td>
<td></td>
</tr>
<tr>
<td>Clinic</td>
<td>0.34 (2.62)</td>
<td>0.38 (2.58)</td>
<td>−0.03 (−0.12 to 0.06)</td>
<td>.48</td>
<td>0.92 (0.72 to 1.17)</td>
<td>.48</td>
<td></td>
</tr>
<tr>
<td>Office</td>
<td>5.87 (9.57)</td>
<td>6.12 (9.61)</td>
<td>−0.25 (−0.59 to 0.09)</td>
<td>.14</td>
<td>0.96 (0.91 to 1.01)</td>
<td>.14</td>
<td></td>
</tr>
<tr>
<td>Hospital</td>
<td>1.94 (4.71)</td>
<td>2.24 (4.69)</td>
<td>−0.30 (−0.46 to −0.14)</td>
<td>&lt;.001</td>
<td>0.87 (0.80 to 0.94)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>Other visitsb</td>
<td>1.80 (4.70)</td>
<td>1.71 (5.42)</td>
<td>0.09 (−0.08 to 0.27)</td>
<td>.31</td>
<td>1.05 (0.95 to 1.17)</td>
<td>.32</td>
<td></td>
</tr>
<tr>
<td>Surgeries</td>
<td>0.02 (0.14)</td>
<td>0.02 (0.18)</td>
<td>−0.01 (−0.01 to 0.00)</td>
<td>.004</td>
<td>0.67 (0.51 to 0.86)</td>
<td>.002</td>
<td></td>
</tr>
<tr>
<td>Prescriptions</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>35.37 (30.47)</td>
<td>38.50 (32.62)</td>
<td>−3.13 (−4.25 to −2.00)</td>
<td>&lt;.001</td>
<td>0.92 (0.89 to 0.95)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>Obesity specific</td>
<td>2.62 (6.50)</td>
<td>2.55 (6.59)</td>
<td>0.08 (−0.16 to 0.31)</td>
<td>.53</td>
<td>1.03 (0.94 to 1.13)</td>
<td>.53</td>
<td></td>
</tr>
</tbody>
</table>

aEffective sample size.
bIncludes visits of unlisted or unknown types.
Health Care Costs

Noom Weight users had lower overall health care costs at 12 months after the index date, with average expenditures of US $3433.89 (SD $10,397.96) per person compared with US $3884.28 (SD $13,661.66) per person for non–Noom Weight users (MD $−450.39, 95% CI $−706.28 to $−194.50; CR 0.91, 95% CI 0.85-0.97; P<.001; Table 4). At 24 months, average overall costs for Noom Weight users were US $7367.97 (SD $19,748.80) per person compared with US $8587.03 (SD $29,190.01) per person for non–Noom Weight users (MD $−1219.06, 95% CI $−2061.56 to $−376.55; CR 0.86, 95% CI 0.78-0.95; P=.005; Table 5). Expenditures for inpatient services, outpatient services, and overall prescriptions were lower for Noom Weight users than for non–Noom Weight users at 12 months, whereas telehealth expenditures were slightly higher. Of these, the reductions in outpatient expenditures, overall prescriptions, and overall costs remained statistically significant through 24 months. The additional analysis limited to patients with at least 1 encounter of each service type (Table S7 in Multimedia Appendix 1) showed significantly lower overall and obesity-specific prescription costs at both time points as well as significantly lower outpatient costs at 12 months for Noom Weight users compared with non–Noom Weight users (all P<.05).

Table 4. Health care costs by service type at 12 months after the index date.

<table>
<thead>
<tr>
<th>Service type</th>
<th>Noom Weight users (US $; n=40,334a), mean (SD)</th>
<th>Non–Noom Weight users (US $; n=10,549b), mean (SD)</th>
<th>Mean difference (95% CI)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inpatient services</td>
<td>24.19 (368.01)</td>
<td>44.29 (497.70)</td>
<td>−20.10 (−30.08 to −10.12)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Telehealth services</td>
<td>6.08 (85.27)</td>
<td>3.52 (46.48)</td>
<td>2.56 (1.37 to 3.76)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Outpatient services</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>492.50 (1360.32)</td>
<td>616.83 (1779.75)</td>
<td>−124.33 (−159.76 to −88.89)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Clinic</td>
<td>16.03 (134.04)</td>
<td>16.25 (151.81)</td>
<td>−0.22 (−2.74 to 2.29)</td>
<td>.86</td>
</tr>
<tr>
<td>Office</td>
<td>268.33 (835.97)</td>
<td>348.77 (1167.06)</td>
<td>−80.43 (−103.24 to −57.63)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Hospital</td>
<td>208.14 (978.29)</td>
<td>251.81 (1193.71)</td>
<td>−43.67 (−68.23 to −19.11)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Other servicesb</td>
<td>47.61 (1117.32)</td>
<td>42.32 (243.35)</td>
<td>5.29 (−6.95 to 17.52)</td>
<td>.40</td>
</tr>
<tr>
<td>Prescriptions</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>2863.51 (10,160.60)</td>
<td>3177.33 (13,482.12)</td>
<td>−313.82 (−565.42 to −62.21)</td>
<td>.02</td>
</tr>
<tr>
<td>Obesity-specific</td>
<td>430.81 (2997.12)</td>
<td>466.96 (3047.48)</td>
<td>−36.15 (−101.33 to 29.02)</td>
<td>.28</td>
</tr>
<tr>
<td>Overall (all service types)c</td>
<td>3433.89 (10,397.96)</td>
<td>3884.28 (13,661.66)</td>
<td>−450.39 (−706.28 to −194.50)</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

aEffective sample size.
bIncludes costs of unlisted or unknown types.
cThe overall cost ratio was 0.91 (95% CI 0.85-0.97; P=.004), based on a gamma regression model and after cases with US $0 costs were removed.

https://mhealth.jmir.org/2023/11/e47473
Table 5. Health care costs by service type at 24 months after the index date.

<table>
<thead>
<tr>
<th>Service type</th>
<th>Noom Weight users (US $; n=11,438)</th>
<th>Non–Noom Weight users (US $; n=4485)</th>
<th>Mean difference (95% CI)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Inpatient services</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>54.65 (581.75)</td>
<td>62.62 (428.17)</td>
<td>−7.96 (−23.70 to 7.78)</td>
<td>.32</td>
</tr>
<tr>
<td><strong>Telehealth services</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>14.04 (208.52)</td>
<td>9.06 (94.49)</td>
<td>4.97 (0.17 to 9.78)</td>
<td>.04</td>
</tr>
<tr>
<td><strong>Outpatient services</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>999.78 (2148.88)</td>
<td>1080.37 (2061.25)</td>
<td>−80.60 (−151.10 to −10.09)</td>
<td>.03</td>
</tr>
<tr>
<td>Clinic</td>
<td>35.10 (239.53)</td>
<td>38.80 (307.65)</td>
<td>−3.70 (−11.97 to 4.57)</td>
<td>.38</td>
</tr>
<tr>
<td>Office</td>
<td>572.34 (1448.81)</td>
<td>598.52 (1399.89)</td>
<td>−26.17 (−71.92 to 19.57)</td>
<td>.26</td>
</tr>
<tr>
<td>Hospital</td>
<td>392.33 (1335.99)</td>
<td>443.05 (1250.56)</td>
<td>−50.72 (−95.66 to −5.79)</td>
<td>.03</td>
</tr>
<tr>
<td>Other servicesb</td>
<td>84.43 (477.39)</td>
<td>80.38 (515.89)</td>
<td>4.05 (−8.55 to 16.65)</td>
<td>.53</td>
</tr>
<tr>
<td><strong>Prescriptions</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>6215.07 (19,439.55)</td>
<td>7354.59 (28,966.20)</td>
<td>−1139.52 (−1972.21 to −306.83)</td>
<td>.007</td>
</tr>
<tr>
<td>Obesity specific</td>
<td>918.06 (5578.53)</td>
<td>1149.87 (6679.35)</td>
<td>−231.81 (−459.45 to −4.16)</td>
<td>.05</td>
</tr>
<tr>
<td>Overall (all service types)c</td>
<td>7367.97 (19,748.80)</td>
<td>8587.03 (29,190.01)</td>
<td>−1219.06 (−2061.56 to −376.55)</td>
<td>.005</td>
</tr>
</tbody>
</table>

aEffective sample size.
bIncludes costs of unlisted or unknown types.
cThe overall cost ratio was 0.86 (95% CI 0.78-0.95; P=.004), based on a gamma regression model and after cases with US $0 costs were removed.

**Discussion**

**Principal Findings**

We showed that HRU is lower for Noom Weight users than for non–Noom Weight users at 12 and 24 months after the index date. Per user, 0.03 fewer inpatient visits, 0.83 fewer outpatient visits, 0.01 fewer surgeries, and 1.39 fewer prescriptions were recorded among Noom Weight users compared with non–Noom Weight users at 12 months after the index date. At 24 months after the index date, 0.04 fewer inpatient visits, 0.58 fewer outpatient visits, 0.01 fewer surgeries, and 3.13 fewer prescriptions were recorded among Noom Weight users compared with non–Noom Weight users. Noom Weight users had higher use of telehealth services at 12 months after the index date (MD 0.02/user), perhaps because of increased connectivity to digital health services owing to their use of Noom Weight or because of increased health responsibility as a result of the program [32]. There were also a greater number of obesity-specific prescriptions for Noom Weight users compared with non–Noom Weight users at 12 months (MD 0.08/user), which may be related to more health-conscious behavior [32] among newly registered Noom Weight users, potentially leading to higher rates of prescriptions. A statistically significant difference did not persist at 24 months.

The results also showed significantly lower health care costs for Noom Weight users compared with non–Noom Weight users at both 12 months and 24 months after the index date. Overall costs for Noom Weight users were US $450 lower per person at 12 months and US $1219 lower per person at 24 months compared with overall costs for individuals who did not use
Noom Weight. Furthermore, extending similar findings at 12 months, outpatient services costs (MD US $80/person) and prescription costs (MD US $1139/person) were lower for Noom Weight users than for non–Noom Weight users at 24 months after the index date.

Overall, our findings demonstrate significantly lower HRU and costs at 12 and 24 months for Noom Weight users compared with demographically similar non–Noom Weight users, with greater impact on HRU and costs observed for Noom Weight users without T2D, without hypertension, with BMI <35 kg/m², with higher Noom Weight engagement, and with longer duration of Noom Weight use.

Limitations
This was an observational study, which therefore does not permit causal associations to be drawn between Noom Weight use and HRU and cost outcomes. Another important limitation was the restricted sample size owing to the linking of 3 separate databases. Users were required to be present in all 3 data sources for inclusion, which sharply reduced the size of the available population. This also adds a risk of bias because the underlying systematic exclusions owing to missing data that may have affected patients in any 1 database would have been projected across all 3 databases, including those not previously affected by them. The requirement for Noom Weight users to use the program for 3 months may have biased this cohort toward including more health-conscious and motivated users, although it should be noted that this engagement criterion is similar to that used for previously studied Noom Weight populations and that this study’s inclusion requirement to use the program at least 10 times in total during this time period is relatively low [25-27,29,33,34]. In addition, this study included only US residents, which may limit its generalizability. However, previous work has shown the comparable effectiveness of Noom Weight use for weight loss across different regions and income levels [16,28]. This may suggest similar cross-national effects on HRU and costs, which would be more affected by access to health care and existing HRU patterns in each country than by the differential impact of Noom Weight use. Furthermore, the study cohorts described here included mostly women and comprised individuals aged <80 years, further limiting the generalizability of the results.

Some potential imbalances between the cohorts may not have been accounted for in our IPTW analyses. Potential racial imbalances could not be accounted for because the Noom Weight user and non–Noom Weight user cohorts had either nonspecific or missing information for race, which prevented reweighting on this variable. Preexisting comorbidities were also not included in reweighting to permit subgroup analyses based on comorbid conditions. However, these were nevertheless reasonably well balanced in the reweighted cohorts. There may also be other confounding variables affecting HRU and costs that were not identified or accounted for in our analyses (eg, education level and income bracket). The potential impact of other common weight loss interventions used concurrently, such as weight loss programs and antiobesity medications, on the study results also requires further investigation.

In particular, an important limitation is some concurrent use of antiobesity medications, which raises the question of whether the effects were driven by the use of medications or the use of Noom Weight; this question cannot be definitively answered by this study. The data suggest that it is unlikely that this was a confound that primarily drove the results observed because there was no significant difference in antiobesity medication use between the Noom Weight user and non–Noom Weight user groups at 24 months after the index date despite significant differences in other types of HRU and costs, and a subgroup analysis of individuals with at least 1 prescription or health care visit showed no difference in obesity-specific prescriptions between the groups at all time points. However, any impact of antiobesity medications is not measured or ruled out by this study. Future research, especially with causal designs, should elucidate when and to what magnitude the concurrent use of antiobesity medications influences other types of HRU and costs. Furthermore, the study excluded individuals who had bariatric or cerebrovascular disease at any time before the study up until before the end of the initial 3-month treatment window. Future studies should examine how receiving bariatric surgery concurrently with Noom Weight use affects HRU and costs, especially on longer time scales, and whether the use of Noom Weight could be associated with motivation to undergo bariatric surgery.

Open insurance claims data were used, which allowed the assessment of direct medical costs in all care settings (eg, inpatient and outpatient) and provided large sample sizes covering patients with diverse backgrounds and medical needs. However, there are limitations associated with the use of open claims data. Open claims databases effectively capture patient activity longitudinally, but they do not necessarily capture all patient claims activity within a given time period. HRU involving service providers not included in the database will not be captured, giving a potentially incomplete picture of HRU and costs, biasing the results if certain types of HRU are less well represented and potentially excluding otherwise eligible patients for claims inactivity if they have unobserved claims. We applied a minimum claim activity criterion of 1 claim per 12-month period during the study period to mimic a continuous enrollment criterion that would be applied to a closed claims data set. Although this was a low threshold that preserved sample size, it may have introduced some bias toward patients more likely to file claims and therefore patients who were potentially sicker. As not all submitted claims in open claims databases are remitted, missing values were imputed to estimate costs. Imputation may potentially over- or underestimate true costs and systematically bias any subcategory of HRU that is particularly affected by missing data. Finally, because open claims databases are based on a large convenience sample that is not random, there may be potential biases or issues with generalizability.

Discrete surgical visits could be readily determined from insurance claims data for HRU analyses. However, individual Current Procedural Terminology codes for activities within each surgery were frequently not available and were aggregated under a master code for the entire procedure. This prevented meaningful cost assessments for surgeries, which would require
the enumeration of the specific line items, and therefore surgical costs were only captured as a subset of overall costs.

**Comparison With Prior Work**

Noom Weight has previously been shown to be an effective treatment for obesity, frequently producing weight loss exceeding 5% of initial body weight [23,27,34,35] in as little as 8 weeks [36] and persisting for up to 52 weeks [25]. However, Noom Weight’s impact and the impact of mHealth technologies generally on HRU and costs among users with overweight or obesity compared with a demographically similar control group have not been previously reported. Therefore, this study contributes to filling a substantial gap in the literature regarding the limited data on health care costs and HRU associated with digital programs. In the following paragraphs, we compare these findings to those of the few publications reporting on the impact of nonsurgical (ie, behavioral, not including bariatric surgery) weight loss on HRU and costs.

One study compared health care costs over 3 years for 4790 users of an employer-sponsored digital weight loss program with those for a propensity-matched control group (n=4790) who did not use the program [37]. Overall costs for those who used the program were US $771 lower per person over 3 years compared with those for nonusers. Specifically, the program was associated with lower outpatient (US $609/person) and inpatient (US $162/person) costs over 3 years. Our results compare favorably, showing even greater cost savings because, compared with non-Noom Weight users, Noom Weight users had lower overall costs of US $1219 per person over 2 years. In the study by Horstman et al [37], cost savings were mostly concentrated in outpatient costs, whereas we found comparatively lower outpatient cost savings over 2 years (US $78/person). This could be because of the limited availability of EHR data in our study in contrast to the health plan data used in the study by Horstman et al [37]. Future studies should collect full-scale health and insurance plan data in addition to the open insurance claims data used in this study.

An investigation by Ding et al [38] on the impact of nonsurgical weight loss on health care costs used insurance claims and EHR data for 20,488 adults with obesity in the IBM MarketScan Explorys Claims-Electronic Medical Record Data Set and found statistically significantly reduced costs for patients with >5% weight loss compared with those maintaining steady weight [38]. This aligns with our finding that Noom Weight users who were in this dedicated weight management program exhibited lower costs than the non–Noom Weight group. Furthermore, Ding et al [38] reported smaller absolute cost reductions after 2 years than in the first year alone, although the study did not directly compare the magnitude and significance of costs from 1 year to 2 years. In this study, cost reductions increased from year 1 through year 2 in absolute value. Although the 2 studies are not directly comparable, this raises the possibility that the cost impact of Noom Weight use may be longer lasting than that observed with nonsurgical weight loss interventions in general. This is consistent with the typical trend of long-term weight regain (potentially correlating with increased costs) among those with nonsurgical weight loss in the absence of intensive lifestyle interventions such as Noom Weight [8]. Future research should test this explanation.

The degree of weight loss among Noom Weight users is closely tied to the level of user engagement, with greater weight loss among patients who more frequently read articles, log data, and interact with coaches [25,27]. Similar results have also been reported with other weight loss programs [39]. In our study, higher Noom Weight engagement was also associated with lower HRU in terms of the number of prescriptions claimed (Table 3). High-engaged Noom Weight users claimed 0.95 (almost 1 unit) fewer prescriptions than low-engaged Noom Weight users through 12 months, increasing to 2.79 fewer prescriptions through 24 months. This was also true for obesity-specific prescriptions, which were fewer for high-engaged Noom Weight users than for low-engaged Noom Weight users at 12 months (MD −0.16) and 24 months (MD −0.52). Although this did not translate into statistically significantly lower costs for high-engaged Noom Weight users compared with low-engaged Noom Weight users, high Noom Weight engagement was associated with statistically significantly lower overall costs of −US $462 per user (95% CI −US $775.62 to −US $148.39) compared with non-Noom Weight use at 12 months, as well as lower overall costs of −US $1446 (95% CI −US $2469 to −US $422) and lower prescription costs of −US $1366 (95% CI −US $2377 to −US $335) compared with non–Noom Weight use at 24 months (Table S4 in Multimedia Appendix 1). In comparison, costs for these service types were not statistically significantly different for low-engaged Noom Weight users compared with non–Noom Weight users at 12 or 24 months.

In addition to subgroup analyses based on Noom Weight engagement, we also performed subgroup analyses according to BMI (<35 kg/m² vs ≥35 kg/m²), T2D diagnosis, and hypertension diagnosis. Costs were significantly lower for the Noom Weight group versus the non–Noom Weight group for more HRU types in samples without T2D (vs samples with T2D), without hypertension (vs samples with hypertension), and with BMI <35 kg/m² (vs samples with BMI ≥35 kg/m²). This could be because these conditions incur substantial health care costs; for example, poor glycemic control, as seen in T2D, is related to higher total health care, hospitalization, and medication costs [40]; in another study, the presence of hypertension substantially increased health care costs [41]. Therefore, cost differences between the Noom Weight user and non–Noom Weight user groups are likely starker without these conditions than with these conditions.

Previous work suggests some potential mechanisms for the results found in this study. We speculate that Noom Weight users may have shown significant cost savings compared with non–Noom Weight users because weight management efforts reduced the incidence of chronic conditions and their associated medical costs [42-44]. We also speculate that Noom Weight’s educational content on healthy behaviors could result in improved medication adherence, especially because a previous study found that Noom Weight users’ health responsibility (eg, taking interest in, and responsibility for, their overall physical health) improved over the course of the program [32,45].
However, because this study did not test causal pathways, future research should test and identify potential mechanisms.

Conclusions

To our knowledge, this is the first study using real-world data to show the economic impact of the use of an mHealth intervention by a cohort of users with overweight and obesity compared with a control cohort not using the mHealth intervention. We show lower HRU and costs for users of the Noom Weight mHealth program compared with non-Noom Weight users over a 2-year follow-up period. Comprehensively examining all service types, we found that inpatient visits, outpatient visits, surgical visits, and prescriptions were lower for Noom Weight users than for non-Noom Weight users for up to 24 months after initiating Noom Weight. Costs per Noom Weight user were statistically significantly lower by US $80 for outpatient services, US $1139 for prescriptions, and US $1219 overall at 24 months, which could correspond to savings of approximately US $609 per person per year during this period. These cost estimates compare favorably with those of previously studied programs. By linking Noom Weight data, EHR data, and insurance claims data, we were able to conduct several subgroup analyses for HRU and costs, including analyses based on T2D diagnosis or hypertension diagnosis, duration of Noom Weight use, user engagement level, and index date BMI. Further research is required to establish the relationship between changes in weight and BMI, as well as in comorbidities, with changes in HRU and costs, including the impact of the differential levels of weight loss. In addition, because this study focused on direct health care costs only, future research should investigate the impact of mHealth interventions on indirect costs (eg, productivity costs) as well.

Acknowledgments

This study was funded by Noom Inc; however, Noom Inc (apart from the authors employed by Noom Inc) had no role to play in the study’s design, execution, analysis, or the decision to publish the results.

Authors’ Contributions

ESM, AF, and AM were responsible for the conceptualization of the study. ESM and AF were responsible for the methodology. ASH, AF, CNM, MB, PB, KS, and AM reviewed and edited the manuscript. OEM was responsible for data curation. KG was responsible for data cleaning and analysis. MS and MW were responsible for data cleaning and analysis supervision as well as writing the protocol. The Introduction and Discussion sections were written by MS and MW. MW reviewed the literature. AZ was the team director and supervisor.

Conflicts of Interest

ESM, AF, ASH, CNM, MB, PB, KS, and AM are employees of Noom Inc and have received a salary and stock options as employees. All other authors declare no other conflicts of interest.

Multimedia Appendix 1

Tables displaying results from subgroup analyses.

[DOCX File, 89 KB - mhealth_v11i1e47473_app1.docx]

References


Abbreviations

| CR | cost ratio |
| EHR | electronic health record |
| HRU | health care resource utilization |
| IPTW | inverse probability of treatment weighting |
| IRR | incidence rate ratio |
| MD | mean difference |
| mHealth | mobile health |
Correction: WeChat-Based HIV e-Report, a New Approach for HIV Serostatus Requests and Disclosures Among Men Who Have Sex With Men: Prospective Subgroup Analysis of a Randomized Controlled Trial

Hai-Tong Sun¹,²*, BSc; Xiao-Ru Fan¹,²*, BSc; Yu-Zhou Gu³, MSc; Yong-Heng Lu⁴, BSc; Jia-Ling Qiu¹,², MSc; Qing-Ling Yang¹,², MSc; Jing-Hua Li¹,², PhD; Jing Gu¹,², PhD; Chun Hao¹,², PhD

¹Department of Medical Statistics, School of Public Health, Sun Yat-Sen University, Guangzhou, China
²Sun Yat-Sen Global Health Institute, Institute of State Governance, Sun Yat-Sen University, Guangzhou, China
³Guangzhou Center for Disease Control and Prevention, Guangzhou, China
⁴Lingnan Community Support Center, Guangzhou, China
* these authors contributed equally

Corresponding Author:
Chun Hao, PhD
Department of Medical Statistics, School of Public Health, Sun Yat-Sen University
74 Zhongshan 2nd Rd Yuexiu District
Guangzhou, 510080
China
Phone: 86 87332517
Email: haochun@mail.sysu.edu.cn

Related Article:
Correction of: https://mhealth.jmir.org/2023/1/e44513
doi:10.2196/48961

In “WeChat-Based HIV e-Report, a New Approach for HIV Serostatus Requests and Disclosures Among Men Who Have Sex With Men: Prospective Subgroup Analysis of a Randomized Controlled Trial” (JMIR mHealth and uHealth 2023;11:e48961), the following errors were corrected:

1. In the originally published article, the title appeared as follows:
   WeChat-Based HIV e-Report, a New Manner for HIV Serostatus Request and Disclosure and Their Associated Factors Among Men Who Have Sex With Men: Prospective Subgroup Analysis of a Randomized Controlled Trials
   This has been corrected to:
   WeChat-Based HIV e-Report, a New Approach for HIV Serostatus Requests and Disclosures Among Men Who Have Sex With Men: Prospective Subgroup Analysis of a Randomized Controlled Trial

2. In the Abstract: Background section of the originally published article, the second sentence appeared as follows:
   However, the reliability of common methods for HIV serostatus requests and disclosure is unsatisfactory.
   This has been corrected to:
   However, the reliability of common methods for HIV serostatus requests and disclosure is unsatisfactory.

3. In the Abstract: Objectives section of the originally published article, the second sentence appeared as follows:
   Additionally, the study aimed to explore its correlates with HIV serostatus requesting and disclosure receiving behavior.
   This has been corrected to:
   Additionally, the study aimed to explore its correlation with HIV serostatus requesting and disclosure receiving behavior.

4. In the Abstract: Methods section of the originally published article, the third sentence appeared as follows:
   Participants completed web-based questionnaires at baseline and at the month 3 follow-up, which covered sociodemographic characteristics, HIV-related information, HIV serostatus requests, HIV serostatus disclosure receiving, and HIV e-report usage.
   This has been corrected to:
   Participants completed web-based questionnaires at baseline and at the month 3 follow-up, which covered sociodemographic characteristics, HIV-related information, HIV serostatus requests, HIV serostatus disclosure receiving, and HIV e-report usage.

https://mhealth.jmir.org/2023/1/e48961
information, HIV serostatus requests, receiving HIV serostatus disclosures, and HIV e-report usage.

5. In the Abstract: Results section of the originally published article, the second sentence appeared as follows:

For HIV serostatus requests, 13.1% (27/205) and 10.5% (16/153) of participants started to use HIV e-reports to request the HIV serostatus from regular and casual male sex partners, respectively. Of the regular and casual male sex partners, 27.3% (42/154) and 16.5% (18/109), respectively, chose HIV e-reports to disclose HIV serostatus. Compared to MSM who did not have HIV e-reports, those who said [...] 

This has been corrected to:

In all, 13.1% (27/205) and 10.5% (16/153) of participants started to use HIV e-reports to request the HIV serostatus from regular and casual male sex partners, respectively. Moreover, 27.3% (42/154) and 16.5% (18/109) of the regular and casual male sex partners, respectively, chose HIV e-reports to disclose their HIV serostatus. Compared to MSM who did not have HIV e-reports, those who had HIV e-reports and stated [...] 

6. In the Abstract: Results section of the originally published article, the last sentence appeared as follows:

Whereas no factor was associated with HIV serostatus disclosure received from partners.

This has been corrected to:

However, no factor was associated with receiving an HIV serostatus disclosure from partners.

7. In the Abstract: Conclusions section of the originally published article, the first sentence appeared as follows:

The HIV e-report has been accepted by the MSM community in Guangzhou and could be applied as a new optional way for HIV serostatus request and disclosure.

This has been corrected to:

The HIV e-report has been accepted by the MSM community in Guangzhou and could be applied as a new optional approach for HIV serostatus requests and disclosures.

8. In the Introduction section of the originally published article, the second paragraph appeared as follows:

Studies indicated that over half of MSM used verbal communication and guessing for HIV serostatus requesting and disclosing among MSM [5, 6]. While taking HIV tests together is a reliable approach to confirm partners’ HIV status, some individuals doubt the reliability of HIV self-testing, and self-test kits may not always be readily available. Deception of HIV serostatus in verbal information is prevalent [7] and difficult to confirm.

This has been corrected to:

Studies indicated that over half of MSM used verbal communication and guessing for HIV serostatus request and disclosure among MSM [5, 6]. While taking HIV tests together is a reliable approach to confirm partners’ HIV status, some individuals doubt the reliability of HIV self-testing, and self-test kits may not always be readily available. Deception of HIV serostatus in verbal information is prevalent [7] and difficult to confirm.

9. In the Introduction section of the originally published article, the third paragraph appeared as follows:

WeChat, a popular social media app with over 1.2 billion active users [8], similar to Twitter or the mix of WhatsApp and Facebook, is an ubiquitous daily use app in China [9]. WeChat miniprograms are subapps within the WeChat ecosystem. It has great potential for health intervention research [10]. In Guangzhou city, a unique and well-established WeChat miniprogram of the HIV testing service system in China is developed by Guangzhou Centers for Disease Control and Prevention (CDC) and the MSM community-based organization Lingnan Partners Community Support Center (hereinafter called “Lingnan Center”) [11].

This has been corrected to:

WeChat, a popular social media app with over 1.2 billion active users [8], similar to Twitter or the mix of WhatsApp and Facebook, is an ubiquitous daily use app in China [9]. WeChat miniprograms are subapps within the WeChat ecosystem. It has great potential for health intervention research [10]. In Guangzhou city, a unique and well-established WeChat miniprogram of the HIV testing service system in China is developed by Guangzhou Centers for Disease Control and Prevention (CDC) and the MSM community-based organization Lingnan Partners Community Support Center (hereinafter called “Lingnan Center”) [11].

10. In the Introduction section of the originally published article, the last paragraph appears as follows:

The objective of this study is to describe the usage of the HIV e-report after it was available in Guangzhou and investigate whether it is associated with promoting HIV serostatus requests, and disclosure-related behaviors among this high-risk population.

This has been corrected to:

The objective of this study is to describe the usage of the HIV e-report after it was available in Guangzhou and investigate whether it is associated with promoting HIV serostatus requests and disclosure-related behaviors among this high-risk population.

11. In the Methods: Recruitment of Participants section of the originally published article, the second sentence of the third paragraph appears as follows:

In all, 13.1% (27/205) and 10.5% (16/153) of participants started to use HIV e-reports to request the HIV serostatus from regular and casual male sex partners, respectively. Moreover, 27.3% (42/154) and 16.5% (18/109) of the regular and casual male sex partners, respectively, chose HIV e-reports to disclose their HIV serostatus. Compared to MSM who did not have HIV e-reports, those who had HIV e-reports and stated [...]
After 3 months, alters participants would receive WeChat messages which contain the link to the follow-up questionnaire.

This has been corrected as follows:

After 3 months, alters would receive WeChat messages which contain the link to the follow-up questionnaire.

12. In the Methods: Measures: Sociodemographic Characteristics section of the originally published article, the first sentence appeared as follows:

All background characteristics of alter participants were collected in the baseline questionnaire.

This has been corrected as follows:

All background characteristics of alters were collected in the baseline questionnaire.

13. In the Methods: Measures: Sociodemographic Characteristics section of the originally published article, the last sentence appeared as follows:

We dichotomize age by 25 years, income by 5000 RMB (US $700) according to median.

This has been corrected as follows:

We dichotomized age by 25 years and income by 5000 RMB (US $700) according to the median.

14. In the Methods: Statistical Analysis section of the originally published article, the second paragraph appeared as follows:

Another bar graph was used to depict the manner of HIV serostatus disclosure receiving at the month 3 follow-up.

This has been corrected as follows:

Another bar graph was used to depict the manner of receiving HIV serostatus disclosures at the month 3 follow-up.

15. In the Results: Characteristics of Participants section of the originally published article, the third paragraph appeared as follows:

A total of 79% (282/357) of participants had intervened by HIV-related programs in the past 3 months. HIV stigma scores ranged from 8 to 23, and at a high level (median 19, IQR 17-22) overall. On average, participants' social norm (median 3, IQR 2.67-3) inclined to a positive direction. Further details on participants' characteristics were presented in Table 1.

This has been corrected as follows:

A total of 79% (282/357) of participants took part in HIV-related programs in the past 3 months. HIV stigma scores ranged from 8 to 23 and were at a high level (median 19, IQR 17-22) overall. On average, participants' social norm (median 3, IQR 2.67-3) inclined to a positive direction. Further details on participants' characteristics were presented in Table 1.

16. In the Results: HIV e-Reports Emerging as the New Approach for HIV Serostatus Requests and Disclosure Receiving section of the originally published article, the section subtitle appeared as follows:

HIV e-Reports Emerging as the New Manner of HIV Serostatus Request and Disclosure Receiving

This has been corrected as follows:

HIV e-Reports Emerging as the New Approach for HIV Serostatus Requests and Disclosure Receiving

17. In the Results: HIV e-Reports Emerging as the New Approach for HIV Serostatus Requests and Disclosure Receiving section of the originally published article, the second paragraph appeared as follows:

At month 3 follow-up, for all 357 participants, 57.4% (205/357) of them had regular male sex partners, 42.9% (153/357) of them had casual male sex partners, and 73.4% (262/357) of them had any kind of male sex partners in the past 3 months.

This has been corrected as follows:

At month 3 follow-up, for all 357 participants, 57.4% (205/357) of them had regular male sex partners, 42.9% (153/357) of them had casual male sex partners, and 73.4% (262/357) of them had either kind of male sex partner in the past 3 months.

18. In the Results: HIV e-Reports Emerging as the New Approach for HIV Serostatus Requests and Disclosure Receiving section of the originally published article, the third sentence of the third paragraph appeared as follows:

Therefore, 2 new request ways for HIV serostatus using the HIV e-report emerged; namely “I requested by sending my own HIV e-report” and “I requested by asking for partner’s HIV e-report.”

This has been corrected as follows:

Therefore, 2 new request approaches for HIV serostatus using the HIV e-report emerged; namely “I requested by sending my own HIV e-report” and “I requested by asking for partner’s HIV e-report.”

19. In the Results: HIV e-Reports Emerging as the New Approach for HIV Serostatus Requests and Disclosure Receiving section of the originally published article, the fourth sentence of the third paragraph appeared as follows:

The proportions of these 2 ways were 10.7% (22/205) and 2.4% (5/205) toward regular male sex partners, and 7.2% (11/153) and 3.3% (5/153) toward casual male sex partners, respectively.

This has been corrected as follows:

The proportions of these 2 approaches were 10.7% (22/205) and 2.4% (5/205) toward regular male sex partners, and 7.2% (11/153) and 3.3% (5/153) toward casual male sex partners, respectively.
20. In the Methods: HIV e-Reports Emerging as the New Approach for HIV Serostatus Requests and Disclosure Receiving section of the originally published article, the title of Table 2 appeared as follows:

Table 2. HIV serostatus request and disclosure receiving behaviors from different male sex partners among alters at month 3 follow-up.

This has been corrected as follows:

Table 2. HIV serostatus request and disclosure receiving behaviors toward different male sex partners among alters at month 3 follow-up.

21. In the Results: Factors Associated With HIV Serostatus Requests and Receiving Disclosure section of the originally published article, the subsection title appeared as follows:

Associated Factors With HIV Serostatus Request and Disclosure Receiving

This has been corrected as follows:

Factors Associated With HIV Serostatus Requests and Receiving Disclosures

22. In the Factors Associated With HIV Serostatus Requests and Receiving Disclosure section of the originally published article, the last paragraph appeared as follows:

All variables listed in Table 2 were not associated with HIV serostatus disclosure receiving (not tabulated).

This has been corrected as follows:

All variables listed in Table 2 were not associated with receiving HIV serostatus disclosures (not tabulated).

23. In the Discussion: Principal Results section of the originally published article, the first two sentences appeared as follows:

e-Report is emerging as a new manner for HIV serostatus request and disclosure for the HIV risk population. MSM chose HIV e-report as the web-based way to disclose their own HIV serostatus or to request partner’s HIV serostatus with authenticity when it was available in Guangzhou.

This has been corrected as follows:

e-Reports are a new approach for HIV serostatus request and disclosure for the HIV risk population. MSM chose HIV e-report as the web-based approach to disclose their own HIV serostatus or to request partner’s HIV serostatus with authenticity when it was available in Guangzhou.

24. In the Discussion: Principal Results section of the originally published article, the fourth sentence appeared as follows:

To the best of our knowledge, this is the first study to discuss the use of HIV e-reports and explore its association.

25. In the Discussion: Principal Results section of the originally published article, the fifth sentence appeared as follows:

HIV e-report, codeveloped by MSM community itself, could be considered a novel approach to promote mutual HIV status disclosure before engaging in sexual behaviors among HIV high-risk population, and being capable to be replicated in other countries and regions based on the ability of building information platforms.

This has been corrected as follows:

HIV e-report, codeveloped by the MSM community itself, could be considered a novel approach to promote mutual HIV status disclosure before engaging in sexual behaviors among HIV high-risk population, and being capable to be replicated in other countries and regions based on the ability of building information platforms.

26. In the Discussion: Principal Results section of the originally published article, the second sentence of the second paragraph appeared as follows:

As e-report is a new modality in the HIV research area, studies to investigate the association between HIV e-report, HIV serostatus request, and disclosure behaviors have rarely been reported.

This has been corrected as follows:

As e-report is a new modality in the HIV research area, studies to investigate the association between HIV e-reports and HIV serostatus request and disclosure behaviors have rarely been reported.

27. In the Discussion: Principal Results section of the originally published article, the sixth sentence of the second paragraph appeared as follows:

However, it is important to emphasize that HIV e-report is not a substitute for condom use.

This has been corrected as follows:

However, it is important to emphasize that the HIV e-report is not a substitute for condom use.

28. In the Discussion: Principal Results section of the originally published article, the first sentence of the third paragraph appeared as follows:

After HIV e-report was available, a new portion of MSM had applied e-report to request sex partner’s HIV serostatus (13.4%, 35/262) and had received sex partner’s e-report as HIV serostatus disclosure (26.2%, 51/195).

This has been corrected as follows:

After the HIV e-report was available, a new proportion of MSM had used the e-report to request their sex partner’s HIV serostatus (13.4%, 35/262).
and had received their sex partner’s e-report as an HIV serostatus disclosure (26.2%, 51/195).

29. In the Discussion: Principal Results section of the originally published article, the third sentence of the third paragraph appeared as follows:

MSM designed it because they feel sending out their own HIV e-report is the most natural and credible way to request male sex partners’ HIV serostatus as well as disclosure of their own HIV serostatus.

This has been corrected as follows:

MSM designed it because they feel sending out their own HIV e-report is the most natural and credible way to request male sex partners’ HIV serostatus as well as disclose their own HIV serostatus.

30. In the Discussion: Principal Results section of the originally published article, the fifth sentence of the fourth paragraph appeared as follows:

Only a few studies have investigated HIV serostatus request behavior, and our finding data contribute to the literature [5,6].

This has been corrected as follows:

Only a few studies have investigated HIV serostatus request behavior, and our data contribute to the literature [5,6].

31. In the Discussion: Principal Results section of the originally published article, the fourth sentence of the fifth paragraph appeared as follows:

We did not identify any factors associated with HIV serostatus disclosure receiving.

This has been corrected as follows:

We did not identify any factors associated with receiving an HIV serostatus disclosure.

32. In the Discussion: Principal Results section of the originally published article, the fourth sentence of the sixth paragraph appeared as follows:

The possible reason may be that disclosure receiving is a passive behavior that is primarily influenced by the characteristics of the person who disclosed their status rather than the recipient.

This has been corrected as follows:

The possible reason may be that receiving a disclosure is a passive behavior that is primarily influenced by the characteristics of the person who disclosed their status rather than the recipient.

33. In the Discussion: Principal Results section of the originally published article, the last sentence of the sixth paragraph appeared as follows:

Active coping strategies used by MSM, such as promoting the active behavior of requests by expanding the use of HIV e-reports, should be promoted.

34. In the Discussion: Limitations section of the originally published article, the third sentence appeared as follows:

Second, there might be selection bias since participants were recruited through HIV testers from a local MSM-friendly clinic in Guangzhou and questionnaires were conducted on the mobile app, which led participants trend to be young and well-educated.

This has been corrected as follows:

Second, there might be selection bias since participants were recruited through HIV testers from a local MSM-friendly clinic in Guangzhou and questionnaires were conducted on the mobile app, which led participants being younger and well-educated.

35. In the Discussion: Limitations section of the originally published article, the last sentence appeared as follows:

Though we find several factors associated with HIV serostatus request, the causation between them needs further study.

This has been corrected as follows:

Though we found several factors associated with HIV serostatus request, the causation between them needs further study.

36. In the Discussion: Conclusions section of the originally published article, the first sentence appeared as follows:

This study indicated that the HIV e-report, the health service tool coproduced by community members, has become acceptable and could be used as a new optional manner for HIV serostatus request and disclosure among sexually transmitted infections high-risk population.

This has been corrected as follows:

This study indicated that the HIV e-report, the health service tool coproduced by community members, has become acceptable and could be used as a new optional approach for HIV serostatus request and disclosure among populations at high risk of sexually transmitted infections.

37. In the Discussion: Conclusions section of the originally published article, the last sentence appeared as follows:

It is anticipated that e-report manner are able to have an extended spectrum of coverage to reach more target populations and ultimately accelerating the decline of infectious disease transmission.

This has been corrected as follows:

It is anticipated that the e-report approach will have an extended spectrum of coverage to reach more
target populations and ultimately accelerate the decline of infectious disease transmission.

The correction will appear in the online version of the paper on the JMIR Publications website on May 17, 2023, together with the publication.
Correction: Evaluation Criteria for Weight Management Apps: Validation Using a Modified Delphi Process

Noemí Robles1,2,3*, PhD; Elisa Puigdomèneh Puig1,3,4*, MSc; Corpus Gómez-Calderón5*, BA; Francesc Saigí-Rubió6,7*, PhD; Guillem Cuatrecasas Cambra8*, MD; Alberto Zamora9,10*, MD, PhD; Montse Moharra4,11*, BA; Guillermo Paluzie9*, MD, PhD; Mariona Balfego8*, PhD; Carme Carrión1,2,3,6*, PhD

1eHealth Lab Research Group, Universitat Oberta de Catalunya, Barcelona, Spain
2eHealth Center, Universitat Oberta de Catalunya, Barcelona, Spain
3Red de Investigación en Servicios de Salud en Enfermedades Crónicas, Barcelona, Spain
4Agència de Qualitat i Avaluació Sanitàries de Catalunya, Barcelona, Spain
5Marina, Salud, Alicante, Spain
6Faculty of Health Sciences, Universitat Oberta de Catalunya, Barcelona, Spain
7Interdisciplinary Research Group on ICTs, Universitat Oberta de Catalunya, Barcelona, Spain
8Clínica Sagrada Familia, CPEN SL Servei d’Endocrinologia i Nutrició, Barcelona, Spain
9Corporació de Salut del Maresme i la Selva, Hospital de Blanes, Blanes, Spain
10Grup de Medicina Trasacional i Ciències de la Decisió, Universitat de Girona, Girona, Spain
11Centro de Investigación Biomédica en Red en Epidemiología y Salud Pública, Barcelona, Spain

* all authors contributed equally

Corresponding Author:
Elisa Puigdomèneh Puig, MSc
Agència de Qualitat i Avaluació Sanitàries de Catalunya
Carrer Roc Boronat 81-95
Barcelona, E08005
Spain
Phone: 34 93 5513476
Email: epuigdomenech@gencat.cat

Related Article:
Correction of: https://mhealth.jmir.org/2020/7/e16899/

(JMIR Mhealth Uhealth 2023;11:e47584) doi:10.2196/47584

In "Assessment of the Efficacy, Safety, and Effectiveness of Weight Control and Obesity Management Mobile Health Interventions: Systematic Review" (JMIR Mhealth Uhealth 2020;8(7):e16899) the authors noted one clarification that should be added:

The Acknowledgments section reads as:

All authors contributed equally. The research for this paper was fully funded by the Instituto de Salud Carlos III from the Spanish Ministry of Science, Innovation and Universities, grant number PI16/01764.

And will be changed to:

All authors contributed equally. The research for this paper was fully funded by the Instituto de Salud Carlos III from the Spanish Ministry of Science, Innovation and Universities, grant number PI16/01764 co-funded by FEDER.

The correction will appear in the online version of the paper on the JMIR Publications website on April 10, 2023 together with the publication of this correction notice. Because this was made after submission to PubMed, PubMed Central, and other full-text repositories, the corrected article has also been resubmitted to those repositories.
Correction: Assessment of the Efficacy, Safety, and Effectiveness of Weight Control and Obesity Management Mobile Health Interventions: Systematic Review

Elisa Puigdomenech Puig\textsuperscript{1,2,3}, MSc; Noemí Robles\textsuperscript{2,3,4}, PhD; Francesc Saigí-Rubió\textsuperscript{5,6}, PhD; Alberto Zamora\textsuperscript{7,8}, MD, PhD; Montse Moharra\textsuperscript{1,9}, BA; Guillermo Paluzie\textsuperscript{7}, MD, PhD; Mariona Balfegó\textsuperscript{10}, PhD; Guillem Cuatrecasas Cambra\textsuperscript{10}, MD; Pilar García-Lordá\textsuperscript{5}, MD, PhD; Carme Carrion\textsuperscript{2,3,4,5}, PhD

\textsuperscript{1}Agència de Qualitat i Avaluació Sanitàries de Catalunya, Barcelona, Spain
\textsuperscript{2}Red de Investigación en Servicios de Salud en Enfermedades Crónicas, Barcelona, Spain
\textsuperscript{3}eHealth Lab, Barcelona, Spain
\textsuperscript{4}eHealth Center, Universitat Oberta de Catalunya, Barcelona, Spain
\textsuperscript{5}Faculty of Health Sciences, Universitat Oberta de Catalunya, Barcelona, Spain
\textsuperscript{6}Interdisciplinary Research Group on ICTs, Barcelona, Spain
\textsuperscript{7}Corporació de Salut del Maresme i la Selva, Hospital de Blanes, Blanes, Spain
\textsuperscript{8}Grup de Medicina Translacional i Ciències de la Decisió, Departament de Ciències Mèdiques, Facultat de Medicina, Universitat de Girona, Girona, Spain
\textsuperscript{9}CIBER Epidemiología y Salud Pública, Barcelona, Spain
\textsuperscript{10}Clínica Sagrada Família, CPEN SL Servei d'Endocrinologia i Nutrició, Barcelona, Spain

**Corresponding Author:**
Carme Carrion, PhD
Faculty of Health Sciences
Universitat Oberta de Catalunya
Rambla del Poblenou, 156
Barcelona
Spain
Phone: 34 934 505 254
Email: mcarrionr@uoc.edu

**Related Article:**
Correction of: https://mhealth.jmir.org/2019/10/e12612/

(**JMIR Mhealth Uhealth 2023;11:e47585**) doi:10.2196/47585

In “Assessment of the Efficacy, Safety, and Effectiveness of Weight Control and Obesity Management Mobile Health Interventions: Systematic Review” (JMIR Mhealth Uhealth 2019;7(10):e12612) the authors noted one clarification that should be added.

In the Acknowledgments section it says:

*All authors contributed equally. The research for this paper was fully funded by the Instituto de Salud Carlos III from the Spanish Ministry of Science, Innovation and Universities, grant number PI16/01764.*

It should say:

*All authors contributed equally. The research for this paper was fully funded by the Instituto de Salud Carlos III from the Spanish Ministry of Science, Innovation and Universities, grant number PI16/01764 co-funded by FEDER.*

The correction will appear in the online version of the paper on the JMIR Publications website on April 10, 2023 together with the publication of this correction notice. Because this was made after submission to PubMed, PubMed Central, and other full-text repositories, the corrected article has also been resubmitted to those repositories.
Correction: Predictors of Playing Augmented Reality Mobile Games While Walking Based on the Theory of Planned Behavior: Web-Based Survey

Hyeseung Elizabeth Koh1,2, MA; Jeeyun Oh1,2, PhD; Michael Mackert1,2,3,4, PhD
1The Center for Health Communication, Moody College of Communication, The University of Texas at Austin, Austin, TX, United States
2Stan Richards School of Advertising and Public Relations, Moody College of Communication, The University of Texas at Austin, Austin, TX, United States
3Department of Population Health, Dell Medical School, The University of Texas at Austin, Austin, TX, United States
4School of Public Health, The University of Texas Health Science Center at Houston, Houston, TX, United States

Corresponding Author:
Hyeseung Elizabeth Koh, MA
Stan Richards School of Advertising and Public Relations
Moody College of Communication
The University of Texas at Austin
300 West Dean Keeton, A1200, BMC 4.338
Austin, TX, 78712
United States
Phone: 1 512 471 1101
Fax: 1 512 471 7018
Email: kohhye@utexas.edu

Related Article:
Correction of: https://mhealth.jmir.org/2017/12/e191/
doi:10.2196/49937

In "Predictors of Playing Augmented Reality Mobile Games While Walking Based on the Theory of Planned Behavior: Web-Based Survey" (JMIR Mhealth Uhealth 2017;5(12):e191) the authors noted one error.

Table 6. Regression results for intention to play a mobile game while walking in study 2 (N=197).

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The correction will appear in the online version of the paper on the JMIR Publications website on June 19, 2023, together with the publication of this correction notice. Because this was made after submission to PubMed, PubMed Central, and other full-text repositories, the corrected article has also been resubmitted to those repositories.

Multimedia Appendix 1
Original published version of “Table 6. Regression results for intention to play a mobile game while walking in study 2 (N=197).”
[DOCX File , 15 KB - mhealth_v11i1e49937_app1.docx ]
Corrigenda and Addenda

Correction: Efficacy, Effectiveness, and Quality of Resilience-Building Mobile Health Apps for Military, Veteran, and Public Safety Personnel Populations: Scoping Literature Review and App Evaluation

Melissa Voth¹,², BEd; Shannon Chisholm², BSc; Hannah Sollid², BSc; Chelsea Jones¹,³,⁴, PhD; Lorraine Smith-MacDonald¹,², PhD; Suzette Brémault-Phillips¹,², PhD

¹Heroes in Mind, Advocacy and Research Consortium, Faculty of Rehabilitation Medicine, University of Alberta, Edmonton, AB, Canada
²Department of Occupational Therapy, Faculty of Rehabilitation, University of Alberta, Edmonton, AB, Canada
³Leiden University Medical Centre, Leiden University, Leiden, Netherlands
⁴Operational Stress Injury Clinic, Alberta Health Services, Edmonton, AB, Canada

Corresponding Author:
Chelsea Jones, PhD
Heroes in Mind, Advocacy and Research Consortium
Faculty of Rehabilitation Medicine
University of Alberta
1-94 Corbett Hall
8205 - 114 Street Edmonton
Edmonton, AB, T6G 2G4
Canada
Phone: 1 7804920404
Email: cweiman@ualberta.ca

Related Article:
Correction of: https://mhealth.jmir.org/2022/1/e26453

In “Efficacy, Effectiveness, and Quality of Resilience-Building Mobile Health Apps for Military, Veteran, and Public Safety Personnel Populations: Scoping Literature Review and App Evaluation ([JMIR Mhealth Uhealth 2022;10(1):e26453]) the authors made the following 4 corrections:

1. In the originally published article, in 8 instances the name of an app appeared as:

   Resilience@Work/Mindarma

   This has been corrected as follows in all 8 instances:

   Mindarma

2. In the originally published article, in the Results: Study Findings: Evidence-Based Merit section, the last sentence appeared as follows:

   Virtual Hope Box, eQuoo, and Resilience@Work/Mindarma were evaluated separately in their respective RCT studies.

   This has been corrected as follows:

   Virtual Hope Box and eQuoo, were evaluated separately in their respective RCT studies. It was noted that Mindarma was utilized as a part of a mindfulness program for first responders [15].

3. In the originally published article, in the Results: Study Findings: Mental Control, Emotional Regulation, Coping, and Self-efficacy section, the following sentence appeared:

   Resilience@Work/Mindarma was the only app in this study that drew from acceptance and commitment therapy principles.

   This sentence has been deleted from the paper.

4. In the originally published article, in the Results: Study Findings: Effect of Apps on Resilience section, the following sentences appeared:

   Similarly, Resilience@Work/Mindarma showed improved adaptive resilience and psychological flexibility [15]. Joyce et al [15] also found that this app significantly increased optimism and mindfulness practice among study participants. This study also found that the app increased use of emotional support from others and help-seeking behavior, which addresses the social support pillar of the pillars of mental resilience.
These sentences have been deleted from the paper.

The correction will appear in the online version of the paper on the JMIR Publications website on August 28 2023, together with the publication of this correction notice. Because this was made after submission to PubMed, PubMed Central, and other full-text repositories, the corrected article has also been resubmitted to those repositories.

Reference
Exploring Digital Biomarkers of Illness Activity in Mood Episodes: Hypotheses Generating and Model Development Study

Gerard Anmella, MD; Filippo Corponi, MD; Bryan M Li, MS; Ariadna Mas, MD; Miriam Sanabra, MD; Isabella Pacchiarotti, MD; Marc Valent, MD; Iria Grande, MD; Antoni Benabarre, MD; Anna Giménez-Palomo, MD; Marina Garriga, MD; Isabel Agasi, RNC; Anna Bastidas, RNC; Myriam Cavero, MD; Tabatha Fernández-Plaza, MD; Néstor Arbelo, MD; Miquel Bioque, MD; Clemente García-Rizo, MD; Norma Verdolini, MD; Santiago Madero, MD; Andrea Murru, MD; Silvia Amoretti, MD; Anabel Martínez-Aran, MD; Victoria Ruiz, RNC; Giovanna Fico, MD; Michele De Prisco, MD; Vincenzo Oliva, MD; Aleix Solanes, MSc; Joaquim Radua, MD; Ludovic Samalin, MD; Antoni Vergari, MSc; Diego Hidalgo-Mazzei, MD

1Department of Psychiatry and Psychology, Institute of Neuroscience, Hospital Clínic de Barcelona, Barcelona, Catalonia, Spain
2Bipolar and Depressive Disorders Unit, Digital Innovation Group, Institut d’Investigacions Biomèdiques August Pi i Sunyer (IDIBAPS), Barcelona, Catalonia, Spain
3Biomedical Research Networking Centre Consortium on Mental Health (CIBERSAM), Instituto de Salud Carlos III, Madrid, Spain
4Department of Medicine, School of Medicine and Health Sciences, University of Barcelona (UB), Barcelona, Catalonia, Spain
5Institute of Neurosciences (UBNeuro), University of Barcelona, Barcelona, Catalonia, Spain
6School of Informatics, University of Edinburgh, Edinburgh, United Kingdom
7Barcelona Clinic Schizophrenia Unit, Institut d’Investigacions Biomèdiques August Pi i Sunyer (IDIBAPS), Barcelona, Catalonia, Spain
8Imaging of Mood- and Anxiety-Related Disorders (IMARD) Group, Institut d’Investigacions Biomèdiques August Pi i Sunyer (IDIBAPS), Barcelona, Catalonia, Spain
9Early Psychosis: Interventions & Clinical-detection (EPIC) Lab, Department of Psychosis Studies, Institute of Psychiatry Psychology and Neuroscience, King’s College London, London, United Kingdom
10Center for Psychiatry Research, Department of Clinical Neuroscience, Karolinska Institutet, Stockholm, Sweden
11Department of Psychiatry, Centre Hospitalier Universitaire (CHU) Clermont-Ferrand, University of Clermont Auvergne, Centre National de la Recherche Scientifique (CNRS), Clermont-Auvergne INP, Institut Pascal (UMR 6602), Clermont-Ferrand, France
12Association Française de Psychiatrie Biologique et Neuropsychopharmacologie (AFPBPN), Paris, France
13Centre for Affective Disorders, Institute of Psychiatry, Psychology & Neuroscience, King’s College London, London, United Kingdom

* these authors contributed equally

Corresponding Author:
Diego Hidalgo-Mazzei, MD, PhD
Department of Psychiatry and Psychology
Institute of Neuroscience
Hospital Clinic de Barcelona
Vilarruel St, 170
Barcelona, Catalonia, 08036
Spain
Phone: 34 932275400 ext 4189
Email: dahidalp@clinic.cat

Abstract

Background: Depressive and manic episodes within bipolar disorder (BD) and major depressive disorder (MDD) involve altered mood, sleep, and activity, alongside physiological alterations wearables can capture.

Objective: Firstly, we explored whether physiological wearable data could predict (aim 1) the severity of an acute affective episode at the intra-individual level and (aim 2) the polarity of an acute affective episode and euthymia among different individuals.
Secondarily, we explored which physiological data were related to prior predictions, generalization across patients, and associations between affective symptoms and physiological data.

**Methods:** We conducted a prospective exploratory observational study including patients with BD and MDD on acute affective episodes (manic, depressed, and mixed) whose physiological data were recorded using a research-grade wearable (Empatica E4) across 3 consecutive time points (acute, response, and remission of episode). Euthymic patients and healthy controls were recorded during a single session (approximately 48 h). Manic and depressive symptoms were assessed using standardized psychometric scales. Physiological wearable data included the following channels: acceleration (ACC), skin temperature, blood volume pulse, heart rate (HR), and electrodermal activity (EDA). Invalid physiological data were removed using a rule-based filter, and channels were time aligned at 1-second time units and segmented at window lengths of 32 seconds, as best-performing parameters. We developed deep learning predictive models, assessed the channels’ individual contribution using permutation feature importance analysis, and computed physiological data to psychometric scales’ items normalized mutual information (NMI). We present a novel, fully automated method for the preprocessing and analysis of physiological data from a research-grade wearable device, including a viable supervised learning pipeline for time-series analyses.

**Results:** Overall, 35 sessions (1512 hours) from 12 patients (manic, depressed, mixed, and euthymic) and 7 healthy controls (mean age 39.7, SD 12.6 years; 6/19, 32% female) were analyzed. The severity of mood episodes was predicted with moderate (62%-85%) accuracies (aim 1), and their polarity with moderate (70%) accuracy (aim 2). The most relevant features for the former tasks were ACC, EDA, and HR. There was a fair agreement in feature importance across classification tasks (Kendall W=0.383). Generalization of the former models on unseen patients was of overall low accuracy, except for the intra-individual models. ACC was associated with “increased motor activity” (NMI>0.55), “insomnia” (NMI=0.6), and “motor inhibition” (NMI=0.75). EDA was associated with “aggressive behavior” (NMI=1.0) and “psychic anxiety” (NMI=0.52).

**Conclusions:** Physiological data from wearables show potential to identify mood episodes and specific symptoms of mania and depression quantitatively, both in BD and MDD. Motor activity and stress-related physiological data (EDA and HR) stand out as potential digital biomarkers for predicting mania and depression, respectively. These findings represent a promising pathway toward personalized psychiatry, in which physiological wearable data could allow the early identification and intervention of mood episodes.

(JMIR Mhealth Uhealth 2023;11:e45405) doi:10.2196/45405

**KEYWORDS**

depression; mania; bipolar disorder; major depressive disorder; machine learning; deep learning; physiological data; digital biomarker; wearable; Empatica E4

**Introduction**

Mood disorders, including bipolar disorder (BD) and major depressive disorder (MDD), are ranked among the top 25 leading causes of disease burden worldwide [1] and are associated with recurrent depressive and manic episodes. Manic episodes are characterized by increased activity and self-esteem, reduced need for sleep, and expansive mood and behavior, whereas during depressive episodes, patients experience decreased energy and activity, sadness, low self-esteem, and social withdrawal [2-4]. These changes in mood, sleep, and activity during mood episodes translate to changes in physiological data that novel research-grade wearables can capture with high precision in real time [5,6]. Linking these digital signals with illness activity could potentially identify digital biomarkers [7].

Biomarkers are characteristics that are measured as an indicator of pathogenic processes (disease-associated biomarkers) or responses to an exposure or intervention (drug-related biomarkers) [8]. These can include molecular, histological, radiographic, or physiological characteristics. Digital biomarkers are objective, quantifiable, and physiological, and behavioral measures are collected using digital devices that are portable, wearable, implantable, or digestible [9]. Traditional biomarkers can be invasive and expensive to measure and are difficult to collect over time, thus giving an incomplete view of the complexity and dynamism of the disease. Alternatively, digital biomarkers are usually noninvasive, modular, and cheaper to measure, and they provide access to continuous and longitudinal measurements, both qualitative and quantitative. Moreover, they offer novel ways of measuring health status by providing perspectives into diseases that were unavailable before, which can supplement and enhance conclusions from traditional biomarkers [10]. Digital biomarkers have the potential to redefine diagnosis, improve the accuracy of diagnostic methods, enhance monitoring, and personalize interventions [11], leading to precision medicine, especially in psychiatric diseases [12].

In the last decade, there has been an exponential growth in the number of digital biomarker studies in the health domain, especially in cardiovascular and respiratory diseases [9]. Wearables are the most common type of digital devices used in digital biomarker studies, especially those incorporating accelerometer sensors that measure physical activity [13]. Wearable devices include wristbands, smartwatches, smart shirts, smart rings, smart electrodes, smart headsets, smart glasses, and so on. Wrist-worn devices are the most common type of wearable device in mental health studies and have shown to be effective in diagnosing anxiety and depression. However, none of the studies used it for treatment. The most commonly used category of data for model development was physical activity data, followed by sleep and heart rate (HR) data [14]. There are several areas in health care in which wearable devices have shown potential, including monitoring, diagnosis,
treatment, and rehabilitation of diseases. Even though wearables have shown accurate activity-tracking measurements and are acceptable for users [15], including feasibility studies in people with mental health problems [16], their implementation in usual clinical practice is still challenging [17].

Wearables collecting actigraphy, the noninvasive method of monitoring human rest and activity [18], can capture altered sleep rhythms in remitted BD [19] and also depressive symptoms [20]. In addition, actigraphy data from wearables have shown accurately predict mood disorder diagnoses and symptom change [21]. Moreover, wearables collecting blood pulse have shown differences in HR variability (HRV) between BD and healthy controls (HCs) [22], as well as between affective states in BD [23]. In addition, people with bipolar and unipolar depression and suicidal behavior have long shown autonomic alterations that can be captured as hyporeactive electrodermal activity (EDA) [24,25], and in recent years, research-grade wearables have incorporated sensors allowing continuous EDA collection [26]. With these upgrades, in the latest years, it is now feasible to monitor mood changes in patients with MDD [27] and also predict the presence and severity of depressive states in BD and MDD with promising accuracy using wearable physiological data [28]. Despite these promising results, the specific roles of these digital signals and their longitudinal potential to measure illness activity and treatment response in mood disorders are still unknown.

The conjuncture of advances in machine learning [29] and the improved precision of wearable devices [30] may help identify physiological patterns of illness activity in mood disorders. Firstly, considering this promising background, we explored whether physiological wearable data could predict the severity of an acute affective episode at the intra-individual level (aim 1) and the polarity of an acute affective episode and euthymia among different individuals (aim 2). Secondarily, we explored which physiological data were related to prior predictions, generalization across patients, and associations between affective symptoms and physiological data.

Methods

Study Design

A prospective exploratory observational study with 3 independent groups (Figure 1): group A, patients on acute affective episodes, manic episodes in BD (n=2), major depressive episodes in BD (n=2), and MDD (n=2), and mixed features manic episodes in BD (n=2); group B, euthymic patients with BD (n=2) and MDD (n=2); and group C, HC (n=7). Potential participants were identified at the outpatient and the acute inpatient or hospitalization at home units by their clinicians (ie, psychiatrists). Physiological data were recorded across 3 consecutive time points for group A: T0-acute (T0): current acute affective episodes according to the Diagnostic and Statistical Manual of Mental Disorders–5 (DSM-5); T1-response (T1): symptom response, as more than 30% improvement in the Young Mania Rating Scale (YMRS) score or the 17-item Hamilton Depression Rating Scale (HDRS) score; and T2-remission (T2): symptomatic remission, with YMRS and HDRS score ≤7 [31]). Euthymic patients (group B) and HCs (group C) were recorded during a single session.

The inclusion criteria were as follows: (1) aged above 18 years; (2) having a diagnosis according to the DSM-5 [32] criteria confirmed with the Structured Clinical Interview for DSM-5 Disorders [33]; and (3) willingness and ability to give consent (reconfirmed upon clinical remission). In addition, euthymic patients (group B) should also (4) score ≤7 on the YMRS and HDRS for at least 8 weeks [31]. HC (group C) should present no current or previous psychiatric disorder according to the DSM-5 criteria and confirmed using the Structured Clinical Interview for DSM-5 Disorders, excluding nicotine substance use disorder. Exclusion criteria for all groups were as follows: (1) concomitant severe cardiovascular or neurological medical conditions with a potential autonomic dysfunction, ongoing cardiovascular arrhythmia, or pacemaker; (2) comorbid current substance use disorder according to the DSM-5 criteria and confirmed using the Structured Clinical Interview for DSM-5 Disorders, excluding nicotine substance use disorder; (3) comorbid current psychiatric disorder with great interference of symptoms (eg, obsessive compulsive disorder with ritualized behaviors); (4) current pharmacological treatment with β-blockers or other pharmacological treatments affecting the autonomic nervous system; and (5) ongoing pregnancy.
Assessments

The following sociodemographic variables were collected: age, sex, DSM-5 psychiatric diagnoses [32], medical and psychiatric comorbidities, years of illness duration, first-degree relative with mental illness, and drug misuse habits. Psychopathological assessments were conducted using the YMRS [34,35] for manic symptoms and the 17-item HDRS [36,37] for depressive symptoms. Clinical assessments were performed during a single session for euthymic patients (group B) and HCs (group C) and at 3 consecutive time points (T0-acute, T1-response, and T2-remission) for patients on acute affective episodes (group A), as described in Figure 1.

Research-Grade Wearable Device for Recording

When choosing a wearable device for a research project, there are several factors that should be considered, including (1) the signals of interest to be captured (eg, stress-related and actigraphy); (2) the users who will be studied (eg, inpatients, outpatients, and HCs); (3) the pragmatic needs of the study (eg, budget, battery life, placement of the devices, and confidentiality of participants); (4) establishing assessment procedures (eg, stress elicitation task, resting, and sleep); and (5) performing qualitative and quantitative analyses on resulting data (eg, visually inspecting the data registered, quantifying data loss, assessing the quality of data, and comparing the data of different wearable devices) [38]. Considering the previous points, the E4 wristband from Empatica [39] was the preferred wearable device for the purpose of our study for several reasons. First, the E4 has shown accuracy in measuring HR, HRV [40], and EDA compared with laboratory conditions [41], as well as for sleep staging [42]. As previously mentioned, these physiological parameters have been shown to be altered in mood disorders and mood episodes [19-23,25-28]. Second, the E4 has been validated in scientific research for detecting emotional arousal, stress [43,44], and mental effort [45] using the aforementioned physiological signals. Furthermore, the E4 has proven to be useful in predicting depressive symptoms in MDD with low relative errors [46,47], predicting self-reported depressive states [48], and identifying and quantifying the severity of anxiety states [49]. In patients with BD, the E4 has shown to be useful in distinguishing manic from euthymic mood states [50,51]. Third, the inpatients included in the study were in a highly restricted setting, which would not allow the use of user-dependent wearables or devices providing external communication (eg, an internet connection). This requirement was fulfilled by the E4 device. Finally, the data recorded by the E4 are of high precision and quality [40,41], with minimal data loss when performing the analyses (see the Results section).

Recording Procedure of Physiological Data

For each recording, patients and HCs were provided with an E4 wristband [39] (Multimedia Appendix 1) for approximately 48 hours (limited by battery life). The research team collected the wearables after each session. Individuals’ behavior was not externally influenced in any manner, further to the requirement of wearing the wristband. Patients with acute affective episodes (group A), during their psychiatric admission in the inpatient unit, were not allowed to leave the hospital at any point until discharge, as it is the standard practice with inpatients. T0-acute,
T1-response, and T2-remission recordings were usually carried out in this setting. This was not the case with patients at the hospitalization at home or outpatient units (a minority of all cases), in which patients were not subject to mobility restrictions. In all cases, both for patients and HCs, participants were asked to wear the wristband during their daily life, with little to no interference in their behavior. They were also asked to put the wristband themselves at the beginning of the recording while researchers checked for adequate contact between the sensors and the skin wrist. Participants received instructions to remove the device when taking a shower to preserve the integrity of the device.

The E4 wristband has sensors that collect physiological data at different sampling rates. The physiological data signals from each recording session were collected from the following channels and sampling rates as raw data: 3D acceleration (ACC) in space over time on an x-, y-, and z-axis (ACC, 32 Hz); EDA (4 Hz); skin temperature (TEMP, 4 Hz); and blood volume pulse (BVP, 64 Hz); or in a processed format: interbeat intervals (IBIs, the time between 2 consecutive heart ventricular contractions) and HR (1 Hz). The BVP signal is obtained using a photoplethysmography sensor that measures volume changes in the blood. Empatica uses 2 algorithms on the BVP signal to construct an IBI with which HR (and HRV) can be calculated. The 2 algorithms are optimized to detect heartbeats and discard beats that contain artifacts [39,40].

### Preprocessing of Physiological Data

Owing to the naturalistic setting of the recording sessions, the data obtained from the E4 wristband are inherently noisy. For instance, some patients show low levels of compliance during an affective episode (eg, mania), which can lead to poor skin contact from the device, hence inaccurate readings for certain channels, or complete removal of the wearable device, resulting in unusable data. To that end, we removed invalid physiological data enforcing the rules-based filter by Kleckner et al [52] and in unusable data. To that end, we removed invalid physiological data enforcing the rules-based filter by Kleckner et al [52] and an additional rule to remove HR values that exceed the physiologically plausible range (25-250 bpm) to quality control the raw data and remove physiologically impossible recordings (Table 1). Quality controlling physiological data from wearable devices is common practice, as this type of data is particularly noisy, and failing to quality control the data favors spurious correlations, and previous works have advised against imputing data in this scenario [53].

We did not use IBI data because of the disproportionately high number of missing values (approximately 70%) relative to data from different channels [54], especially because it is only a derivation of BVP. Therefore, we did not calculate HRV features. In sum, a total of 7 channels from the E4 device (ACC_X, ACC_Y, ACC_Z, BVP, EDA, HR, and TEMP) were used as physiological data to build the prediction models. Different time units (µ) and window lengths (w) were explored during tuning, and the best combination was selected. Because the sampling rate varied across different channels, the recordings were time aligned. If a channel’s sampling rate was higher than 1 Hz, that channel was downsampled by taking the average value across samples within µ. We compared different time units (µ=1, 2, 4, 32, and 64 Hz), and we used 1 Hz because it showed the best performance; therefore, a time unit µ=1 second was set across all channels. Upon time alignment, each recording was then segmented into a predefined number of segments using a tunable window length (w), taking values in real-time seconds (s) (only powers of 2, specifically from $2^0$ [1 s] to $2^{11}$ [2048 s]), were explored for computational convenience. Of note, by tuning the hyperparameter w, an interesting pattern appeared across tasks, whereby a value of $2^5$ (ie, 32 s) emerged as an optimal point, whereas smaller or higher values were associated with a deterioration in validation performance (U-shaped performance); therefore, µ=1 Hz and w=$2^5$ (32 s) were used for analyses as the best-performing algorithm (Multimedia Appendix 2).

To obtain an equal number of segments from each class for model evaluation, we randomly selected 20 segments from each session and stored them as a held-out test set, which was never observed by the model during either training or validation. We then randomly assigned the remaining segments to the train and validation sets with ratios of 80% and 20%, respectively. Each segment was normalized (scaled to [0, 1]) using the per-channel global (across all segments) minimum and maximum values derived from the train set.

### Table 1. Rules-based filter for invalid physiological data.

<table>
<thead>
<tr>
<th>Rules</th>
<th>Filter for invalid data</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>To prevent “floor” artifacts (eg, electrode loses contact with skin) and “ceiling” artifacts (circuit is overloaded)—EDA not in a valid range</td>
<td>$0.05 \text{ to } 60 , \mu S^{b}$</td>
</tr>
<tr>
<td>2</td>
<td>EDA changes too quickly—EDA slope not in a valid range</td>
<td>$-10 \text{ to } +10 , \mu S/\text{second}$</td>
</tr>
<tr>
<td>3</td>
<td>Skin temperature suggests the EDA sensor is not being worn—skin temperature not in a valid range</td>
<td>$30 \text{ to } 40 , ^\circ C$</td>
</tr>
<tr>
<td>4$^c$</td>
<td>HR not in a valid range</td>
<td>$25 \text{ to } 250 , \text{bpm}^{e}$</td>
</tr>
<tr>
<td>5</td>
<td>Transitional data surrounding segments identified as invalid via the preceding rules—account for transition effects</td>
<td>Within 5 seconds</td>
</tr>
</tbody>
</table>

$^a$EDA: electrodermal activity.

$^b$µS: microsiemens.

$^c$Addition to the algorithm used by Kleckner et al [52].

$^d$HR: heart rate.

$^e$bpm: beats per minute.
Data Analyses

Tasks

The recording segments produced with the preprocessing steps described earlier were used in supervised learning experiments as input to the supervised models. For aim 1, models were trained on 3-class classification tasks (T0-acute, T1-response, and T2-remission) for each individual on an acute affective episode (manic BD, depressed BD, mixed BD, and euthymic BD). For aim 2, one model was trained on a 7-class classification task (manic BD, depressed BD, mixed BD, depressed MDD, euthymic BD, euthymic MDD, and HCs).

Segments from each class under a given task were extracted in the same number to obtain perfectly balanced classes. As sets were designed to be perfectly balanced, we adopted accuracy as our primary metric but also reported the $F_1$-score, precision, and recall and computed the area under the receiver operating characteristic (AUROC) curves. It should be noted that ours is a multiclass setting, but as we had perfectly balanced sets, micro-, macro-, and weighted averages coincided. For the AUROC curves, the one-vs-rest multiclass strategy was adopted, also known as one-vs-all, which amounts to computing a receiver operating characteristic (ROC) curve for each class, so that at a given step, a given class is regarded as positive and the remaining classes are lumped together as a single negative class.

As part of our exploratory data analysis, to quantify the association between physiological data and affective symptoms measured by the YMRS and HDRS scale items, their normalized mutual information (NMI) was computed.

For each task, with the exception of the one about distinguishing members of a group of only HCs, as we were interested in testing the degree to which a model can generalize to different individuals, unseen during training, and sharing the same psychiatric label (diagnosis and psychopathological status), we prepared a test set of segments from recordings collected from an independent group of individuals. Therefore, the model was tested on this extra, independent holdout set to obtain an estimate of the out-of-sample generalization performance.

Model

We elected a Bidirectional Long Short-Term Memory (BiLSTM) model [55] as our model architecture. BiLSTM is a type of recurrent neural network (RNN), a class of deep learning model specifically designed to handle sequence data such as time series. RNNs process streams of data one time step at a time, and they store information regarding previous time steps in a hidden unit, such that the model output at each time step is informed by the current time step as well as by previous ones. Long short-term memory (LSTM) units represent an improvement over vanilla RNNs, as they address gradient instability by modeling the hidden state with cells that decide what to keep in memory and what to discard. This feature makes LSTM more efficient in capturing long-range dependencies. In contrast to a simple LSTM, BiLSTM reads the input sequence in 2 directions, from start to end and from end to start, thereby allowing for a richer representation. Although other deep learning architectures suitable for time series have been developed (more recently, the transformer [56]), as the aim of this work was exploratory rather than benchmarking different models, we contented ourselves with a single popular architectural choice for time series. By the same token, we used a simple shallow BiLSTM with 128 hidden units and tanh activation, followed by a single dense layer with softmax activation, to output the possible classes. The BiLSTM model was trained using the Adam optimizer [57] for 120 epochs with a learning rate of 0.001 and a batch size of 32 to minimize the cross-entropy between the ground-truth distribution over classes and the probability distribution of belonging to such classes outputted by the last network layer. To reduce overfitting, dropout [58] and early stopping were used. The choice of hyperparameters was based on a random search that yielded the best performance in the validation set.

Permutation Feature Importance

To assess the channels’ individual impact on the test set performance in the aforementioned tasks, we adopted a perturbation-based approach. For each channel at a time, we randomly permuted its values in the test set segments and computed the difference in performance relative to the baseline model. We chose this approach because it has a straightforward interpretation and provides a highly compressed, global insight into the importance of the channels. Agreement on channels’ relevance across different tasks was measured using the Kendall W.

Code and Data Availability

The codebase was written in Python (version 3.8; Python Software Foundation), where the deep learning models were implemented in TensorFlow and developed on a single NVIDIA RTX 2080Ti. The repository for this study can be found on the internet [59].

Ethics Approval and Confidentiality

This study was conducted in accordance with the ethical principles of the Declaration of Helsinki and Good Clinical Practice and the Hospital Clinic Ethics and Research Board (HC/2021/104). All participants provided written informed consent before their inclusion in the study. All data were collected anonymously and stored encrypted in servers complying with all General Data Protection Regulation and Health Insurance Portability and Accountability Act regulations.

Results

Overview

A total of 35 sessions from 12 patients (manic, depressed, mixed, and euthymic) and 7 HCs (mean age 39.7, SD 12.6 years; 6/19, 32% female) were analyzed, totaling 1512 hours recorded. The median percentage of data per recording session dropped from further analysis of quality control was 11.05 (range 2.50-34.21). A clinical demographic overview of the study sample is presented in Table 2.
Table 2. Clinical demographic overview of the study sample.

<table>
<thead>
<tr>
<th>Diagnosis</th>
<th>Age (years)</th>
<th>Sex</th>
<th>HDRS&lt;sup&gt;a&lt;/sup&gt; score</th>
<th>YMRS&lt;sup&gt;b&lt;/sup&gt; score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>T0&lt;sup&gt;c&lt;/sup&gt;</td>
<td>T1&lt;sup&gt;d&lt;/sup&gt;</td>
</tr>
<tr>
<td>Manic BD&lt;sup&gt;f&lt;/sup&gt;</td>
<td>40</td>
<td>Male</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>Manic BD&lt;sup&gt;g&lt;/sup&gt;</td>
<td>21</td>
<td>Male</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>Depressed BD&lt;sup&gt;h&lt;/sup&gt;</td>
<td>33</td>
<td>Male</td>
<td>23</td>
<td>6</td>
</tr>
<tr>
<td>Depressed BD&lt;sup&gt;e,h&lt;/sup&gt;</td>
<td>36</td>
<td>Male</td>
<td>17</td>
<td>12</td>
</tr>
<tr>
<td>Mixed BD</td>
<td>30</td>
<td>Female</td>
<td>8</td>
<td>4</td>
</tr>
<tr>
<td>Mixed BD&lt;sup&gt;e&lt;/sup&gt;</td>
<td>40</td>
<td>Male</td>
<td>11</td>
<td>2</td>
</tr>
<tr>
<td>Depressed MDD&lt;sup&gt;i&lt;/sup&gt;</td>
<td>57</td>
<td>Male</td>
<td>33</td>
<td>13</td>
</tr>
<tr>
<td>Depressed MDD&lt;sup&gt;g&lt;/sup&gt;</td>
<td>45</td>
<td>Male</td>
<td>27</td>
<td>11</td>
</tr>
<tr>
<td>Euthymic BD</td>
<td>54</td>
<td>Male</td>
<td>3</td>
<td>—</td>
</tr>
<tr>
<td>Euthymic BD&lt;sup&gt;g&lt;/sup&gt;</td>
<td>61</td>
<td>Male</td>
<td>1</td>
<td>—</td>
</tr>
<tr>
<td>Euthymic MDD</td>
<td>60</td>
<td>Female</td>
<td>4</td>
<td>—</td>
</tr>
<tr>
<td>Euthymic MDD&lt;sup&gt;g&lt;/sup&gt;</td>
<td>60</td>
<td>Male</td>
<td>3</td>
<td>—</td>
</tr>
<tr>
<td>HC&lt;sup&gt;k&lt;/sup&gt;</td>
<td>32</td>
<td>Female</td>
<td>0</td>
<td>—</td>
</tr>
<tr>
<td>HC&lt;sup&gt;g&lt;/sup&gt;</td>
<td>34</td>
<td>Male</td>
<td>0</td>
<td>—</td>
</tr>
<tr>
<td>HC</td>
<td>28</td>
<td>Female</td>
<td>0</td>
<td>—</td>
</tr>
<tr>
<td>HC</td>
<td>29</td>
<td>Male</td>
<td>0</td>
<td>—</td>
</tr>
<tr>
<td>HC</td>
<td>31</td>
<td>Male</td>
<td>2</td>
<td>—</td>
</tr>
<tr>
<td>HC</td>
<td>32</td>
<td>Female</td>
<td>1</td>
<td>—</td>
</tr>
<tr>
<td>HC</td>
<td>31</td>
<td>Male</td>
<td>0</td>
<td>—</td>
</tr>
</tbody>
</table>

<sup>a</sup>HDRS: Hamilton Depression Rating Scale.
<sup>b</sup>YMRS: Young Mania Rating Scale.
<sup>c</sup>T0: current acute Diagnostic and Statistical Manual of Mental Disorders–5 affective episodes or only register for euthymic patients and healthy controls.
<sup>d</sup>T1: symptoms' response.
<sup>e</sup>T2: symptomatic remission.
<sup>f</sup>BD: bipolar disorder.
<sup>g</sup>The recording segments extracted from the marked subjects were used to check the models’ ability to generalize to clinically similar subjects, unseen during training.
<sup>h</sup>All registers performed at the hospitalization at home or outpatient units.
<sup>i</sup>MDD: major depressive disorder.
<sup>j</sup>Euthymic patients and healthy controls were recorded during a single session (T0).
<sup>k</sup>HC: healthy control.

**Aim 1: Prediction of the Severity of an Acute Affective Episode at the Intra-individual Level**

The 3-class classification tasks (T0-acute, T1-response, T2-remission; accuracy expected by chance: 1/3=33%) to predict the severity of an acute affective episode showed accuracies ranging from 62% (depressed BD) to 85% (depressed MDD). The generalization models on unseen patients showed accuracies ranging from 28% (depressed MDD) to 57% (manic BD; Table 3). The confusion matrix is shown in Multimedia Appendix 3. This means that the model showed moderate to high accuracies for classifying the severity of each acute affective episode, with the best prediction models classifying individuals with depressed MDD and manic BD. However, generalization of the models was of very low accuracy for depressed MDD and mixed BD (by chance; approximately 30%), of low accuracy (slightly above chance; >40%) for mixed BD, and of moderate accuracy (>55%) for manic BD.

The permutation importance analysis for the classification tasks for aims 1 and 2 is shown in Figure 2. Kendall W was 0.383, indicating fair agreement in feature importance across both intra- and inter-individual classification tasks. ACC was the most relevant channel for predicting mania, whereas EDA and HR, followed by TEMP, were the most relevant channels for predicting both BD and unipolar depression (aim 1). The BVP
channel did not change performance for either better or worse (Figure 2).

Table 3. Prediction of the severity of an acute affective episode: model and generalization on unseen patients.

<table>
<thead>
<tr>
<th>Individuals with affective episodes and performance metric</th>
<th>Model</th>
<th>Generalization</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Manic BD</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Accuracy (^b) (%)</td>
<td>70</td>
<td>56.67</td>
</tr>
<tr>
<td>(F_1)-score</td>
<td>0.6978</td>
<td>0.5279</td>
</tr>
<tr>
<td>Precision</td>
<td>0.6979</td>
<td>0.5381</td>
</tr>
<tr>
<td>Recall</td>
<td>0.7000</td>
<td>0.5667</td>
</tr>
<tr>
<td>AUROC (^c)</td>
<td>0.6980</td>
<td>0.5432</td>
</tr>
<tr>
<td><strong>Depressed BD</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Accuracy (^b) (%)</td>
<td>61.67</td>
<td>41.67</td>
</tr>
<tr>
<td>(F_1)-score</td>
<td>0.6171</td>
<td>0.3968</td>
</tr>
<tr>
<td>Precision</td>
<td>0.6273</td>
<td>0.4085</td>
</tr>
<tr>
<td>Recall</td>
<td>0.6167</td>
<td>0.4167</td>
</tr>
<tr>
<td>AUROC</td>
<td>0.6115</td>
<td>0.4067</td>
</tr>
<tr>
<td><strong>Mixed BD</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Accuracy (^b) (%)</td>
<td>63.33</td>
<td>30</td>
</tr>
<tr>
<td>(F_1)-score</td>
<td>0.6333</td>
<td>0.2576</td>
</tr>
<tr>
<td>Precision</td>
<td>0.6333</td>
<td>0.3004</td>
</tr>
<tr>
<td>Recall</td>
<td>0.6333</td>
<td>0.3068</td>
</tr>
<tr>
<td>AUROC</td>
<td>0.6333</td>
<td>0.3012</td>
</tr>
<tr>
<td><strong>Depressed MDD</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Accuracy (^b) (%)</td>
<td>85</td>
<td>28.33</td>
</tr>
<tr>
<td>(F_1)-score</td>
<td>0.8492</td>
<td>0.2451</td>
</tr>
<tr>
<td>Precision</td>
<td>0.8774</td>
<td>0.2581</td>
</tr>
<tr>
<td>Recall</td>
<td>0.8500</td>
<td>0.2833</td>
</tr>
<tr>
<td>AUROC</td>
<td>0.8672</td>
<td>0.2856</td>
</tr>
</tbody>
</table>

\(^a\)BD: bipolar disorder.

\(^b\)Accuracy expected by chance for a 3-class classification task is \(1/3=33\%\). Thus, accuracies above 33\% suggest that the model can predict outcomes better than random guessing, and higher values for accuracy indicate better predictive capacity of the model. Note that the test set was designed to have the same number of samples in each class. This is reflected in the values of \(F_1\)-score, precision, and recall being very close to each other and to that of accuracy.

\(^c\)AUROC: area under the receiver operating characteristic.

\(^d\)MDD: major depressive disorder.
Aim 2: Prediction of the Polarity of an Acute Affective Episode and Euthymia Among Different Individuals

The 7-class classification task (accuracy expected by chance: 1/7 = 14%) to predict the polarity of affective episodes and euthymia showed an accuracy of 70%. The best classifications were depressed and euthymic MDD, followed by depressed BD, and the worst was manic BD, followed by HCs. The generalization model showed an accuracy of 15.7% (slightly above chance). The classification task for 7 HCs showed an accuracy of 50% (Table 4). The confusion matrix is shown in Multimedia Appendix 4. Thus, both models showed predictions above chance, but their generalization was poor. Moreover, the model including patients with acute affective episodes obtained higher accuracy (70%) than the model including 7 HCs (50%). This increased prediction capacity suggests that psychopathological symptoms during acute affective episodes may translate into physiological alterations that are not present in HCs.

The most relevant channels for predicting the polarity of affective episodes, euthymia, and HCs among different individuals (aim 2) were EDA, followed by ACC, HR, and TEMP (all channels showed >30% permutation importance). The BVP channel permutation importance was approximately 0%. These results were highly similar for the classification task of 7 HCs, but EDA showed only 4.9% permutation importance (Figure 2).
Table 4. Prediction of the polarity of an acute affective episode and euthymia among different individuals: model and generalization on unseen patients.

<table>
<thead>
<tr>
<th>Individuals with affective episodes and performance metric</th>
<th>Model</th>
<th>Generalization</th>
</tr>
</thead>
<tbody>
<tr>
<td>6 patients (acute affective episodes and euthymia) and 1 HC(^a)</td>
<td>70</td>
<td>15.7</td>
</tr>
<tr>
<td>Accuracy(^b) (%)</td>
<td>0.6927</td>
<td>0.1516</td>
</tr>
<tr>
<td>(F_1)-score</td>
<td>0.6889</td>
<td>0.1513</td>
</tr>
<tr>
<td>Precision</td>
<td>0.6934</td>
<td>0.1517</td>
</tr>
<tr>
<td>Recall</td>
<td>0.6900</td>
<td>0.1510</td>
</tr>
<tr>
<td>AUROC(^c)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

7 HCs

| Accuracy\(^b\) (%) | 50    | d |
| \(F_1\)-score      | 0.4923 |   |
| Precision           | 0.4911 |   |
| Recall              | 0.4988 |   |
| AUROC               | 0.4998 |   |

\(^a\)HC: healthy control.
\(^b\)Accuracy expected by chance for a 3-class classification task is 1/3≈33%. Thus, accuracies above 33% suggest that the model can predict outcomes better than random guessing, and higher values for accuracy indicate better predictive capacity of the model. Note that the test set was designed to have the same number of samples in each class. This is reflected in the values of \(F_1\)-score, precision, and recall being very close to each other and to that of accuracy.

\(^c\)AUROC: area under the receiver operating characteristic.

\(^d\)As we were interested in predicting affective psychopathology, we tested the degree to which a model can generalize to different individuals for each task except for the one about distinguishing members of a group of only HCs.

Symptom Association With Physiological Data

The tile plots for the NMI between physiological data and the YMRS and HDRS scale items for the former intra-individual (aim 1) and between-individuals (aim 2) classification tasks are shown in Figures 3 and 4, respectively. TEMP had the highest association with psychometric scales (NMI approximately 1.0), and BVP had the lowest consistency (NMI scores oscillating from 0 to 1).

Figure 3. Tile plots for the normalized mutual information analysis between physiological data and psychometric scales’ items: intra-individual level. For each scales’ item the mutual information (MI) with respect to each of the channels was measured and scaled to 0 to 1 dividing by the maximum MI value for that item. Values of zero indicate no associations, values of 1 indicate the maximum recorded MI across all channels for an individual item. ACC_X: x-axis acceleration; ACC_Y: y-axis acceleration; ACC_Z: z-axis acceleration; BD: bipolar disorder; BVP: blood volume pulse; EDA: electrodermal activity; HDRS: Hamilton Depression Rating Scale; HR: heart rate; MDD: major depressive disorder; TEMP: temperature; YMRS: Young Mania Rating Scale.
**Figure 4.** Tile plot for the normalized mutual information analysis between physiological data and psychometric scales’ items: between-individual level. For each scales’ item, the mutual information (MI) with respect to each of the channels was measured and scaled to 0 to 1 dividing by the maximum MI value for that item. Values of “0” indicate no associations; values of 1 indicate the maximum recorded MI across all channels for an individual item. ACC_X: x-axis acceleration; ACC_Y: y-axis acceleration; ACC_Z: z-axis acceleration; BVP: blood volume pulse; EDA: electrodermal activity; HC: healthy controls; HDRS: Hamilton Depression Rating Scale; HR: heart rate; TEMP: temperature; YMRS: Young Mania Rating Scale.

**Intra-individual NMI Analysis**

Motor activity (ACC) channels were highly associated with manic symptoms (NMI>0.6), and stress-related channels (EDA and HR) with depressive symptoms (NMI from 0.4 to 1.0), as shown in Figure 3.

**Between-Individuals NMI Analysis**

“Increased motor activity” (YMRS item 2 [YMRS2]) was associated with ACC (NMI>0.55), “aggressive behavior” (YMRS9) with EDA (NMI=1.0), “insomnia” (HDRS4-6) with ACC (NMI=0.6), “motor inhibition” (HDRS8) with ACC (NMI=0.75), and “psychic anxiety” (HDRS10) with EDA (NMI=0.52), as shown in Figure 4.

**Discussion**

**Principal Findings**

Although other studies have used raw physiological data to predict mental health status, this is the first study to present a novel fully automated method for the analysis of raw physiological data from a research-grade wearable device, including a rules-based filter for invalid physiological data, whereas all other studies presented methods that required manual interventions at some point in the pipeline [46,47,51,60], thus hindering the replicability and scalability of results. Moreover, our preprocessing pipeline is strictly based on the best-performing algorithm for analysis (ie, not arbitrarily decided), whereas other studies decided arbitrary cutoff points for analyzing raw physiological data (eg, ACC data recorded at 32 Hz sampling rates analyzed arbitrarily in 1-min epochs [50]). Our method may allow other research teams to use a viable supervised learning pipeline for time-series analyses for a popular research-grade wristband [39]. In addition, our work integrates physiological digital data from all sensors captured by a research-grade wearable, and we assessed the relevance of each channel (ACC, TEMP, BVP, HR, and EDA) in the prediction models. In contrast, other studies have focused on specific digital signals, such as actigraphy and EDA) and predesigned features (eg, amplitude of skin conductance response peaks) [51] but arbitrarily disregarded other digital signals, such as TEMP, or derived features, such as HRV. Furthermore, we aimed to distinguish the severity of mania and depression in a progressive and longitudinal manner according to the usual clinical resolution of mood episodes. We believe that the potential quantification of affective episodes is harder but a clinically more relevant task that may allow a more accurate and precise understanding of the disease rather than a mere dichotomous (acute vs remission) classification, as done in previous studies [50,51]. In addition, we included in the same work analyses at the intra-individual level and between different individuals, analyses targeting specific mood symptoms and generalization of the models on unseen patients. We believe that the use of different analysis methods allows us to examine the data from complementary perspectives to answer specific research questions. In addition, these different approaches may reveal random associations or artifacts that would stay hidden without replication. On the basis of these exploratory results, we propose hypotheses for future testing [61] in current and other similar projects.

Note that both (1) intra- and (2) inter-individual analyses approach different research questions: the (1) intra-individual analytical approach looks at the course of an index episode within a single patient and examines whether different states (from the acute phase to response and remission) can be distinguished from each other; on the other hand, the (2) inter-individual analytical approach takes a cross-sectional view and studies the degree to which different mood disorder states (comprising the full spectrum from depression to mixed state, mania, and euthymia) can be separated. Both analyses try to identify digital biomarkers of illness activity using physiological data collected with a wristband. However, intra-individual analyses look for a fine-grained quantification of illness activity that may allow the identification of low-severity mood states (or prodromal phases) in comparison with moderate to severe ones. Conversely, inter-individual analyses could potentially...
Studies comparing intra- and inter-individual models show that although intra-individual (cross-subject or patient-specific) models are trained on the data of a single subject, they perform better than intersubject (within-subject or generalized) models [65]. However, some studies have shown that hybrid models trained on multiple subjects and then fine-tuned on subject-specific data led to the best performance, without requiring as much data from a specific subject [66]. In intersubject studies, models generally see more data, as multiple subjects are included, but must contend with greater data variability, which introduces different challenges. In fact, there is both intra- and intersubject variability owing to time-variant factors related to the experimental setting and underlying psychological parameters. This impedes direct transferability or generalization among sessions and subjects [62]. To illustrate this, in a study aimed at evaluating a seizure detection model using physiological data and determining its application in a real-world setting, 2 procedures were applied: intra- and intersubject evaluation. Intrasubject evaluation focuses on the performance of the methodology when applied to data from a single patient, whereas intersubject evaluation assesses the performance of multiple patients with potentially different types of epilepsy and seizure manifestations [63].

Notably, the out-of-sample generalizations of both models differ vastly. Whereas the intra-individual model requires multiple seizures recorded per subject and will produce individualized models tailored to a single patient, the inter-individual model requires seizures recorded from multiple participants and will provide intersubject models to be used over wider populations.

Figure 5. Severity versus Mood-Phase Classification Models: visual grounds for both intra- and inter-individual analyses. On the left, a severity classification model for a patient with depression (acute-response-remission phases). On the right, a mood-phase classification model (depression, mania, and euthymia). Note that on the left model, the same individual is compared at 3 different states (corresponding to a reduction in depressive psychopathology). Thus, individual-level characteristics (age, sex, and gait) should go through little to no variation across; should remain the same on the 3 longitudinal registers; and therefore, the shift in the covariate distribution should be relatively contained and not influence the classification of the model (capturing mood-relevant signals). In contrast, on the right, 3 different individuals at 3 different mood states are compared. In this case, the model would potentially distinguish between mood phases (mania vs depression), or cases from healthy controls, but may not be able to distinguish longitudinal changes in disease severity over the course of an index episode. In addition, in the latter model, subject-specific characteristics may be overlapped with mood-relevant signals, thus acting as confounders for the model. T0: current acute Diagnostic and Statistical Manual of Mental Disorders–5 affective episodes; T1: symptoms’ response; T2: symptomatic remission.

Studies comparing mood phases (mania vs depression) or cases from HCs but may not be suitable for assessing the severity of mood episodes, as represented in Figure 5. Studies in similar areas, such as brain computer interfaces for the rehabilitation of motor impairments [62] or seizure forecasting [63], emphasized the importance of the subject-wise approach (modeling each subject separately). In many instances, despite work on domain adaptation [64] to learn subject-invariant representations, a model has to be fine-tuned to the level of the single patient.

Figure 5. Severity Classification Model

Intra-Individual

Inter-Individual

Severity Classification Model

Patient depression

Response (T1)

Remission (T2)

Patient mania

Patient euthymia

Mood-Phase Classification Model

Acute (T0)

Anmella et al

https://mhealth.jmir.org/2023/1/e45405

JMIR Mhealth Uhealth 2023 | vol. 11 | e45405 | p.1273

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Clinically, the end goal is to have a model inferring mood states at the individual level, regardless of whether such a model is shared across subjects or if each subject has a tailored model. Although most digital biomarker research has focused on diagnosis classification, few studies have aimed to detect longitudinal symptom change. Developing methods to detect changes in mood symptoms has the potential to prompt just-in-time interventions to prevent full-blown affective relapses and clinical deterioration and evaluate the response to pharmacological treatments with objective measures [21].

In our sample, both intra- and inter-individual models for respectively assessing differences in severity of acute affective episodes over time (Table 3) and differences in the polarity of acute affective episodes, euthymia, and HCs (Table 4) showed accuracies considerably above chance. Although preliminary, these results indicate that there may be objective differences in digital signals (ie, digital biomarkers) according to the psychopathological severity of patients (intra-individual models) and that patients with BD or MDD may present particular patterns of digital signals for mood episodes of mania and depression (inter-individual models). However, with few patients and measurements per model, these digital biomarkers may be challenging to identify and even harder to generalize.

Motor activity (from ACC) was the most relevant digital signal for predicting the severity of mania and mixed mania (but not for unipolar or bipolar depression) and also for predicting the polarity of acute affective episodes between individuals (Figure 2). In line with our results, other research groups have found that wearable motor activity data can distinguish mania from remission in patients with BD at the intra-individual level [50]. Moreover, other studies have shown that motor activity data could identify mood episodes and euthymia among different individuals, including mania versus euthymia [51], depression versus HCs [60], and mania versus depression versus HCs [74]. In fact, “activation,” which comprises having objective (motor activity) and related subjective (energy) levels emerging from underlying physiological changes, has been widely recognized as a key feature from mania [75]. Previous literature proposes that mood and activation represent distinct dimensions of BD [76] with distinct intervention approaches [77]. In addition, dysregulation of patterns of activity has been observed in BD both in acute phases and euthymia and has been proposed as a potential biomarker for BD [78]. However, it should be noted that mania may be better characterized by differences in robustness, variability, predictability, or complexity of activation rather than mean levels of activity [75], so future analyses should explore which characteristics of motor activity are key for the former predictions.

In contrast, “stress-related” digital signals (EDA and HR) were the most relevant for predicting the severity of both unipolar and bipolar depression (but not mania or mixed mania) and were also prominent for predicting the polarity of acute affective episodes between individuals (Figure 2). In fact, when looking at psychic anxiety as a symptom (item 10 from HDRS), EDA and HR showed strong associations (Figure 4). Moreover, EDA showed relevance for predicting the polarity of affective episodes between individuals but did not differentiate between HCs (38% vs 4.9%), as shown in Figure 2. This suggests that EDA may be a specific marker for psychopathological alterations that are not present in HCs. Furthermore, skin TEMP (a proposed marker of stress) was also a relevant physiological signal for predicting the severity of unipolar and bipolar depression (Figure 2). These findings are in line with previous literature [26,79-82] and reinforce the hypothesis that stress plays a key role in people with depression. Whereas patients with manic episodes usually lack insight into their symptoms, patients with depression are usually aware of their altered state and bear much distress and anxiety [83], which may be translated into physiological alterations, as suggested in our findings.

Generalizations of the former models on unseen patients were of overall low accuracy, which may be due to high psychopathological and individual heterogeneity, as well as external factors. Although mood episodes share many psychopathological aspects, they can present with multiple combinations of symptoms [68,76,84]. Each digital signal may provide information on a specific symptom dimension (altered motor activity, sleep disturbances, and stress-related symptoms) rather than the entire affective episode (manic, depressive, or mixed). We hypothesized that training the models with a larger sample, including patients with different symptom combinations for each affective episode, will result in more precise generalizations. Thus, exploring how patients cluster according to physiological data might help toward a dimensional (rather than categorical) disease classification. Deep learning is a promising approach for clustering high-dimensional, unstructured data [85], and new methods have been proposed specifically for data from wearable devices (multivariate time series) [86,87]. Apart from polymorphic psychopathological presentations in mood episodes, there is high between-subject heterogeneity in physiological data. For instance, skin TEMP, HR, and EDA vary within a physiological range in the same individual according to external (ie, atmospheric humidity or ambient TEMP) or internal factors (ie, hydration, diet, caffeine intake, and drugs) [52], and there are also individual-level patterns (eg, specific gaits, circadian rhythms, basal skin TEMP, or HR). This calls for ad-hoc techniques to disentangle between-patient heterogeneity from mood-related signals [88] and consider the role of potential confounders in the models (eg, drugs, medical comorbidities, physical activity, atmospheric conditions, and diet). Notwithstanding, generalizations of the intra-individual models for manic BD and depressed BD were above chance, in contrast to the generalization of the inter-individual model (almost by chance). This may suggest that individual heterogeneity is partially controlled for when comparing the same individual at different time points. This way, physiological changes may be more related to psychopathology rather than simply to individual characteristics (eg, gait, sex, and age). However, intra-individual comparisons do not control for external factors (eg, humidity, atmospheric TEMP, exercise, or hydration), which should be considered and controlled for.

When exploring the association between affective symptoms and physiological data, skin TEMP showed the highest association with psychometric scales (NMI approximately 1.0; Figures 3 and 4). Skin TEMP has been proposed as an objective...
The authors acknowledge the contribution of all the participants of the study.

Regarding the most relevant inputs for the previous models, physiological data related to specific symptom dimensions (e.g., ACC with motor activity and EDA and HR variation with stress response or anxiety) seemed to be more relevant signals for predicting mood episode severity and polarity rather than more raw data, such as BVP with nearly 0% permutation importance in all models (Figures 2-4), which do not seem to have a direct clinical translation to physiological alterations related to mental health symptoms. We hypothesized that complex features with potential clinical translation (i.e., indicating stress response or autonomic dysfunction), such as HRV [22,23,94], which is calculated from BVP, and EDA reactivity, calculated from EDA [26], may be of greater value than second-to-second changes in motor activity (ACC), EDA, pulse (BVP), and TEMP. We hypothesized that adding derived features as input to the models will probably result in better predictions, as shown by other research groups when identifying mood states in BD using the same wristband device [51]. Therefore, we are currently exploring derived features from raw data (i.e., statistical, time-domain, and frequency-domain features) [53], assessing EDA reactivity by extracting information in the tonic and phasic components of skin conductance using novel automated methods [18,53,95], and performing stress elicitation to assess potential alterations (hyporeactivity) in the phasic component of EDA during mood episodes [26]. Finally, considering the sleep and circadian rhythm disturbances in mood disorders in both euthymia [19,96] and acute phases [97-99], we are exploring automated methods to separate sleep from wake times [87,100,101]. Our goal is to evaluate sleep disturbances and differences in physiological signals during sleep and wake periods during mood episodes [77].

Limitations

We acknowledge several limitations in this study. First, the limited sample size for model development does not allow us to make strong claims about generalization performance [102]. However, most recordings were longer than 40 hours and each patient on an acute mood episode was recorded longitudinally at 3 time points (acute, response, and remission). In fact, our data set in terms of recording hours is well above other data sets modeled with deep learning in health care settings: the deep convolutional approach proposed by Musallam et al [103] was applied to 60 hours of electroencephalogram recordings [104]. In addition, the wearable device used (E4), allows fine-grained collection of digital physiological data (from 1 Hz to 64 Hz) for precision longitudinal time-series analyses. Regarding sample size in terms of the number of subjects, previous endeavors used as few as 12 subjects [46]. Unfortunately, this type of data, that is, recorded with a research-grade wearable device on a population with a psychiatric condition (arguably interfering with compliance to instructions), is expensive and time-consuming to collect. Second, potential confounding variables such as sex, age, pharmacological treatments, exercise, or BMI were not controlled for, and some of the study sample was not matched by age and sex. This may have biased the results, as those variables have been found to affect motor activity data, especially in between-group comparisons [60]. The within-subject design allows partial mitigation of both the weakness of a small sample size and the influence of confounders, so the models can capture mood-related signals. Therefore, we performed intra-individual comparisons across consecutive time points. In fact, the generalization of intra-individual models obtained substantially better accuracies, showing glimpses of capturing the severity of manic and depressive psychopathology.

Future works will further explore the capabilities of advanced automated machine learning models for identifying affective illness activity and the role of confounders in this association. Of particular interest are the application of clustering algorithms [87], exploring derived features (HRV [94] and EDA reactivity [26]), the role of wake and sleep periods [77,105], and the potential of physiological data to predict treatment responses and detect prodromal signs of mood episodes [106]. Future projects will include (1) studying the role of psychotic symptoms in patients with affective disorders, as well as in patients with schizophrenia; (2) assessing the role of smartphone-based derived data, including ecologic momentary assessments and passive data [107-109], in patients with BD using the SIMPLE smartphone app [110,111]; and (3) investigating the potential of combining physiological wearable data with peripheral biomarkers [112,113] and speech features [114-118].

Conclusions

Physiological wearable data may have the potential to identify and predict the severity of mania and depression in mood disorders as well as specific symptoms quantitatively. Motor activity appears to be the most relevant digital biomarker for predicting mania, whereas stress-related digital biomarkers (EDA and HR) appear to be the most relevant for predicting both bipolar and unipolar depression. In the context of biomarkers in mood disorders, these findings represent a promising pathway toward personalized psychiatry, in which clinical decisions and treatments could be supported by passive continuous and objective digital data.
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Data Availability
The data supporting the findings of this study are available upon request from the corresponding author.

Authors’ Contributions
GA and DH-M were responsible for data planning, project conception, and coordination. A Mas, MS, IP, MV, IG, A Benabarre, AG-P, MG, IA, A Bastidas, MC, TF-P, NA, MB, CG-R, NV, SM, SA, AM-A, and VR were responsible for recruitment. FC, BML, AV, MDP, VO, AS, and JR were responsible for data analysis. GA, FC, BML, and DH-M were responsible for manuscript preparation. All authors revised the final manuscript.

Conflicts of Interest
GA has received continuing medical education (CME)-related honoraria or consulting fees from Janssen-Cilag, Lundbeck, Lundbeck and Otsuka, and Angelini. IP has received CME-related honoraria, or consulting fees from ADAMED, Janssen-Cilag, and Lundbeck. IG has received grants and served as consultant, advisor or CME speaker for the following identities: Angelini, Casen Recordati, Ferrer, Janssen Cilag, and Lundbeck, Lundbeck-Otsuka, Lyue, SEI Healthcare. AG-P has received CME-related honoraria, or consulting fees from Janssen-Cilag, Lundbeck, Casen Recordati and Angelini. MC has received grants and served as consultant, advisor or CME speaker for the following entities: Lundbeck, Esteve, Pfizer. NA has received CME-related financing from Janssen-Cilag, Lundbeck, Adamed, Pfizer, Angelini and Boston Scientific. MB has been a consultant for, received grant/research support and honoraria from, and been on the speakers/advisory board of has received honoraria from talks and/or consultancy of Adamed, Angelini, Casen-Recordati, Exeltis, Ferrer, Janssen, Lundbeck, Neuraxpharm, Otsuka, Pfizer and Sanofi. NV has received financial support for CME activities and travel funds from the following entities: Angelini, Janssen-Cilag,
Lundbeck, Otsuka. SM has received CME-related honoraria, or consulting fees from Janssen-Cilag, Lundbeck, Lundbeck/Otsuka, and Angelini. A Murr has received grants and served as consultant, advisor or CME speaker for the following entities: Angelini, Idorsia, Lundbeck, Pfizer, Takeda. LS has received CME-related honoraria, or consulting fees from Boehringer-Ingelheim, Janssen, Lundbeck/Otsuka, Sanofi-Aventis. AHY has received honoraria for lectures and advisory boards for all major pharmaceutical companies with drugs used in affective and related disorders. EV has received research support from or served as consultant, adviser or speaker for AB-Biotics, Abbott, Abbvie, Adamed, Angelini, Biogen, Celon, Danippon Sumitomo Pharma, Ferrer, Gedeon Richter, GH Research, Glaxo SmithKline, Janssen, Lundbeck, Organon, Otsuka, Rovi, Sage pharmaceuticals, Sanofi-Aventis, Shire, Sunovion, Takeda, and Viatris. DH-M has received CME-related honoraria and served as consultant for Abbott, Angelini, Ethypharm Digital Therapy and Janssen-Cilag. All authors report no financial or other relationship relevant to the subject of this article.

Multimedia Appendix 1
Empatica E4.

Multimedia Appendix 2
Validation set performance (accuracy) as a function of time alignment (Hz) and window length (w).

Multimedia Appendix 3
Confusion matrix for the prediction of the severity of an acute affective episode: models and generalization. BD: bipolar disorder; MDD: major depressive disorder.

Multimedia Appendix 4
Confusion matrix for the prediction of the polarity of affective episodes, euthymia, and healthy controls: models and generalization. BD: bipolar disorder; HC: healthy controls; MDD: major depressive disorder; T0: current acute Diagnostic and Statistical Manual of Mental Disorders–5 affective episodes.

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64. Anmella et alJMIR MHEALTH AND UHEALTH 2023 | vol. 11 | e45405 | p.1280https://mhealth.jmir.org/2023/1/e45405


https://mhealth.jmir.org/2023/11/e45405

JMIR Mhealth Uhealth 2023 | vol. 11 | e45405 | p.1281

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Abbreviations

ACC: acceleration
AUROC: area under the receiver operating characteristic
BD: bipolar disorder
BiLSTM: Bidirectional Long Short-Term Memory
BVP: blood volume pulse
DSM-5: Diagnostic and Statistical Manual of Mental Disorders–5
EDA: electrodermal activity
HC: healthy control
HDRS: Hamilton Depression Rating Scale
HR: heart rate
HRV: heart rate variability
IBI: interbeat interval
LSTM: long short-term memory
MDD: major depressive disorder
NMI: normalized mutual information
RNN: recurrent neural network
ROC: receiver operating characteristic
T0: current acute Diagnostic and Statistical Manual of Mental Disorders–5 affective episodes
T1: symptoms’ response
T2: symptomatic remission
TEMP: temperature
YMRS: Young Mania Rating Scale

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Review

Associations Between Social Cognitive Determinants and Movement-Related Behaviors in Studies Using Ecological Momentary Assessment Methods: Systematic Review

Kelsey M Bittel¹, MS; Kate Y O’Briant¹, BS; Rena M Ragaglia¹, BS; Lake Buseth¹, BS; Courtney Murtha¹, BS; Jessica Yu¹, BS; Jennifer M Stanely¹, BS; Brynn L Hudgins¹, MS; Derek J Hevel¹, PhD; Jaclyn P Maher¹, PhD

Department of Kinesiology, University Of North Carolina Greensboro, Greensboro, NC, United States

Corresponding Author:
Kelsey M Bittel, MS
Department of Kinesiology
University Of North Carolina Greensboro
1408 Walker Avenue
Greensboro, NC, 27412
United States
Phone: 1 8147690663
Email: bittekelsey@gmail.com

Abstract

Background: The social cognitive framework is a long-standing framework within physical activity promotion literature to explain and predict movement-related behaviors. However, applications of the social cognitive framework to explain and predict movement-related behaviors have typically examined the relationships between determinants and behavior across macrotimescales (eg, weeks and months). There is more recent evidence suggesting that movement-related behaviors and their social cognitive determinants (eg, self-efficacy and intentions) change across microtimescales (eg, hours and days). Therefore, efforts have been devoted to examining the relationship between social cognitive determinants and movement-related behaviors across microtimescales. Ecological momentary assessment (EMA) is a growing methodology that can capture movement-related behaviors and social cognitive determinants as they change across microtimescales.

Objective: The objective of this systematic review was to summarize evidence from EMA studies examining associations between social cognitive determinants and movement-related behaviors (ie, physical activity and sedentary behavior).

Methods: Studies were included if they quantitatively tested such an association at the momentary or day level and excluded if they were an active intervention. Using keyword searches, articles were identified across the PubMed, SPORTDiscus, and PsycINFO databases. Articles were first assessed through abstract and title screening followed by full-text review. Each article was screened independently by 2 reviewers. For eligible articles, data regarding study design, associations between social cognitive determinants and movement-related behaviors, and study quality (ie, Methodological Quality Questionnaire and Checklist for Reporting Ecological Momentary Assessment Studies) were extracted. At least 4 articles were required to draw a conclusion regarding the overall associations between a social cognitive determinant and movement-related behavior. For the social cognitive determinants in which a conclusion regarding an overall association could be drawn, 60% of the articles needed to document a similar association (ie, positive, negative, or null) to conclude that the association existed in a particular direction.

Results: A total of 24 articles including 1891 participants were eligible for the review. At the day level, intentions and self-efficacy were positively associated with physical activity. No other associations could be determined because of conflicting findings or the small number of studies investigating associations.

Conclusions: Future research would benefit from validating EMA assessments of social cognitive determinants and systematically investigating associations across different operationalizations of key constructs. Despite the only recent emergence of EMA to understand social cognitive determinants of movement-related behaviors, the findings indicate that daily intentions and self-efficacy play an important role in regulating physical activity in everyday life.

Trial Registration: PROSPERO CRD42022328500; https://www.crd.york.ac.uk/prospero/display_record.php?RecordID=328500

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Introduction

Background

The World Health Organization recommends that adults engage in at least 150 minutes of moderate-intensity or 75 minutes of vigorous-intensity physical activity (PA; or an equivalent combination of both) per week and limit the amount of time spent engaging in sedentary behavior (SB) [1]. Despite these recommendations, approximately 28% of adults do not meet PA guidelines [2]. Furthermore, on average, adults engage in 8.2 hours per day of SB [3]. This represents a considerable health burden as individuals who are physically inactive and do not meet PA guidelines have a 20% to 30% increased chance of premature death versus individuals who are active and meet PA guidelines [2,4]. Physical inactivity and SB can also lead to chronic diseases and are a contributing factor to 35 pathological and clinical conditions (eg, obesity, type 2 diabetes, and cardiovascular diseases) [5]. Considering the risks associated with physical inactivity and SB, understanding the factors that influence movement-related behaviors such as PA and SB is paramount.

There are a number of different theoretical approaches to understand and explain PA and SB engagement (eg, the humanistic framework, the dual process framework, and ecological models) [6]. Social cognitive framework represents one of the most used and long-standing theoretical frameworks within the movement-related behavior literature to explain and predict behavioral engagement [6]. Social cognitive framework emphasizes key determinants of behavior as individuals’ cognitions about the anticipated outcomes of a behavior and their ability to engage in a behavior [7,8]. In line with these theories, individuals will focus their efforts toward (eg, intentions) and subsequently engage in a behavior if their beliefs about the behavior are positive (eg, outcome expectations) and they are confident in their ability to engage in the behavior (eg, self-efficacy) [9-13]. There are 2 prominent theories that are considered part of the social cognitive framework are Social Cognitive Theory and the Theory of Planned Behavior [9,10].

Specifically, Social Cognitive Theory identifies self-efficacy—an individual’s belief in their ability to engage in a behavior—and outcome expectations—the perception of consequences (positive or negative) of an individual’s action—as key determinants of behavior [8,10]. The Theory of Planned Behavior posits that intention, or one’s willingness to try to engage in a behavior, is the main antecedent of behavior [7,9]. The Theory of Planned Behavior also proposes that intention formation is predicted by three factors: (1) attitudes or the extent to which one has positive or negative evaluations of a behavior, (2) subjective norms or the perceived social pressure to engage in a behavior, and (3) perceived behavioral control or the extent to which a person has the capacity and free will to engage in a behavior [7,9]. Furthermore, both theories acknowledge that facilitators and barriers can help or hinder engagement in a behavior, respectively [7-10]. Therefore, these theories outline social cognitive determinants hypothesized to influence movement-related behaviors.

Several reviews have indicated that social cognitive determinants predict PA behavior in observational studies. However, there is experimental evidence indicating that the extent to which these determinants predict changes in behavior is generally much weaker [14-16]. Within the last decade, evidence has accumulated suggesting that PA and SB are independent health behaviors [17,18], and studies have applied social cognitive frameworks to explain and predict SB. Findings across SB studies appear to mirror those of PA studies, with evidence for relationships between social cognitive determinants and behavior indicating stronger relationships in observational studies than in experimental studies [19-21].

A potential reason for the limited effectiveness of social cognitive determinants in explaining and predicting PA and SB is that the timescale in which these relationships are assessed is not the timescale in which social cognitive determinants influence decisions to engage in a behavior [10,22]. Most of the research investigating associations between social cognitive determinants and PA or SB tends to assess these constructs infrequently and ask participants to report their usual level of social cognitive determinants or behavior over macrotimescales (eg, weeks and months) [21,23]. However, PA and SB are repeat-occurrence behaviors, meaning that these behaviors are typically engaged in multiple times per week or even multiple times per day [24]. Furthermore, the day is an elemental structure in human life. Days are easily defined and universally experienced because of the light-dark cycles of the sun and associated sleep-wake cycles. Moreover, people self-regulate and restore self-regulatory resources throughout these cycles [25]. The changing contexts of people’s daily lives could also influence daily and within-day motivation and movement-related behaviors. Therefore, methods that capture typical levels of movement-related behaviors and social cognitive determinants on a macrotimescale may overlook important information regarding decisions to engage in a bout of PA or SB across microtimescales (eg, hours and days). Previous research has documented that social cognitive determinants, PA, and SB are dynamic, varying within individuals across time and space [26-28]. Investigating associations between social cognitive determinants and movement-related behaviors in the content of daily life across microtimescales can elucidate the motivational determinants of movement-related behaviors and potentially enhance intervention efforts.

Recent evidence of the dynamic and time-varying nature of PA and SB has increased in part from advances in methodology to assess behavior and its determinants. Ecological momentary assessment (EMA) has gained popularity over the last decade in the movement-related behavior literature as a methodology to capture fluctuations in behavior and social cognitive determinants across microtimescales in naturalistic settings [29,30]. EMA is a real-time data capture methodology that repeatedly assesses individuals on a phenomenon of interest in...
their natural environment (eg, motivation and behavior) [31]. EMA is useful for assessing phenomena that change across time and space, such as movement-related behaviors and their determinants. For instance, an individual’s engagement in PA behaviors may change over the course of the day, as may their feelings of confidence (ie, self-efficacy) in engaging in PA. To study these fluctuations in behavior as well as how these 2 constructs might covary, a smartphone-based EMA protocol could assess self-efficacy at predetermined (eg, every 2 hours) or randomly occurring (eg, anytime between 8 AM and 8 PM) times throughout the day. In addition, monitoring via an accelerometer could be conducted. In an EMA protocol, when participants receive a notification to complete a questionnaire through an app or website on their smartphone that measures self-efficacy to engage in PA over the following 2 hours, they are asked to briefly stop what they are doing to complete the questionnaire. Responses on the smartphone are date- and time-stamped to facilitate easy pairing of the smartphone questionnaire and accelerometer data in the 2-hour window (referenced in the self-efficacy assessment) after the EMA prompt. As these notifications happen repeatedly, researchers are able to capture these constructs and their associations as individuals go about their day-to-day activities, allowing them to examine these associations across the changing contexts of everyday life.

Therefore, EMA methodology can reduce recall biases and enhance ecological validity by evaluating a phenomenon of interest close in time to when it occurs in real-world settings as individuals go about their normal day-to-day lives [29]. Today, EMA protocols can be delivered through various media (ie, apps on mobile devices, internet-based questionnaires, and SMS text messages) that can provide time stamps of participant responses. As noted, this can facilitate the pairing of EMA responses with other time-stamped data sources such as accelerometers and allows for the investigation of the temporal sequence of relationships between key constructs. Previous research has established the feasibility and validity of using smartphone-based EMA to assess PA and SB as well as their determinants in diverse populations across their life span [28,32-35].

Objectives

The use of EMA to capture and understand PA and SB has increased over the past decade. As a result, recent reviews have summarized EMA findings regarding various determinants of PA and SB, including affective states [36] and environmental contexts [37]. However, there is yet to be a review summarizing the associations between social cognitive determinants and movement-related behaviors from studies using EMA methodologies. This systematic review aimed to summarize the literature regarding within-day and day-level associations between social cognitive determinants and movement-related behaviors using within-day or daily EMA methodologies. The decision to focus exclusively on within-day and day-level associations was based on the repeat-occurrence nature of movement-related behaviors and the fact that assessment schedules occurring less frequently than the day level may not be sensitive to the changing contexts in everyday life and the factors driving decisions to engage in occasions of PA or SB. This rationale is bolstered by the fact that the day represents a natural and fundamental reoccurring event in human life.

Methods

This systematic review was conducted and reported in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [38] and was registered in PROSPERO (CRD42022328500).

Inclusion and Exclusion Criteria

Articles that met the following criteria were included in the review: (1) human-participant research, (2) available in English, (3) quantitative data available for at least one association between a social cognitive determinant (ie, the independent variable) and movement-related behavior (ie, the dependent variable), and (4) within-day or daily EMA study design. Social cognitive determinants were defined as constructs specified within Social Cognitive Theory and the Theory of Planned Behavior, 2 popular social cognitive frameworks in the movement-related behavior literature [7-9,22,39]. Therefore, social cognitive determinants of interest for this systematic review included intentions, attitudes, subjective norms, perceived behavioral control, self-efficacy, outcome expectations, risk perceptions, barriers, facilitators, goals, and plans regarding movement-related behaviors. To focus on naturally occurring associations between social cognitive determinants and movement-related behaviors, articles were excluded if they used an active experimental design. In addition, articles were excluded if they were not published in a peer-reviewed scholarly journal.

Search Process

Literature searches were conducted on May 25, 2022, in the PubMed, SPORTDiscus, and PsycINFO databases to identify relevant articles that used EMA methods to examine associations between social cognitive determinants and movement-related behaviors. No date restrictions were applied in the searches. This process is shown in the PRISMA flow diagram in Figure 1. In total, 3 sets of search terms were used to identify potentially relevant articles. The first set of search terms used general terms, including the following: (“physical activity” OR “exercise” OR “sedentary behavior” OR “movement behavior” OR “physical exercise” OR “sitting”) AND (“ecological momentary assessment” OR “EMA” OR “daily diary” OR “experience sampling”). The second set of search terms included the general terms (from the first search) along with specific terms related to psychological determinants: (“social cognitive” OR “motivation” OR “psychosocial” OR “behavioral cognitions”). The third set of search terms included the general terms from the first search along with specific terms related to social cognitive determinants: (“self-efficacy” OR “outcome expectation” OR “intention” OR “attitude” OR “subjective norm” OR “control” OR “risk perception” OR “barriers” OR “facilitators” OR “goal” OR “plan”). See Multimedia Appendix 1 for the complete search term queries in each database. These specific social cognitive terms were selected by identifying constructs outlined within the Theory of Planned Behavior and Social Cognitive Theory, 2 of the most prominent social cognitive frameworks [6]. The first search using general terms

https://mhealth.jmir.org/2023/1/e44104

JMIR MHealth UHealth 2023 | vol. 11 | e44104 | p.1286

Bittel et al

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was completed so as to not miss any EMA movement-related behavior articles that may have assessed social cognitive determinants but did not have them as their focus. All articles were collected in Zotero (Corporation for Digital Scholarship) and uploaded to Rayyan (Rayyan Systems Inc), a web tool used to provide support for systematic reviews [40].

Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram for the literature search on social cognitive determinants, movement-related behaviors, and ecological momentary assessment (EMA) methods.

### Article Screening and Coding

A total of 9 reviewers were involved in the process of screening and extracting information from the eligible articles. All reviewers received training on EMA studies of movement-related behaviors and social cognitive determinants from an expert in this content area (JPM). Following training, all reviewers screened the same 50 abstracts to determine whether the full text should be examined for eligibility. All reviewers then met with the content area expert to discuss and resolve discrepancies. Following this, reviewers independently screened assigned abstracts. One reviewer (KMB) screened all abstracts, and one additional reviewer (KYO, RMR, LB, CM, JY, JMS, BLH, or DJH) was assigned to each abstract. Following screening of all abstracts, discrepancies were discussed and resolved between each pair of reviewers with the content area expert.

The articles retained after title and abstract screening were gathered as full texts. In total, 2 reviewers (KMB and JPM) reviewed the full articles independently to determine eligibility and came together to discuss and resolve any discrepancies. A flowchart using the PRISMA 2020 guidelines shows the screening process for eligible articles (Figure 1) [41].

After identifying the articles to be included in this systematic review, 4 reviewers (KMB, RMR, KYO, and BLH) independently extracted relevant information from 8 articles, met with the content area expert (JPM) to discuss and resolve any discrepancies, and then independently coded the remaining articles. One reviewer (KMB) extracted relevant information from all the articles, and one additional reviewer (RMR, KYO, or BLH) was assigned to each article. Finally, the reviewers and content area expert met to discuss and resolve any discrepancies regarding article information extraction.
For each eligible article, the extracted information focused on study participant characteristics, study design characteristics, study main findings, and methodological quality assessments according to 2 established instruments. First, the Methodological Quality Questionnaire (MQQ) [42] assessed overall study quality based on 9 dimensions (ie, theoretical or conceptual definition, research design, sampling design, sample, evidence of reliability and validity, data analysis, implications for practice, and implications for policy). MQQ scores can range from 0 to 27. Second, the Checklist for Reporting Ecological Momentary Assessment Studies (CREMAS) [43] assessed quality with regard to reporting EMA methodology on 5 dimensions that outline specific criteria that have to be included in the title, introduction, methods, results, and discussion. Across these 5 dimensions, there were 16 items (ie, title and keywords, rationale, training, technology, wave duration, monitoring period, prompting design, prompt frequency, design features, attrition, prompt delivery, latency, compliance rate, missing data, limitations, and conclusions).

CREMAS scores can range from 0 to 16, with 1 point per item addressed. For both the MQQ and CREMAS, higher scores indicate better methodological quality.

Analysis

The associations between social cognitive determinants and movement-related behaviors were assessed using the guidelines developed by Sallis et al [44]. An association was supported if 60% to 100% of the articles reported such an association. No association was supported if 0% to 33% of the articles reported an association. An indeterminate or inconclusive association was supported if 34% to 59% of the articles reported an association. Statistical significance ($P<.05$) and parameter estimates (and 95% CIs, if reported) were used to determine whether any association between a social cognitive determinant and movement-related behaviors existed and the direction of the association (ie, positive or negative), respectively. All findings from individual articles were presented; however, at least 4 articles were needed to make an assessment regarding an overall association between a given social cognitive determinant and movement-related behavior in this systematic review. The choice to conduct a systematic review of results was based on the substantial diversity of study designs, operationalizations of social cognitive determinants and movement-related behaviors, and analyses to test associations (eg, multilevel linear regression, multilevel logistic regression, multilevel negative binomial model, and time-varying effect modeling).

Results

Overview

A total of 3510 articles were identified across all the database searches. After duplicates were removed (781/3510, 22.25%), the remaining articles were screened by title and abstract (2729/3510, 77.75%). After screening, 2.02% (55/2729) of the articles were identified for full-text retrieval. Of those 55 articles, 31 (56%) were excluded, leaving 24 (44%) articles from 21 unique studies to be included in this systematic review (Figure 1). The publication year, sample and study characteristics, and methodological quality scores of each article are presented in Table 1.
<table>
<thead>
<tr>
<th>Study</th>
<th>Sample size, N</th>
<th>Age (years), mean (SD)</th>
<th>Sex or gender (% of female and women participants)</th>
<th>Population</th>
<th>EMA delivery medium</th>
<th>EMA protocol design</th>
<th>Social cognitive determinants of interest</th>
<th>Behavioral constructs of interest</th>
<th>Behavioral assessment method</th>
<th>CRE-MAS rating</th>
<th>MQQ rating</th>
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</thead>
<tbody>
<tr>
<td>Arigo et al [45]</td>
<td>75</td>
<td>51.61 (5.43)</td>
<td>100</td>
<td>Adult women</td>
<td>Website</td>
<td>5 prompts per day for 10 days; single wave; signal contingent</td>
<td>Intentions</td>
<td>PA^d</td>
<td>Accelerometer</td>
<td>10</td>
<td>21</td>
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<tr>
<td>Cook et al [46]</td>
<td>55</td>
<td>20-69^e</td>
<td>15</td>
<td>Adults with HIV</td>
<td>Website</td>
<td>1 prompt per day for 30 days; single wave; signal contingent</td>
<td>Self-efficacy</td>
<td>PA</td>
<td>Accelerometer</td>
<td>9</td>
<td>16</td>
</tr>
<tr>
<td>Maher et al^f [47]</td>
<td>116</td>
<td>40.3 (9.6)</td>
<td>74.2</td>
<td>Adults</td>
<td>Smartphone</td>
<td>8 prompts per day for 4 days; multiple waves; signal contingent</td>
<td>Intentions, self-efficacy, and outcome expectations</td>
<td>PA</td>
<td>Accelerometer</td>
<td>15</td>
<td>22</td>
</tr>
<tr>
<td>Maher et alf [48]</td>
<td>116</td>
<td>40.3 (9.6)</td>
<td>74.2</td>
<td>Adults</td>
<td>Smartphone</td>
<td>8 prompts per day for 4 days; multiple waves; signal contingent</td>
<td>Intentions</td>
<td>PA</td>
<td>Accelerometer</td>
<td>15</td>
<td>27</td>
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<td>74.2</td>
<td>Adults</td>
<td>Smartphone</td>
<td>8 prompts per day for 4 days; multiple waves; signal contingent</td>
<td>Intentions, self-efficacy, and outcome expectations</td>
<td>PA</td>
<td>Accelerometer</td>
<td>13</td>
<td>25</td>
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<tr>
<td>Maher and Dunton^g [50]</td>
<td>103</td>
<td>72 (7)</td>
<td>62</td>
<td>Older adults</td>
<td>Smartphone</td>
<td>6 prompts per day for 10 days; single wave; signal contingent</td>
<td>Intentions and self-efficacy</td>
<td>SB^h</td>
<td>Accelerometer</td>
<td>15</td>
<td>27</td>
</tr>
<tr>
<td>Maher and Dunton^g [51]</td>
<td>103</td>
<td>72.4 (7.44)</td>
<td>62.5</td>
<td>Older adults</td>
<td>Smartphone</td>
<td>6 prompts per day for 10 days; single wave; signal contingent</td>
<td>Intentions and self-efficacy</td>
<td>PA and SB</td>
<td>Accelerometer</td>
<td>15</td>
<td>27</td>
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<tr>
<td>Reifsteck et al [52]</td>
<td>17</td>
<td>21.82 (0.64)</td>
<td>47.06</td>
<td>College student athletes</td>
<td>Smartphone</td>
<td>4 prompts per day for 7 days; single wave; signal contingent</td>
<td>Intentions, self-efficacy, and outcome expectations</td>
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<td>Accelerometer</td>
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<td>Study</td>
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<td>Age (years), mean (SD)</td>
<td>Sex or gender (% of female and women participants)</td>
<td>Race and ethnicity (% of White or non-Hispanic White participants)</td>
<td>Population</td>
<td>EMAa delivery medium</td>
<td>EMA protocol design</td>
<td>Social cognitive determinants of interest</td>
<td>Behavioral constructs of interest</td>
<td>Behavioral assessment method</td>
<td>CRE-MASb rating</td>
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<td>Zenk et al [53]</td>
<td>97</td>
<td>25-65e</td>
<td>100</td>
<td>0</td>
<td>Adult women</td>
<td>Website</td>
<td>5 prompts per day4 for 7 days; single wave; signal contingent</td>
<td>Barriers</td>
<td>PA and SB</td>
<td>Accelerometer</td>
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<tr>
<td>Anderson [54]</td>
<td>76</td>
<td>40.29 (13.69)</td>
<td>57.9</td>
<td>85.5</td>
<td>Adults</td>
<td>Website</td>
<td>1 prompt per day for 14 days; single wave; interval contingent</td>
<td>Planning</td>
<td>PA</td>
<td>Self-report</td>
<td>11</td>
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<tr>
<td>Carraro and Gaudreau [55]</td>
<td>97</td>
<td>20.45 (4.61)</td>
<td>68</td>
<td>71</td>
<td>College students</td>
<td>Website</td>
<td>1 prompt per day for 6 days; single wave; interval contingent</td>
<td>Action planning and coping planning</td>
<td>PA</td>
<td>Self-report</td>
<td>13</td>
</tr>
<tr>
<td>Dunton et al [56]</td>
<td>23</td>
<td>60.65 (8.22)</td>
<td>70</td>
<td>91</td>
<td>Older adults</td>
<td>PDA</td>
<td>4 prompts per day for 14 days; single wave; interval contingent</td>
<td>Self-efficacy</td>
<td>PA</td>
<td>Self-report</td>
<td>14</td>
</tr>
<tr>
<td>McDonald et al [57]</td>
<td>7</td>
<td>62.71</td>
<td>71.4</td>
<td>Not collected</td>
<td>Older adults</td>
<td>PDA</td>
<td>2 prompts per day for a minimum of 2 months (maximum of 7 months); single wave; interval contingent</td>
<td>Intentions, perceived behavioral control</td>
<td>PA</td>
<td>Accelerometer</td>
<td>11</td>
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<tr>
<td>Bermudez et al [58]</td>
<td>111</td>
<td>62.32 (10.85)</td>
<td>14.4</td>
<td>Not collected</td>
<td>Adults with cardiac disease</td>
<td>PDA</td>
<td>1 prompt per day for 21 days; single wave; event contingent</td>
<td>Intentions, perceived behavioral control, subjective norms, and explicit attitudes</td>
<td>PA</td>
<td>Accelerometer</td>
<td>8</td>
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<tr>
<td>Berli et al [59]</td>
<td>120</td>
<td>Women: 43.39 (12.67); men: 45.07 (13.92)</td>
<td>50</td>
<td>Not collected</td>
<td>Adult dual-smoker couples</td>
<td>Smartphone</td>
<td>1 prompt per day for 28 days; single wave; event contingent</td>
<td>Intentions, self-efficacy, and action planning</td>
<td>PA</td>
<td>Accelerometer</td>
<td>12</td>
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<td>Study</td>
<td>Sample size, N</td>
<td>Age (years), mean (SD)</td>
<td>Sex or gender (% of female and men participants)</td>
<td>Race and ethnicity (% of White or non-Hispanic White participants)</td>
<td>Population</td>
<td>EMA delivery medium</td>
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<td>Behavioral constructs of interest</td>
<td>Social cognitive determinants of interest</td>
<td>Behavioral assessment method</td>
<td>CRE-MASb rating</td>
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<tr>
<td>Bond et al [60]</td>
<td>21</td>
<td>48.5 (2.8)</td>
<td>81</td>
<td>71.4</td>
<td>Adults who had undergone bariatric surgery</td>
<td>PDA</td>
<td>1 prompt per day for 6 days; single wave; event contingent</td>
<td>Intentions</td>
<td>PA</td>
<td>Self-report</td>
<td>11</td>
</tr>
<tr>
<td>Borowski et al [61]</td>
<td>61</td>
<td>41.4 (9.9)</td>
<td>88.5</td>
<td>90.2</td>
<td>Adults</td>
<td>Website</td>
<td>1 prompt per day for 7 days; single wave; event contingent</td>
<td>Barriers</td>
<td>PA</td>
<td>Self-report</td>
<td>10</td>
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<tr>
<td>Conroy et al [62]</td>
<td>63</td>
<td>Not collected</td>
<td>58.7</td>
<td>87</td>
<td>College students</td>
<td>Website</td>
<td>1 prompt per day for 14 days; single wave; event contingent</td>
<td>Intentions</td>
<td>PA</td>
<td>Self-report</td>
<td>14</td>
</tr>
<tr>
<td>Conroy et al [63]</td>
<td>128</td>
<td>21.3 (1.1)</td>
<td>58.6</td>
<td>89</td>
<td>College students</td>
<td>Website</td>
<td>1 prompt per day for 14 days; single wave; event contingent</td>
<td>Intentions</td>
<td>SB</td>
<td>Accelerometer</td>
<td>12</td>
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<tr>
<td>Curtis et al [64]</td>
<td>185</td>
<td>61.7 (5.9)</td>
<td>Not collected</td>
<td>55.1</td>
<td>Older adults</td>
<td>Website</td>
<td>1 prompt per day for 7 days; single wave; event contingent</td>
<td>Self-efficacy</td>
<td>PA</td>
<td>Self-report</td>
<td>10</td>
</tr>
<tr>
<td>Maher and Conroy [65]</td>
<td>100</td>
<td>74.2 (8.2)</td>
<td>67</td>
<td>99</td>
<td>Older adults</td>
<td>PDA</td>
<td>2 prompts per day for 14 days; single wave; event contingent</td>
<td>Intentions, self-efficacy, action planning, and coping planning</td>
<td>SB</td>
<td>Accelerometer and self-report</td>
<td>12</td>
</tr>
<tr>
<td>Rebar et al [66]</td>
<td>103</td>
<td>21.57 (2.97)</td>
<td>Not collected</td>
<td>52</td>
<td>College students</td>
<td>Website</td>
<td>1 prompt per day for 7 days; single wave; event contingent</td>
<td>Intentions</td>
<td>PA</td>
<td>Self-report</td>
<td>11</td>
</tr>
<tr>
<td>Swahninger et al [67]</td>
<td>198</td>
<td>Women: 45.31 (13.51); men: 47.29 (13.94)</td>
<td>Not collected</td>
<td>50</td>
<td>Adult couples</td>
<td>Smartphone</td>
<td>1 prompt per day for 14 days; single wave; event contingent</td>
<td>Self-efficacy</td>
<td>PA</td>
<td>Accelerometer</td>
<td>8</td>
</tr>
</tbody>
</table>
In total, 38% (9/24) of the articles indicated that EMA prompting was a signal-contingent design (ie, occurring at randomly prompted times) [45-53]. A total of 17% (4/24) of the articles reported on studies that used interval-contingent design (ie, occurring at fixed times) [52,54,56,57], whereas 46% (11/24) of the articles reported on studies that used event-contingent design (eg, self-initiated EMA questionnaire after a specific event) [55,58-65,67,68].

Regarding design considerations to reduce participant burden, the studies reported in 17% (4/24) of the articles did not ask about social cognitive determinants at every EMA prompt to limit the number of items in each prompt [47-49,56]. The studies reported in 8% (2/24) of the articles customized the time of the prompts based on each participant’s wake and sleep schedules [45,57], whereas another study had participants select their own start day to fit their work schedule [61].

EMA protocols were delivered via smartphone (8/24, 33%), PDA (6/24, 25%), or website (10/24, 42%). Among the articles that reported on studies that used a smartphone to deliver EMA protocols, commercially available apps including Personal Analytics Companion (1/24, 4%) [66], movisensXS (2/24, 8%) [50,51], and MyExperience (3/24, 12%) [47-49] were used. A total of 8% (2/24) of the articles reported on studies that had participants complete the study protocol on a smartphone but did not specify the platform used to deliver the EMA prompts [59,67]. PDA devices comprised handheld computers (3/24, 12%) [56,60,68], tablets (2/24, 8%) [58,65], and a wrist-worn Patient-Reported Outcomes Diary device (1/24, 4%) [57].

Articles on studies that used websites either did not specify the platform used to deliver EMA prompts [56,60,68], tablets (2/24, 8%) [58,65], and a wrist-worn Patient-Reported Outcomes Diary device (1/24, 4%) [57].

Studies that delivered between 4 and 8 prompts per day [45,47-53,56].

In total, 38% (9/24) of the articles indicated that EMA prompting was a signal-contingent design (ie, occurring at randomly prompted times) [45-53]. A total of 17% (4/24) of the articles reported on studies that used interval-contingent design (ie, occurring at fixed times) [52,54,56,57], whereas 46% (11/24) of the articles reported on studies that used event-contingent design (eg, self-initiated EMA questionnaire after a specific event) [55,58-65,67,68].

Regarding design considerations to reduce participant burden, the studies reported in 17% (4/24) of the articles did not ask about social cognitive determinants at every EMA prompt to limit the number of items in each prompt [47-49,56]. The studies reported in 8% (2/24) of the articles customized the time of the prompts based on each participant’s wake and sleep schedules [45,57], whereas another study had participants select their own start day to fit their work schedule [61].

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Articles on studies that used websites either did not specify the
website [45,52,53,55,62-64] or did specify it using Prolific [54], Qualtrics [61], or REDCap (Research Electronic Data Capture; Vanderbilt University) [46].

All articles (24/24, 100%) reported participants’ compliance or response rates within the EMA protocol. These rates ranged from 56.9% to 95%, indicating general compliance with the EMA methodology.

Social Cognitive Determinants

Intentions (15/24, 62%) [45,47-51,55,57-60,62,63,65,66] and self-efficacy (14/24, 58%) [46,47,49-51,56-59,64-68] were the most frequently assessed social cognitive determinants. Of the 14 articles categorized as reporting on studies that assessed self-efficacy [57,58], 2 (14%) operationalized their construct of interest as perceived behavioral control; however, perceived behavioral control is generally considered synonymous with self-efficacy [9,69], so the findings were combined into 1 category for this review. Other social cognitive determinants assessed included planning (4/24, 17%) [52,54,59,65], outcome expectations (3/24, 12%) [47,49,66], barriers (2/24, 8%) [53,61], and explicit attitudes (1/24, 4%) [58].

Intentions and self-efficacy were primarily assessed using 1 to 2 items, but 4% (1/24) of the articles reported on studies that used 4 items to assess self-efficacy [46]. The studies reported in 29% (7/24) of the articles adapted social cognitive determinant items from validated scales [46,54,55,58,59,61,65], but almost all (5/7, 71%) reduced the number of items or adapted the time frame of the items for delivery as part of their EMA protocol. Common behavioral targets assessed with social cognitive determinant items included engaging in PA [46,53,56,58-62,64,66-68], engaging in a specified duration of PA [46,55,57,61,63,65-68], or limiting SB to a specified total amount of time [53,63,65,66].

Movement-Related Behaviors

Methods for assessing movement-related behaviors included device-based (15/24, 62%) and self-reported (8/24, 33%) assessments or both (1/24, 4%) [65]. Common devices used included the ActiGraph GT3x or GT3x+ (7/24, 29%) [45,55,58,59,63,66,67], ActiGraph GT2M (3/24, 12%) [47-49], ActiGraph GT1M (1/24, 4%) [53], Fitbit Alta HR (1/24, 4%) [46], and activPAL 3 (3/24, 12%) [50,51,65]. A total of 4% (1/24) of the articles reported on studies that provided participants with either the ActiGraph GT1M or GT3x+ device [68], and 4% (1/24) used the Patient-Reported Outcomes Diary device [57]. In total, 75% (18/24) of the articles reported on studies that required a minimum threshold of valid wear time for data to be included in the analysis [45-53,56,58,59,61,63,65-68]. Minutes of moderate- to vigorous-intensity PA (MVPA) were the most common operationalization of PA (12/24, 50%) [45,47-49,53,55,56,58,59,63,66,67], and minutes of sedentary time were the most common operationalization of SB (5/24, 21%) [50,51,53,55,65] using device-based measures.

Among the self-reported measures of movement-related behaviors, the studies reported in 25% (6/24) of the articles adapted items from existing validated measures, including the International Physical Activity Questionnaire—Short Form by Sjöström et al [63,65], Godin Leisure-Time Exercise Questionnaire by Godin and Shephard [52,54,61], and a measure of sedentary time in older adults developed by Gardiner et al [65]. Other assessments of daily movement-related behaviors included checklists in which participants indicated the activities they had participated in that day and for how long [56,64]. Bond et al [60] and Rebar et al [66] assessed the daily duration of MVPA using items created for the study.

Methodological Quality

The average MQQ score was 21.38 (SD 4.31; range 14-27), with 21% (5/24) of the articles scoring 27 (the highest possible score). The interrater reliability for the MQQ scores was 98.3%, which is an acceptable level of agreement [55]. On the basis of the 9 criteria of the MQQ, the most frequently omitted information pertained to evidence of reliability and validity provided for the data collected (12/24, 50%) [45,46,53,56,58,60-63,66,67] followed by implications for policy (11/24, 46%) [45,46,53,55-59,61,64,67].

The average CREMAS score was 11.92 (SD 2.21; range 8-15). The interrater reliability for the CREMAS scores was 93.75%. Commonly omitted elements of the CREMAS among applicable articles included participant training procedures, latency, and missing data analysis. Of the 20 articles in which latency was applicable (eg, interval- and signal-contingent designs), none reported latency. A total of 54% (13/24) of the articles did not report any missing data analyses [45,46,52-54,58-61,64-67]. In total, 50% (12/24) of the articles did not report any training to familiarize participants with the EMA protocol [46,49,53,56,58,61,64,66-68]. Except for the studies reported in 12% (3/24) of the articles [47-49], wave duration (ie, the number of data collection waves in a study) was not applicable as all other studies collected data over a single wave.

PA and Social Cognitive Determinants

This systematic review identified studies examining associations between specific social cognitive determinants (ie, intentions, self-efficacy, outcome expectations, planning, perceived barriers, and attitudes) and PA; however, the availability of data regarding these associations differed at the momentary and daily levels. The findings are summarized in the following sections.

Intentions

Momentary Associations

The studies reported in 25% (6/24) of the articles assessed associations between intentions and PA at the momentary level, which is shown in Table 2. Of those 6 articles, 3 (50%) focused on direct relationships between momentary intentions and subsequent PA. Among college student athletes, Reifstreck et al [52] documented a positive association between intentions and behavior such that, on occasions when participants reported stronger-than-usual intentions, they engaged in more device-based MVPA over the following 3 hours. Similarly, Arigo et al [45] found a weak positive association between the number of intended minutes and minutes of device-based MVPA over the following 3 hours among adults, although the results were not significant. However, this positive association between intentions and behavior became stronger and more significant on occasions when participants experienced less contentment...
or body satisfaction than usual. Conversely, Pickering et al [49] found a null association between momentary intentions and subsequent device-based MVPA among adults. However, on occasions when adults had higher self-efficacy to engage in PA than was typical for them, momentary intentions were positively associated with subsequent MVPA. As only 12% (3/24) of the articles reported on studies that investigated momentary intention–PA relationships and we determined a priori that there must be at least 4 articles present to draw a conclusion regarding an overall association, this cannot be made at this time.

In total, 12% (3/24) of the articles focused specifically on time-varying moderators of intention-PA relationships, with all articles (3/3, 100%) reporting on studies that used device-based measures of PA. Time of day and day of the week were moderators investigated by Maher et al [47,51]. Time-varying effect models applied by Maher et al [47] revealed that intentions to be physically active positively predicted subsequent MVPA in the mornings and evenings but not in the afternoons. On weekdays, intentions were unrelated to subsequent PA on weekends. Using a similar approach, Maher and Dunton [51] found that, among older adults, intentions to be active were positively associated with subsequent time spent upright (ie, standing or stepping) during the morning, afternoon, and evening on both weekdays and weekends, although the magnitude of the associations changed throughout the day. Finally, Maher et al [48] investigated affect states and physical context as moderators of the intention-PA coupling and found that individuals were more likely to follow through with their intentions to be physically active on occasions when they reported greater positive affect than was typical for them (at the same time that they reported their intentions). Owing to the range of time-varying moderators investigated, conclusions regarding consistent moderators of intention-PA relationships at the momentary level cannot be drawn.
Table 2. Associations between social cognitive determinants and physical activity and sedentary behavior.

<table>
<thead>
<tr>
<th>Social cognitive determinant and timescale of associations</th>
<th>Positive association</th>
<th>Negative association</th>
<th>Null association</th>
<th>Moderators</th>
<th>Overall association</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Physical activity</strong></td>
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<tr>
<td><strong>Intentions predicting physical activity</strong></td>
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<tr>
<td>Momentary associations</td>
<td>Reifsteck et al [52]</td>
<td>No articles reported a negative association</td>
<td>Pickering et al [49]</td>
<td>Self-efficacy: Pickering et al [49]</td>
<td>N/A^b</td>
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<tr>
<td><strong>Self-efficacy predicting physical activity</strong></td>
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<tr>
<td>Momentary associations</td>
<td>Cook et al [46]</td>
<td>No articles reported a negative association</td>
<td>Reifsteck et al [52]</td>
<td>Intentions: Pickering et al [49]</td>
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<tr>
<td>Daily associations</td>
<td>Berli et al [59]</td>
<td>Bermudez et al [58]</td>
<td>Bermudez et al [58]</td>
<td>Time of day: Maher et al [47] and Maher and Dunton [51]</td>
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<td></td>
<td>Bermudez et al [58]</td>
<td>McDonald et al [57]</td>
<td>McDonald et al [57]</td>
<td>Day of the week: Maher et al [47] and Maher and Dunton [51]</td>
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<td></td>
<td>Bond et al [60]</td>
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<td></td>
<td>McDonald et al [57]</td>
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<td><strong>Outcome expectations predicting physical activity</strong></td>
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<tr>
<td>Momentary associations</td>
<td>Reifsteck et al [52]</td>
<td>No articles reported a negative association</td>
<td>Maher et al [47]</td>
<td>No articles assessed moderators</td>
<td>N/A</td>
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<tr>
<td><strong>Planning predicting physical activity</strong></td>
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<tr>
<td>Daily associations</td>
<td>Carraro and Gaudreau [55]</td>
<td>No articles reported a negative association</td>
<td>Carraro and Gaudreau [55]</td>
<td>Typical plans: Anderson [54]</td>
<td>N/A</td>
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<td></td>
<td>Anderson [54]</td>
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<td>Goal conflict: Carraro and Gaudreau [55]</td>
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<td></td>
<td>Berli et al [59]</td>
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<tr>
<td><strong>Barriers predicting physical activity</strong></td>
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<tr>
<td>Daily associations</td>
<td>No articles reported a positive association</td>
<td></td>
<td>Zenk et al [53]</td>
<td>No articles assessed moderators</td>
<td>N/A</td>
</tr>
</tbody>
</table>
### Social Cognitive Determinant and Timescale of Associations

<table>
<thead>
<tr>
<th>Attitudes Predicting Physical Activity</th>
<th>Positive Association</th>
<th>Negative Association</th>
<th>Null Association</th>
<th>Moderators</th>
<th>Overall Association</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily Associations</td>
<td>No articles reported a positive association</td>
<td>No articles reported a negative association</td>
<td>Bermudez et al [58]</td>
<td>No articles assessed moderators</td>
<td>N/A</td>
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<tr>
<td>Sedentary Behavior</td>
<td>Daily associations</td>
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<tr>
<td>Intentions Predicting Sedentary Behavior</td>
<td>Momentary associations</td>
<td>No articles reported a positive association</td>
<td>Maher and Dunton [50]</td>
<td>No articles assessed moderators</td>
<td>N/A</td>
</tr>
<tr>
<td>Daily associations</td>
<td>No articles reported a positive association</td>
<td>No articles reported a null association</td>
<td>Time of day: Maher and Dunton [51]</td>
<td>No articles assessed moderators</td>
<td>N/A</td>
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<tr>
<td>Self-efficacy Predicting Sedentary Behavior</td>
<td>Momentary associations</td>
<td>No articles reported a positive association</td>
<td>Maher and Dunton [50]</td>
<td>No articles assessed moderators</td>
<td>N/A</td>
</tr>
<tr>
<td>Planning Predicting Sedentary Behavior</td>
<td>Daily associations</td>
<td>No articles reported a positive association</td>
<td>Maher and Conroy [65]</td>
<td>No articles assessed moderators</td>
<td>N/A</td>
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<tr>
<td>Barriers Predicting Sedentary Behavior</td>
<td>Daily associations</td>
<td>No articles reported a positive association</td>
<td>No articles reported a negative association</td>
<td>Zenk et al [53]</td>
<td>No articles assessed moderators</td>
</tr>
</tbody>
</table>

a A total of 4 articles were needed to make an overall association.
b N/A: not applicable; <4 articles on the social cognitive determinant, so an overall association cannot be determined.
c+: Positive association (≥60% of the studies showing an association).
d?: inconclusive (34%-59% of the studies showing an association).

### Daily Associations

The studies reported in 25% (6/24) of the articles assessed the association between intentions and PA at the day level. Of these 6 articles, 4 (67%) documented positive associations between daily intentions and behavior regardless of whether intentions were assessed upon waking [60] or the previous evening [59]. Furthermore, these associations were consistent across different operationalizations of PA, including self-reported MVPA [60,62] and device-based MVPA [57-59]. Conversely, Rebar et al [66] found a null association between intentions to exercise the following day and self-reported exercise; however, on nights when university students experienced more ego depletion (limited cognitive and physical capabilities), they were more likely to successfully enact those exercise intentions the following day. McDonald et al [57] observed older adults in the months leading up to and following retirement and found that intentions did not consistently predict PA in all participants. The findings indicate that intentions to be active were positively associated with (1/24, 4%), negatively associated with (1/24, 4%), or not related to (5/24, 21%) likelihood of engaging in a PA bout depending on the participant. On the basis of the criteria by Sallis et al [44], the findings indicate an overall positive association between intentions and subsequent PA at the day level (ie, ≥60 of the articles; 4/6, 67% reported a consistent positive association); however, further investigation of moderators of these daily associations is warranted.

### Self-efficacy Associations

#### Momentary Associations

The studies reported in 25% (6/24) of the articles assessed associations between self-efficacy and PA at the momentary level, which is shown in Table 2. Of these 6 articles, 4 (67%) focused on direct relationships between momentary self-efficacy and subsequent PA. Among older adults, Dunton et al [56] found a positive association between momentary self-efficacy and subsequent self-reported MVPA. Similarly, Cook et al [46]
found a positive association between momentary self-efficacy and device-based MVPA, although a null association was found between momentary self-efficacy and total steps.

Conversely, both Pickering et al [49] and Reifsteck et al [52] found null associations between momentary self-efficacy and subsequent device-based MVPA among adults and college student athletes, respectively. Pickering et al [49] did find that momentary intentions moderated momentary self-efficacy–behavior relationships such that, on occasions when adults had stronger intentions to engage in PA than usual, momentary self-efficacy was positively associated with subsequent MVPA. On the basis of the criteria by Sallis et al [44], the findings indicate a positive association between self-efficacy and PA at the day level (ie, ≥60% of the articles—4/6, 67%—reported consistent positive associations); however, further investigation of moderators of these daily associations is necessary.

### Outcome Expectations

#### Momentary Associations

The studies reported in 12% (3/24) of the articles assessed outcome expectations and PA at the momentary level, shown in Table 2. Among college student athletes, Reifsteck et al [52] found that, on occasions when outcome expectations regarding PA were higher than usual, individuals engaged in more device-based MVPA over the following 3 hours. However, using an identical measure of outcome expectations and PA as in the study by Reifsteck et al [52], Pickering et al [49] found null associations between momentary outcome expectations and PA among adults. Furthermore, Maher et al [47] found that momentary outcome expectations were not associated with subsequent PA regardless of time of day or day of the week. As only 12% (3/24) of the articles reported on studies that investigated momentary outcome expectation–PA relationships and we determined a priori that there must be at least 4 articles present to draw a conclusion regarding an overall association, this cannot be made at this time.

#### Daily Associations

None of the articles reported on studies that examined associations between daily outcome expectations and PA.

### Planning

#### Momentary Associations

None of the articles reported on studies that examined associations between planning and PA at the momentary level.

#### Daily Associations

The studies reported in 12% (3/24) of the articles assessed associations between daily planning and PA. Of these 3 articles, 1 (33%) reported on a study that investigated general planning [54], 1 (33%) reported on a study that investigated action planning [55], and 1 (33%) focused on action and coping planning [55]. General planning and action planning were both found to be positively associated with self-reported PA [54,55] and device-based [59] daily MVPA; however, daily coping planning and self-reported PA were not associated [55]. As only 12% (3/24) of the articles reported on studies that investigated daily planning–PA relationships and we determined a priori that there must be at least 4 articles present to draw a conclusion regarding an overall association, this cannot be made at this time.

Regarding moderators, Anderson [54] found that usual levels of planning moderated associations between daily planning and PA such that, for individuals who tended to have weaker PA planning, on days when they reported stronger-than-usual plans...
to be active, they engaged in more self-reported MVPA. Carraro and Gaudreau [55] found that a time-varying factor—daily academic goal conflict—moderated associations between daily action planning and PA such that daily action planning was positively associated with daily self-reported PA on days during which individuals experienced lower academic goal conflict. Although these studies suggest possible time-invariant and time-varying moderators of daily planning–PA relationships, because of the limited number of studies investigating such moderators, conclusions cannot be drawn at this time.

**Perceived Barriers**

**Momentary Associations**

None of the articles reported on studies that examined associations between momentary barriers and PA.

**Daily Associations**

Borowski et al [61] documented a negative association between daily barriers to exercise (eg, no time, feeling tired, and air or noise pollution) and self-reported PA, and for each additional barrier reported, participants engaged in 27% fewer minutes of PA that day. Zenk et al [53] examined associations between different types of barriers and device-based PA and found that the extent to which African American women endorsed poor weather as a barrier to PA was associated with less PA but that environmental (eg, no sidewalk or no indoor facilities) and social (eg, no one to exercise with and safety or crime concerns) barriers were not associated with PA. Owing to the limited number of articles, an overall association between daily barriers and PA cannot be determined at this time.

**Attitudes**

**Momentary Associations**

None of the articles reported on studies that examined associations between momentary attitudes and PA.

**Daily Associations**

Bermudez et al [58] found that neither affective nor instrumental attitudes on a given day were associated with device-based MVPA or light-intensity PA. As only 4% (1/24) of the studies investigated this topic, an overall association between attitudes and PA cannot be determined at this time.

**SB and Social Cognitive Determinants**

**Overview**

This systematic review identified studies examining associations between specific social cognitive determinants (ie, intentions, self-efficacy, planning, and perceived barriers) and SB, but the availability of data regarding these associations differed at the momentary and daily levels. However, because of the limited number of studies investigating such associations, overall associations between each social cognitive determinant and SB cannot be determined at this time. Nevertheless, we report our findings in the following sections.

**Intentions**

**Momentary Associations**

Maher and Dunton [50] found that, on occasions when older adults had stronger intentions than usual to limit their SB, they subsequently engaged in less device-based SB in the following 2-hour period. Using the same data set, Maher and Dunton [51] found that, on weekdays, momentary intentions to limit SB negatively predicted subsequent SB across the entire day, but on weekends, intentions only negatively predicted SB in the morning, afternoon, and early evening.

**Daily Associations**

Conroy et al [63] examined day-level associations between end-of-day intentions to limit SB and next-day SB among university students and found that, on days when university students had stronger-than-usual intentions to limit their SB, they subsequently engaged in less self-reported SB the following day.

**Self-efficacy**

**Momentary Associations**

Maher et al [50,51] have published 2 articles examining associations between momentary self-efficacy and SB. Maher and Dunton [50] found that, on occasions when older adults had stronger self-efficacy to limit SB, they subsequently engaged in less device-based SB over the following 2 hours. Investigation of day of the week and time of day as moderators of this association revealed that self-efficacy to limit SB was negatively associated with SB throughout the day as moderators of this association. Maher and Dunton [51] found that, on weekdays, momentary intentions to limit SB only negatively predicted SB across the entire day, but on weekends, self-efficacy to limit SB was only associated with subsequent SB in the afternoon [51].

**Daily Associations**

Maher and Dunton [50] found that, on occasions when older adults had stronger intentions than usual to limit their SB, they subsequently engaged in less device-based SB in the following 2-hour period. Using the same data set, Maher and Dunton [51] found that, on occasions when older adults had stronger self-efficacy to limit SB, they subsequently engaged in less device-based SB over the following 2 hours. Investigation of day of the week and time of day as moderators of this association revealed that self-efficacy to limit SB was negatively associated with SB throughout the day as moderators of this association.

**Planning**

**Momentary Associations**

None of the articles reported on studies that examined associations between momentary plans and SB.

**Daily Associations**

Maher et al [50,51] have published 2 articles examining associations between momentary self-efficacy and SB. Maher and Dunton [50] found that, on occasions when older adults had stronger self-efficacy to limit SB, they subsequently engaged in less device-based SB over the following 2 hours. Investigation of day of the week and time of day as moderators of this association revealed that self-efficacy to limit SB was negatively associated with SB throughout the day as moderators of this association.

**Perceived Barriers**

**Momentary Associations**

None of the articles reported on studies that examined associations between barriers and SB.

**Daily Associations**

Zenk et al [53] found null associations between weather, environment, and social barriers to engaging in PA and device-based SB on a given day among African American women.
Discussion

Principal Findings

This review is the first to summarize the available EMA evidence of associations between social cognitive determinants and movement-related behaviors at the momentary and daily levels. Although this review included 24 articles comprising 21 unique studies, there were limited studies investigating each individual social cognitive determinant’s relationship with subsequent behavior, especially after accounting for the timescale of assessment (i.e., momentary level vs day level). The largest evidence base and, therefore, the strongest conclusions in the systematic review pertain to relationships between intentions and PA and between self-efficacy and PA. Overall, synthesizing the available evidence contributes to our preliminary understanding of the impact of social cognitive determinants on subsequent movement-related behaviors in real-world environments, identifies gaps in the literature to direct future movement-related behavior EMA research, and can begin to inform intervention efforts that are designed to deliver contextually relevant motivation content during periods of opportunity and vulnerability.

This systematic review suggests that positive associations exist among intentions, self-efficacy, and PA at the day level. It is not surprising that intentions and self-efficacy, which are prominent constructs posited to directly influence behavior within social cognitive frameworks [70,71], emerged as consistent and positive predictors of PA at the day level in this systematic review. However, articles that reported on studies investigating associations among intentions, self-efficacy, and PA at the momentary level (6/24, 25% and 6/24, 25%, respectively) revealed mixed findings. For instance, although a sufficient number of studies investigated associations between momentary self-efficacy and subsequent PA to determine an overall association, conflicting findings across the studies resulted in an inconclusive overall association. Several time-varying moderators were documented across the articles at the momentary level. It is possible that associations between momentary social cognitive determinants and subsequent PA may be affected by contextual factors that change across time and space as individuals navigate their daily lives, whereas day-level associations may be less affected by immediate contextual features of one’s current environment.

This systematic review suggests that more research is needed to better understand associations between social cognitive determinants and subsequent movement-related behaviors in the context of everyday life. For instance, results from this systematic review suggest that no studies used daily or within-day EMA methodology to examine relationships between PA facilitators (e.g., optimal weather) and subsequent PA behavior or between outcome expectations and attitudes and subsequent SB. In addition, there were not enough eligible articles that reported on studies investigating relationships between any social cognitive determinant and SB to draw conclusions. In addition, although some social cognitive determinants such as daily planning appeared to indicate consistent associations with PA across the studies, <4 studies investigated this association, which prevented a conclusion from being drawn. Further complicating the state of the literature in this area is that a variety of measures were used to assess both social cognitive determinants and behavior. Such diversity may have contributed to the discrepant findings across the studies. For instance, among the studies investigating associations between momentary self-efficacy and PA (where an inconclusive overall association was determined; only 2/4, 50% indicated a positive association), Dunton et al [56] assessed participants’ confidence in engaging in PA and found a positive association with PA, whereas Pickering et al [49] assessed participants’ confidence in engaging in PA despite possible barriers and found a null association. However, even across the diverse assessments used, we were able to find consistent trends in relationships between some social cognitive determinants and behaviors (e.g., daily associations between intentions and PA), increasing the confidence in our conclusions on those relationships as the diversity of measures reduces the likelihood that the effect is the result of measurement bias. Greater consistency across the studies in the assessment of social cognitive determinants and behavior would allow for more precise conclusions on associations between social cognitive determinants and movement-related behavior and would be more appropriate to quantitatively estimate associations in a meta-analysis.

Limitations of This Review

Although studies using EMA methods can uncover more nuanced associations between social cognitive determinants and movement-related behaviors by collecting ecologically valid and intensive longitudinal data, the limitations of the studies included in this review should be noted. First, the findings synthesized in this review may not apply to all developmental periods across the life span or individuals of racially or ethnically minoritized backgrounds. No studies included in this review focused on child or adolescent samples, and almost all studies (12/14, 86% that reported race and ethnicity) featured samples in which most participants identified as White or non-Hispanic White. Given that PA levels decline rapidly throughout late childhood and adolescence and racial and ethnic minorities experience physical inactivity–related health disparities [72], EMA may be a critical methodological tool to understand relationships between motivation and behavior in these vulnerable populations. In addition, the studies featured in this review comprised insufficiently active or sedentary individuals as well as those who were sufficiently active; therefore, it is likely that the results are aggregated across individuals at various stages of the behavior change continuum. There is evidence suggesting that social cognitive determinants may differentially regulate behavior across the behavior change continuum, which is an important direction to explore in EMA work to understand movement-related behaviors [24,73]. Further influencing the generalizability of the findings is the lack of missing data analysis in several studies included in this review (12/24, 50%). Such an analysis is essential in EMA studies to determine if data are missing at random or in systematic patterns, which may influence the extent to which documented associations translate to all occasions or all people [43,74].

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Bittel et al

JMIR Mhealth Uhealth 2023 | vol. 11 | e44104 | p.1299

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Most EMA studies included in this review (16/24, 67%) created measures to assess social cognitive determinants or behavior. Although such an approach is common in EMA research as fewer items are used to limit participant burden and fatigue that may result from repeated, intensive assessments [29], the items used in the studies in this review rarely presented psychometric data to establish the validity or reliability of the measures, and the studies often appeared to create items based on face validity. More rigorous and systematic approaches are necessary to develop EMA items to assess social cognitive determinants and movement-related behaviors (for a more in-depth discussion, see the study by Reichert et al [75]).

Furthermore, the limitations of the systematic review itself should be addressed. Although this review assessed the quality of the studies and study reporting through the MQQ and CREMAS, respectively, the information was not used in the interpretation of the results. Neither quality assessment tool specifies thresholds for low-, medium-, or high-quality articles. Therefore, we chose to present the raw scores on each assessment tool. On the basis of those scores, of the 24 articles included in the review, only 5 (21%) scored <18 on the MQQ, and 7 (29%) scored <11 on the CREMAS, which would indicate that those articles satisfied less than two-thirds of the criteria specified within the respective quality assessment tools.

In addition, the inclusion and exclusion criteria of this review did not place any restrictions on the participant sample size necessary for inclusion. A small participant sample size can affect the likelihood of obtaining significant results as well as the magnitude of the association documented. Only 17% (4/24) of the articles included in this review reported on studies that had <50 participants—a threshold determined through simulation to provide adequate power for variance, SE, and fixed-effects estimates at both the between- and within-person levels [76,77]. However, the findings presented in this review primarily focus on within-person findings (or the extent to which social cognitive determinants predict subsequent behavior on a given day or moment). Therefore, power for the analysis is derived from the number of occasions in the analytic sample, and because of the intensive assessments that are a hallmark of EMA, studies typically generate many observations per person. For instance, the study by McDonald et al [57] had the smallest participant sample size of the studies included in the review (N=7) but collected daily assessments from 2 to 7 months, resulting in between 87 and 196 observations per participant. Furthermore, the size of the associations was not considered to fully interpret the relationships documented across the studies as few (7/24, 29%) reported effect sizes. As the volume of studies in this area increases, a meta-analysis should be conducted that accounts for the sample size and effect sizes of relevant studies to further characterize momentary and daily associations between social cognitive determinants and movement-related behaviors.

**Future Directions**

PA and SB are considered independent health behaviors with different processes regulating each behavior and different health consequences associated with each [78]; however, most of the research investigating relationships between social cognitive determinants and movement-related behaviors focuses on PA. Given the prevalence of excessive SB as well as recent calls to design movement-related behavior interventions to initially focus on reducing SB and over time build to engaging in MVPA [79,80], EMA studies specifically addressing social cognitive determinant–SB relationships are necessary to develop and refine theoretical frameworks to explain and predict SB.

Across both behaviors, intentions and self-efficacy were the most investigated social cognitive determinants. This is not surprising as the Theory of Planned Behavior and Social Cognitive Theory posit that intentions and self-efficacy are proximal determinants of behavior, respectively [7,9,10,39]. However, based on preliminary evidence from this review, momentary self-efficacy and daily planning may also be important motivational determinants of behavior, but this is based on a limited number of studies. Interestingly, the relationships between planning and PA seemed to depend on the type of planning used (eg, action planning vs coping planning), but it is unclear why these differences might exist across microtimescales given the consistent finding across macrotimescales [81]. Perhaps associations between coping planning and movement-related behavior on microtimescales depend on whether an anticipated barrier is encountered in one’s daily experiences. Similarly, although many studies (12/24, 50%) indicated that self-efficacy was assessed, further inspection of items revealed subtle differences in the type of self-efficacy assessed across the studies (eg, task self-efficacy and barrier self-efficacy), which may be differentially related to behavior and are likely important to consider in future EMA research [82,83].

Findings from this review provide evidence that both time-varying and time-invariant factors can moderate associations between social cognitive determinants and subsequent movement-related behaviors at the momentary and daily levels. A recent systematic review of studies investigating the PA intention-behavior coupling across microtimescales (eg, weeks and months) found that consistent moderators of the intention-behavior coupling included motivational factors such as intention stability, intention commitment, low goal conflict, affective attitude, anticipated regret, perceived behavioral control or self-efficacy, and exercise identity [69]. Although some EMA studies have investigated some of these motivational factors as moderators [49,55], more work is needed to establish whether between-person moderators across macrotimescales also serve as within-person moderators across microtimescales. In addition, to date, only a handful of studies have investigated the moderating role of affective states and physical and social contexts on social cognitive determinant–behavior relationships [48]. There is recent evidence suggesting that these time-varying contextual factors can influence behavior, and it may be that this influence on behavior is through motivational processes [36,37]. Future research should continue to investigate context-sensitive moderators as this work is an essential first step in theory refinement that is sensitive to the contexts that people encounter in their daily lived experiences [84].

This systematic review focused on observational EMA studies to better understand the naturally occurring relationships between social cognitive determinants and subsequent behavior.
However, using intensive assessment methods such as EMA and accelerometry to understand how social cognitive determinant–movement-related behavior relationships change over the course of an intervention may be important for developing more effective behavioral interventions. For instance, Basen-Engquist et al [85] had endometrial cancer survivors complete 3-, 10-, and 12-day EMA protocols spaced over the course of a 6-month PA intervention. Although the authors aggregated data across these 3 time points to determine momentary associations among self-efficacy, outcome expectations, and PA, such data could reveal the extent to which associations between social cognitive determinants and subsequent behavior change over the course of an intervention. Such data could also reveal the extent to which behavior change content delivered at a specific point in the intervention is able to affect social cognitive determinant–behavior relationships. Collecting EMA data regarding social cognitive determinant–behavior relationships may help identify potent intervention content in the context of everyday life.

Conclusions

This systematic review synthesized EMA-derived associations between social cognitive determinants and subsequent movement-related behavior over microtimescales. Overall, based on the available evidence, social cognitive determinants do regulate movement-related behaviors in the context of everyday life. Specifically, daily intentions and self-efficacy appeared to have a consistent and positive link with PA behavior across the studies using self-reported and device-based measures of behavior. Future research is necessary to determine whether these associations extend to the momentary level, investigate associations among a broader range of social cognitive determinants and movement-related behaviors in diverse populations across the life span, and explore time-varying and time-invariant moderators of these associations. In addition, efforts should be devoted to developing more rigorous study designs, including validating EMA social cognitive determinant assessments and conducting missing data analyses. Ultimately, this systematic review provides foundational knowledge for understanding the motivational determinants of movement-related behaviors within people and is essential for directing future research regarding movement-related behaviors in the context of daily life. In addition, such inquiries are necessary to inform the development of interventions to promote active lifestyles in the context of everyday life.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Full search term queries. [DOCX File, 13 KB - mhealth_v11i1e44104_app1.docx]

References


Abbreviations

CREMAS: Checklist for Reporting Ecological Momentary Assessment Studies
EMA: ecological momentary assessment
MQQ: Methodological Quality Questionnaire
MVPA: moderate- to vigorous-intensity physical activity
PA: physical activity
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
REDCap: Research Electronic Data Capture
SB: sedentary behavior

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Reliability and Validity of Noncognitive Ecological Momentary Assessment Survey Response Times as an Indicator of Cognitive Processing Speed in People’s Natural Environment: Intensive Longitudinal Study

Raymond Hernandez¹, PhD; Claire Hoogendoorn²,³, PhD; Jeffrey S Gonzalez²,³, PhD; Haomiao Jin¹,⁴, PhD; Elizabeth A Pyatak⁵, PhD; Donna Spruijt-Metz¹,⁶,⁷, PhD; Doerte U Junghaenel¹,², PhD; Pey-Jiuan Lee¹, MS; Stefan Schneider¹,⁷, PhD

¹Center of Economic and Social Research, University of Southern California, Los Angeles, CA, United States
²Ferkauf Graduate School of Psychology, Yeshiva University, Bronx, NY, United States
³Fleischer Institute for Diabetes and Metabolism, Division of Endocrinology, Department of Medicine, Albert Einstein College of Medicine, Bronx, NY, United States
⁴School of Health Sciences, Faculty of Health and Medical Sciences, University of Surrey, Guildford, United Kingdom
⁵Chan Division of Occupational Science and Occupational Therapy, University of Southern California, Los Angeles, CA, United States
⁶Keck School of Medicine, University of Southern California, Los Angeles, CA, United States
⁷Department of Psychology, University of Southern California, Los Angeles, CA, United States

Abstract

Background: Various populations with chronic conditions are at risk for decreased cognitive performance, making assessment of their cognition important. Formal mobile cognitive assessments measure cognitive performance with greater ecological validity than traditional laboratory-based testing but add to participant task demands. Given that responding to a survey is considered a cognitively demanding task itself, information that is passively collected as a by-product of ecological momentary assessment (EMA) may be a means through which people’s cognitive performance in their natural environment can be estimated when formal ambulatory cognitive assessment is not feasible. We specifically examined whether the item response times (RTs) to EMA questions (eg, mood) can serve as approximations of cognitive processing speed.

Objective: This study aims to investigate whether the RTs from noncognitive EMA surveys can serve as approximate indicators of between-person (BP) differences and momentary within-person (WP) variability in cognitive processing speed.

Methods: Data from a 2-week EMA study investigating the relationships among glucose, emotion, and functioning in adults with type 1 diabetes were analyzed. Validated mobile cognitive tests assessing processing speed (Symbol Search task) and sustained attention (Go-No Go task) were administered together with noncognitive EMA surveys 5 to 6 times per day via smartphones. Multilevel modeling was used to examine the reliability of EMA RTs, their convergent validity with the Symbol Search task, and their divergent validity with the Go-No Go task. Other tests of the validity of EMA RTs included the examination of their associations with age, depression, fatigue, and the time of day.

Results: Overall, in BP analyses, evidence was found supporting the reliability and convergent validity of EMA question RTs from even a single repeatedly administered EMA item as a measure of average processing speed. BP correlations between the Symbol Search task and EMA RTs ranged from 0.43 to 0.58 (P<.001). EMA RTs had significant BP associations with age (P<.001), as expected, but not with depression (P=.20) or average fatigue (P=.18). In WP analyses, the RTs to 16 slider items and all 22 EMA items (including the 16 slider items) had acceptable (>0.70) WP reliability. After correcting for unreliability in
multilevel models, EMA RTs from most combinations of items showed moderate WP correlations with the Symbol Search task (ranged from 0.29 to 0.58; \( P < .001 \)) and demonstrated theoretically expected relationships with momentary fatigue and the time of day. The associations between EMA RTs and the Symbol Search task were greater than those between EMA RTs and the Go-No Go task at both the BP and WP levels, providing evidence of divergent validity.

**Conclusions:** Assessing the RTs to EMA items (eg, mood) may be a method of approximating people’s average levels of and momentary fluctuations in processing speed without adding tasks beyond the survey questions.

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**KEYWORDS**
cognitive performance; processing speed; ecological momentary assessment; ambulatory assessment; type 1 diabetes; survey response times; paradata; chronic illness; smartphone; mobile health; mHealth; mobile phone

**Introduction**

**Background**

Various illnesses are risk factors for decreased cognitive performance, including type 1 diabetes (T1D), type 2 diabetes, depression, and cardiovascular disease [1-4], making the assessment of cognition in these populations important. Although the measurement of the cognitive performance of individuals with various chronic illnesses in their real-world environments is potentially useful (eg, as it provides ecologically valid measures) [5], formal ambulatory cognitive assessment is at times infeasible because of limited resources and time demands already placed on participants from other ambulatory assessment tasks. We attempt to capitalize on the growing use of the ecological momentary assessment (EMA) methodology in behavioral health research [6-8] and propose a novel approach for assessing a central cognitive measure, processing speed, using EMA survey paradata. Paradata are data about the response process, such as response times (RTs) when answering survey questions [9,10], that can be passively captured alongside survey responses. Measuring cognitive performance via EMA paradata could create novel opportunities for researchers to examine respondents’ real-time cognitive performance in studies in which formal ambulatory cognitive testing cannot be readily implemented. This, in turn, could allow for a more frequent investigation of the antecedents, correlates, and consequences of changes in processing speed across a wider range of individuals and populations with chronic conditions.

Several behavioral health-focused EMA studies have used formal ambulatory cognitive tests in various populations, including individuals with T1D [11-13], breast cancer survivors [14], and people with fibromyalgia [15]. Formal ambulatory cognitive assessments have been viewed as a gold standard for capturing people’s cognitive performance in their natural environment and overcome several limitations of traditional cognitive testing, including the ability to represent cognitive performance in real-world settings, increased frequency with which tests can be administered, and the ability to capture changes over short time frames [5]. However, formal ambulatory cognitive assessments often require more time to complete than other EMA measures. For instance, assessing a single aspect of cognition often requires 45 to 60 seconds [5,16], whereas the measurement of constructs such as stress requires the completion of a single item. Therefore, to administer formal ambulatory cognitive tests, researchers must at times limit the number of survey items included to keep the overall time to complete EMA surveys manageable. They also often require a costly setup and the use of specific programs or apps, which can be obstacles to implementation for many researchers. The difficulties in implementing formal ambulatory assessments limit our ability to more frequently investigate cognitive performance in everyday real-world settings in populations with chronic conditions. When considering T1D specifically, ambulatory cognitive performance has rarely been assessed [12,13,16], limiting our understanding of time-varying correlates and ultimately our understanding of the multifactorial pathways connecting diabetes to cognitive performance and decline.

Cognitive performance may potentially be inferred from EMA survey paradata (eg, RTs to mood items) and thus could be a means to approximate people’s momentary cognitive functioning in their natural environments without the time demand of additional formal cognitive testing. Paradata have been investigated as a means of approximating the cognitive aspects underlying survey responding in traditional (non-EMA) survey studies. For instance, a study examining survey response behaviors at older ages found that the time of survey initiation and time of survey completion were related to mild cognitive impairment [8]. In another study, survey RTs and answer changes were operationalized as indicators of cognitive effort [9]. However, to date, very few studies have investigated the potential use of paradata in EMA surveys as indicators of cognitive performance [10]. One study found a moderate association between the time to complete EMA surveys and processing speed [10] but did not examine the effect of the types of EMA items or the degree of within-person (WP) reliability of EMA RTs.

**This Study**

The purpose of this study was to investigate whether the RTs to noncognitive EMA questions (eg, mood, stress, and activity done) can serve as approximate indicators of person-level differences and momentary WP fluctuations in processing speed. Aside from individuals’ average processing speed (person-level differences), momentary fluctuations in processing speed may also be useful to assess via EMA survey paradata. For instance, intraindividual cognitive variability increases with age, even among those who remain cognitively healthy [17], and variability is a risk factor for mild cognitive impairment and Alzheimer disease and related dementias [18-22], even after adjusting for average performance [18]. In addition, WP variability in processing speed, as measured by formal cognitive...
tests, has been shown to be affected by momentary factors, including caffeine consumption [23], social context [24], and fatigue [14]. We acknowledge that RTs to survey items have been proposed to contain different types of information, including the level of cognitive effort invested [25]; processing speed [26]; and, for self-reports of current mood, the level of emotional clarity [27]. Therefore, survey item RTs likely reflect a combination of several factors. Thus, we did not expect a complete overlap between RTs and the results of mobile cognitive testing but did expect a substantial association.

We capitalized on preexisting data from an EMA study in which adults with T1D completed 2 weeks of EMA surveys together with smartphone-based mobile processing speed and sustained attention tests [16]. Cognitive tests provided validated processing speed and attention measures against which we compared the EMA survey RTs. The makeup of the sample, adults with T1D, allowed for analyses in a sample for which processing speed may be especially relevant. In individuals with T1D, previous studies have found relationships between blood glucose metrics and cognitive performance, including processing speed [11,28,29].

As the primary test of convergent validity, we examined the associations between the RTs to different subsets of EMA items and the scores of mobile cognitive testing. We hypothesized that if EMA survey RTs captured processing speed, slower RTs would be associated with worse performance on the formal processing speed test, both at the between-person (BP) and WP levels.

As secondary tests of convergent validity, we examined the associations between the RTs to different subsets of EMA items and depression symptoms, age, fatigue, and a diurnal cycle. In a review, individuals with major depression were found to have lower processing speed than controls [30], so we expected greater depression symptoms to be associated with slower mean EMA survey RTs. Aging has often been linked to decreased processing speed through various neurobiological pathways [31,32], so greater age was hypothesized to be associated with slower mean EMA survey RTs. We hypothesized that fatigue would have associations with EMA survey RTs at both the BP and WP levels. At the BP level, chronic fatigue syndrome has been associated with slower overall processing speed [33]. At the WP level, processing speed was slower among breast cancer survivors reporting higher than usual fatigue [14]. Finally, cognitive abilities have been found to be at the lowest level during early morning and nighttime, increasing throughout the day until evening [34]. EMA survey RTs were expected to follow a similar diurnal pattern.

To assess divergent validity, we tested the association between EMA item RTs and sustained attention ability. We anticipated that if EMA RTs are indicators of processing speed, they would have stronger associations with processing speed than with sustained attention ability. Although both processing speed and sustained attention ability are fundamental cognitive skills, they are distinct aspects of cognitive performance that are measured using different tests [5,35]. For instance, sustained attention tests are often scored for accuracy, whereas processing speed tests are scored for speed [36].

**Methods**

**Study Design**

The goal of the EMA study from which data were analyzed was to investigate the relationships among momentary emotion, function, and glucose, the full methodology of which has been outlined previously [16]. Participants were recruited from 3 clinical sites, and the inclusion criteria were as follows: age of >18 years, familiarity with using a smartphone, and sufficient visual acuity, cognitive ability, and manual dexterity to complete study tasks, such as processing speed tests [16]. Consent to participate was provided on the web through the REDCap (Research Electronic Data Capture; Vanderbilt University) e-consent framework [37]. Study procedures included the completion of baseline surveys; 2 weeks of phone-based EMA and cognitive testing with 5 to 6 assessments per day, wearing a continuous glucose monitor and accelerometer during the EMA period; and follow-up surveys.

**Ethics Approval**

The data collection procedures were approved by the University of Southern California institutional review board (proposal HS-18-01014).

**Measures**

**EMA Item RTs**

RTs to the 22 noncognitive EMA survey items listed in Table 1 were examined as potential processing speed indicators. All items were derived from validated measures or used in prior EMA research [16]. The items were presented one at a time on study phone screens via the mobile EMA app [38]. The participants were not informed that their EMA survey RTs were being measured. Whether participants should be informed of the collection of paradata continues to be debated [39]. RTs were recorded in seconds (to three decimal places) for each item. Values of <0.2 seconds or >30 seconds were considered missing in analyses (5979/461,896, 1.29% of observations) because prior literature suggested that ultrafast EMA RTs are likely indicative of careless responding [40] and because RTs of >30 seconds were deemed outliers that may have been caused by disruptions in completing the survey. Log transformation was applied to the RTs to create more normal distributions.
Table 1. Ecological momentary assessment items from which response times were analyzed.

<table>
<thead>
<tr>
<th>Item type and question or questions</th>
<th>Response option or options</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>16 slider scale items</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Positive affect</strong></td>
<td></td>
</tr>
<tr>
<td>Right now, how content do you feel?</td>
<td>0 (not at all) to 100 (extremely)</td>
</tr>
<tr>
<td>Right now, how happy do you feel?</td>
<td></td>
</tr>
<tr>
<td>Right now, how excited do you feel?</td>
<td></td>
</tr>
<tr>
<td>Right now, how enthusiastic do you feel?</td>
<td></td>
</tr>
<tr>
<td><strong>Negative affect</strong></td>
<td>0 (not at all) to 100 (extremely)</td>
</tr>
<tr>
<td>Right now, how disappointed do you feel?</td>
<td></td>
</tr>
<tr>
<td>Right now, how sad do you feel?</td>
<td></td>
</tr>
<tr>
<td>Right now, how upset do you feel?</td>
<td></td>
</tr>
<tr>
<td>Right now, how anxious do you feel?</td>
<td></td>
</tr>
<tr>
<td><strong>Activity engagement (with reference to the activity the participant reporting doing right before the survey)</strong></td>
<td></td>
</tr>
<tr>
<td>How well were you able to do this activity?</td>
<td>0 (unable) to 100 (extremely well)</td>
</tr>
<tr>
<td>How satisfied are you with the way you did this activity?</td>
<td>0 (not satisfied) to 100 (extremely satisfied)</td>
</tr>
<tr>
<td>How important is this activity to you?</td>
<td>0 (not important) to 100 (extremely important)</td>
</tr>
<tr>
<td><strong>Stress</strong></td>
<td></td>
</tr>
<tr>
<td>How stressed are you right now?</td>
<td>0 (not at all stressed) to 100 (extremely stressed)</td>
</tr>
<tr>
<td>How stressed do you feel about your diabetes or diabetes management right now?</td>
<td>0 (not at all stressed) to 100 (extremely stressed)</td>
</tr>
<tr>
<td>Right now, how tense do you feel?</td>
<td>0 (not at all) to 100 (extremely)</td>
</tr>
<tr>
<td><strong>Fatigue</strong></td>
<td></td>
</tr>
<tr>
<td>At this moment, how tired do you feel?</td>
<td>0 (not at all) to 100 (extremely)</td>
</tr>
<tr>
<td><strong>Pain</strong></td>
<td></td>
</tr>
<tr>
<td>At this moment, how much bodily pain do you have?</td>
<td>0 (none) to 100 (extreme pain)</td>
</tr>
<tr>
<td><strong>3 multiple-choice items</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Activity done</strong></td>
<td>10 choices (eg, work and relaxing)</td>
</tr>
<tr>
<td>Where were you doing right before starting this survey?</td>
<td></td>
</tr>
<tr>
<td><strong>Where activity was done</strong></td>
<td>5 choices (eg, home)</td>
</tr>
<tr>
<td>Where were you when doing this activity?</td>
<td></td>
</tr>
<tr>
<td><strong>Subjective blood sugar level</strong></td>
<td>Likert 0-4: very low, low, just right, high, and very high</td>
</tr>
<tr>
<td>How does your blood sugar feel right now?</td>
<td></td>
</tr>
<tr>
<td><strong>3 checkbox items</strong></td>
<td></td>
</tr>
<tr>
<td><strong>With whom</strong></td>
<td>8 choices (eg, alone and friend)</td>
</tr>
<tr>
<td>Who were you with when doing this activity?</td>
<td></td>
</tr>
<tr>
<td><strong>Diabetes intrusiveness</strong></td>
<td>4 choices (eg, no and yes because of my devices)</td>
</tr>
<tr>
<td>Did your diabetes get in the way of doing this activity?</td>
<td></td>
</tr>
<tr>
<td><strong>Eat or drink</strong></td>
<td>Ate, drank, and neither</td>
</tr>
<tr>
<td>Did you eat or drink in the last 3 hours?</td>
<td></td>
</tr>
</tbody>
</table>

Our primary set of noncognitive EMA survey RTs was the RTs to the 16 slider items, but other noncognitive EMA survey RT combinations were also examined. To compare the reliability and validity of EMA RTs across types of EMA items, we classified the items by response option type and further by item content domains, where possible, as presented in Table 1. We note that the EMA items were chosen to serve the goal from the overarching study of investigating the relationships between various measures and blood glucose metrics and were not deliberately crafted to ensure a sufficient range of item content domains.
characteristics. The 16 slider items were designated as primary because they comprised the largest group of items with the same type of response options and thus seemed most likely to have the highest reliability among the EMA item groups. As there were relatively few multiple-choice and checkbox items, we did not create subgroups by item content for the items with these response options. Grouping was applied to the extent feasible to allow for the investigation of the impact of item characteristics on the validity and reliability of EMA RTs as indicators of processing speed. Given the prior findings that the content of survey items and the type of response options may affect RTs [41,42], we carefully examined the extent to which the association between EMA survey RTs and processing speed differed according to these item characteristics.

**Processing Speed Test**

At the end of each EMA survey, participants were prompted to complete the Symbol Search task, a phone-based mobile processing speed test [5]. This task has previously demonstrated construct validity and was found to correlate at $r=0.74$ with its standard laboratory version [5]. In this task, participants were presented with 2 cards at the top and bottom of the screen, each with 2 symbols (Figure 1). They were asked to choose the card at the bottom of the screen that matched the card on top as quickly as they could for 20 trials. One Symbol Search session was approximately 45 seconds long. When Symbol Search RTs were $<0.2$ or $>5$ seconds (9557/287,543, 3.32% of observations) or they were part of sessions with $<70\%$ accuracy (a cutoff for inattentive responding; 2956/287,543, 1.03% of observations) [43], they were considered missing (12,513/287,543, 4.35% of observations).

![Figure 1](https://mhealth.jmir.org/2023/1/e45203/f1.png)

**Other Measures**

The measures of fatigue, depression, age, and the time of day were also used for validity testing. The momentary fatigue item (ie, “At this moment, how tired do you feel?”) was similar to that used in a previous EMA study [14]. Depression was measured using the Patient Health Questionnaire-8 (PHQ-8) [44] at baseline, along with age. The time of day when each ambulatory assessment was completed was automatically recorded using the EMA app. Sustained attention ability was assessed using an ambulatory cognitive assessment, the Go-No Go task [35], which was administered immediately before the Symbol Search task. In the Go-No Go task, the participants were shown a series of 75 images of a mountain or city, presented one at a time for 800 ms. They were asked to tap an indicated button when seeing an image of a city but to abstain from tapping when presented with an image of a mountain. The measure $d'$ was computed as the sustained attention ability score, a metric that considers both the number of correct city taps and incorrect mountain taps using a signal detection approach [35].

**Statistical Analyses**

**Analysis Strategy Overview**

Multilevel modeling was used to evaluate (1) the WP and BP reliability of EMA RTs, (2) WP and BP correlations of EMA RTs with the Symbol Search task (primary convergent validity test), and (3) WP and BP associations of EMA RTs with other constructs (secondary convergent validity and divergent validity tests). Analyses of reliability and convergent validity were conducted in a parallel fashion for EMA RTs and for the Symbol Search task. Thus, the results of the reliability and validity testing of EMA RTs could be directly compared with the findings from the Symbol Search analyses. For instance, the magnitude of the correlation between EMA RTs and fatigue can be compared with the size of the association between the Symbol Search task and fatigue.
To examine the extent to which the characteristics of EMA items may impact the reliability and validity of EMA RTs, analyses were conducted using the RTs to all 22 EMA items, as well as using the RTs to subgroups of EMA items and the RTs to individual items. The groupings of item RTs were as presented in Table 1: 16 slider scale items, 4 positive affect slider items, 4 negative affect slider items, 3 activity engagement slider items, 3 stress slider items, 3 multiple-choice items, and 3 checkbox items. The 16 slider items consisted of the slider item subgroups and slider items addressing fatigue and pain in combination. Single-item EMA RTs from each of the 22 EMA items were also included in the analyses as the lower benchmarks of the reliability and validity of EMA RTs provided by this minimal information source and to examine the extent to which the various individual item RTs provided similar or markedly different information when used as an indicator of processing speed.

### Reliability

Both the BP and WP reliabilities of EMA RTs and the Symbol Search task were estimated. BP reliability describes the consistency of a person’s mean value across all measurement occasions of a given measure (ie, RTs) [45]. It can be calculated as BP reliability = Var(BP)/(Var(BP) + Var(WP)/n) [46], where Var(BP) is the BP variance in the average of scores across measurement occasions, Var(WP) is the variance of scores across measurement occasions within a person, and n is the number of measurement occasions. The equation implies that greater WP variation in EMA RTs decreases the consistency of the average of RTs across all measurement points and that a greater number of measurements (eg, more EMA surveys) increases reliability. An average of 70 surveys were completed over the 2 weeks of the study, and we estimated the BP reliabilities for increasing numbers of measurement occasions (from 2 to 70). This allowed the examination of how BP reliability increased as a function of the number of ambulatory assessments. The variance components Var(BP) and Var(WP) were estimated using a 2-level multilevel model, in which measurement occasions were nested in participants. BP intraclass correlation coefficients (ICCs) were also computed for each measure, which represent BP reliabilities associated with a single measurement occasion (ie, n=1).

To estimate the WP reliabilities of the measures, we capitalized on the fact that the RTs from multiple EMA items (and from multiple Symbol Search trials) were available at each measurement occasion (ie, at each EMA prompt). WP reliability is the consistency of the mean RT across EMA items within a single measurement occasion. The formula is WP reliability = Var(WP_occasion)/(Var(WP_occasion) + Var(WP_occasion)/i) [47], where Var(WP_occasion) is the variance within a person across different measurement occasions, Var(WP_occasion) is the variance of RTs across the EMA items administered within a given measurement occasion, and i is the number of EMA items. The variance components Var(WP_occasion) and Var(WP_occasion) were estimated using 3-level multilevel models (EMA items or trials nested in measurement occasions nested in people).

### Validity

As the primary convergent validity test, the WP and BP correlations of EMA RTs with the Symbol Search task were examined using bivariate multilevel models, in which both measures were entered as bivariate (ie, correlated) dependent variables. Specifically, 3-level models (items nested in measurement occasions nested in people) were specified, whereby the WP correlation was estimated at level 2 and the BP correlation was estimated at level 3. This had the advantage that the correlations at both levels were adjusted for the unreliability due to variance in RTs within measurement occasions (estimated at level 1). For exploratory purposes, 2-level models were also examined to allow for comparison with the results from the 3-level models. In these 2-level models, rather than estimating the variance in RTs within measurement occasions at level 1, we used the observed (manifest) average of RTs.

Secondary convergent validity and divergent validity tests were conducted similarly with 3-level multilevel models. As fatigue ratings and Go-No Go (sustained attention ability) varied both within and between individuals, we estimated both between-individual and within-individual correlations of fatigue and Go-No Go with EMA RTs (and, for comparison, with the Symbol Search task, examined in separate models). For the BP variables age and depression, we estimated only BP correlations with EMA RTs (and with the Symbol Search task, in separate models). The diurnal cycle of EMA RTs was also examined to test whether the pattern was consistent with previous research on the diurnal cycle of cognitive performance. A multilevel cosinor model [49] was used, in which EMA RTs for a measurement occasion were regressed on the sine and cosine of the hour (0-24 hours) during which the survey was conducted. A 3-level multilevel model (EMA items nested in measurement occasions nested in individuals) was used again, in which EMA RTs were regressed on the sine and cosine of the time of day at level 2 to estimate WP changes in EMA RTs by the time of day. For comparison, a cosinor model was also tested for the Symbol Search task. All reliability and validity analyses were conducted in Mplus (version 8.8; Muthén & Muthén) [50] with the R package MplusAutomation [48] in the statistical software R (R Foundation for Statistical Computing) [51].

### Results

#### Sample Characteristics

The analyses were conducted on data from 198 participants (Table 2). A total of ≥4 EMA prompts (together with Symbol Search assessments) were completed on 81.9% (2321/2834) of the data collection days pooled across all participants. The median EMA completion rate over the 2-week study period was 92%. The mean score on the PHQ-8 was 5.44 (SD 4.30), with scores of >9 indicating moderate or more severe depressive symptoms. Overall, 15.7% (31/198) of the participants had PHQ-8 scores of >9. In terms of fatigue, the mean level reported in EMA was 42.70 (SD 18.60), with ratings given on a scale ranging from 0 to 100.
Table 2. Demographic and health characteristics (n=198).

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years), mean (SD; range)</td>
<td>39.8 (14.4; 18-75)</td>
</tr>
<tr>
<td><strong>Gender, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Men</td>
<td>89 (44.9)</td>
</tr>
<tr>
<td>Women</td>
<td>109 (55.1)</td>
</tr>
<tr>
<td><strong>Ethnicity, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>57 (28.8)</td>
</tr>
<tr>
<td>Latino</td>
<td>81 (40.9)</td>
</tr>
<tr>
<td>African American</td>
<td>29 (14.6)</td>
</tr>
<tr>
<td>Multiethnic</td>
<td>14 (7.1)</td>
</tr>
<tr>
<td>Asian</td>
<td>7 (3.5)</td>
</tr>
<tr>
<td>Other</td>
<td>6 (3)</td>
</tr>
<tr>
<td>Not reported</td>
<td>4 (2)</td>
</tr>
<tr>
<td><strong>Preferred language, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>English</td>
<td>177 (89.4)</td>
</tr>
<tr>
<td>Spanish</td>
<td>21 (10.6)</td>
</tr>
<tr>
<td><strong>Employment status, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Full time</td>
<td>70 (35.4)</td>
</tr>
<tr>
<td>Part time</td>
<td>23 (11.6)</td>
</tr>
<tr>
<td>Full-time homemaker</td>
<td>10 (5.1)</td>
</tr>
<tr>
<td>Student</td>
<td>18 (9.1)</td>
</tr>
<tr>
<td>Unemployed</td>
<td>27 (13.6)</td>
</tr>
<tr>
<td>Retired</td>
<td>15 (7.6)</td>
</tr>
<tr>
<td>Disabled</td>
<td>23 (11.6)</td>
</tr>
<tr>
<td>Other</td>
<td>8 (4)</td>
</tr>
<tr>
<td>Not reported</td>
<td>4 (2)</td>
</tr>
<tr>
<td><strong>Education, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>High school graduate or less</td>
<td>50 (25.3)</td>
</tr>
<tr>
<td>Some college</td>
<td>68 (34.3)</td>
</tr>
<tr>
<td>Bachelor’s degree</td>
<td>55 (27.8)</td>
</tr>
<tr>
<td>Graduate degree</td>
<td>22 (11.1)</td>
</tr>
<tr>
<td>Not provided</td>
<td>3 (1.5)</td>
</tr>
<tr>
<td><strong>Annual household income (US $), n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>&lt;25,000</td>
<td>48 (24.2)</td>
</tr>
<tr>
<td>25,000-49,999</td>
<td>44 (22.2)</td>
</tr>
<tr>
<td>50,000-74,999</td>
<td>15 (7.6)</td>
</tr>
<tr>
<td>≥75,000</td>
<td>40 (20.2)</td>
</tr>
<tr>
<td>Not provided</td>
<td>51 (25.8)</td>
</tr>
<tr>
<td><strong>Average blood glucose over at least 10 days of CGM(^a) data (mg/dL; n=154), mean (SD; range)</strong></td>
<td>183.6 (55.0; 98.5-419.8)</td>
</tr>
<tr>
<td><strong>Time since T1D(^b) diagnosis (years; n=195), mean (SD; range)</strong></td>
<td>20.9 (12.6; 1-57)</td>
</tr>
<tr>
<td><strong>Insulin delivery system, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>AID(^c)</td>
<td>45 (22.7)</td>
</tr>
</tbody>
</table>
Reliability

The reliabilities of the Symbol Search task and EMA RTs are listed in Table 3. The Symbol Search task had a BP ICC of 0.71, suggesting acceptable BP reliability from 1 assessment. With 3 measurement occasions, the BP reliability for the Symbol Search task increased to 0.88. The WP reliability of the Symbol Search task was 0.76, indicating acceptable consistency (>0.7) \cite{52} of the RTs within a single Symbol Search measurement occasion.

Table 3. Reliability of the response times to the Symbol Search task and different sets of ecological momentary assessment (EMA) items.

<table>
<thead>
<tr>
<th>Item</th>
<th>20 SS$^a$ trials</th>
<th>16 slider items</th>
<th>4 positive affect items</th>
<th>4 negative affect items</th>
<th>3 activity engagement items</th>
<th>3 stress items</th>
<th>3 MC$^b$ items, 5-10 choices</th>
<th>3 checkbox items, 3-8 boxes</th>
<th>Slider, MC, and checkbox items</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICC$^c$</td>
<td>0.71</td>
<td>0.56</td>
<td>0.44</td>
<td>0.43</td>
<td>0.42</td>
<td>0.44</td>
<td>0.31</td>
<td>0.39</td>
<td>0.56</td>
</tr>
<tr>
<td>Between-person reliability of the mean of 3 EMA surveys</td>
<td>0.88</td>
<td>0.79</td>
<td>0.70</td>
<td>0.70</td>
<td>0.69</td>
<td>0.70</td>
<td>0.57</td>
<td>0.66</td>
<td>0.79</td>
</tr>
<tr>
<td>Between-person reliability of the mean of 70 EMA surveys</td>
<td>0.99</td>
<td>0.99</td>
<td>0.98</td>
<td>0.98</td>
<td>0.98</td>
<td>0.98</td>
<td>0.97</td>
<td>0.98</td>
<td>0.99</td>
</tr>
<tr>
<td>Within-person reliability</td>
<td>0.76</td>
<td>0.82</td>
<td>0.58</td>
<td>0.59</td>
<td>0.60</td>
<td>0.49</td>
<td>0.08</td>
<td>0.22</td>
<td>0.80</td>
</tr>
</tbody>
</table>

$^a$SS: Symbol Search (higher values indicate worse processing speed).

$^b$MC: multiple-choice.

$^c$ICC: intraclass correlation coefficient.

EMA RTs from the 16 slider items had a BP ICC of 0.56, which was lower than the BP Symbol Search ICC. With 3 measurement occasions, the BP reliability of EMA RTs from the 16 slider items increased to 0.79. The WP reliability of EMA RTs from the 16 slider items was 0.82, which was slightly higher than that of the Symbol Search task. The BP and WP reliability values of EMA RTs from all 22 EMA items were nearly identical to those from the 16 slider items.

In terms of RTs from other sets of EMA items comprising 3 to 4 questions, BP ICCs ranged from 0.31 for the 3 multiple-choice items to 0.44 for the 4 positive affect slider items. With 3 measurement occasions, only the BP reliability of the RTs for the 3 multiple-choice items was notably <0.70, with a value of 0.57. WP reliability for the EMA RTs of the slider item subgroups ranged from 0.49 to 0.60. RTs for the 3 multiple-choice and 3 checkbox items had much lower WP reliabilities, with values of 0.08 and 0.22, respectively.

Figure 2 depicts how the BP reliability for both the Symbol Search task and EMA RTs to 16 slider items varies as a function of the number of measurement occasions. For the Symbol Search task, just 1 measurement occasion is sufficient for a BP reliability of at least 0.70. RTs for 16 slider items crossed the threshold of 0.70 BP reliability upon the completion of 2 EMA surveys.
Figure 2. Between-person reliability of the Symbol Search task and ecological momentary assessment (EMA) response times to 16 slider items by the number of measurement occasions.

Figure 3. Within-person reliability of the Symbol Search task and ecological momentary assessment (EMA) response times to 16 slider items by the number of trials or the number of EMA items completed. Note that each Symbol Search session had 20 trials, but only the reliability of up to 16 trials was plotted in the figure to correspond with the 16 slider items.

BP reliabilities for the RTs to single EMA items are presented in Tables S1 and S2 in Multimedia Appendix 1. Note that using RTs from a single item does not allow for the calculation of WP reliability. Overall, the BP reliabilities of single items from a single EMA measurement occasion (ICC) ranged from 0.17 for the multiple-choice activity engagement item to 0.36 for the diabetes stress item. For the average of 3 measurement occasions, the BP reliabilities of the RTs to single EMA items ranged from 0.50 to 0.63. For the average of 7 measurement occasions, BP reliabilities were at least 0.7 for all items except the multiple-choice items.

Validity

Associations Between EMA RTs and the Symbol Search Task

At the BP level, the correlation between the Symbol Search task and EMA RTs was 0.58 when all EMA items were used, and correlations ranged from 0.49 to 0.57 when subsets of EMA items were used to estimate person-level average EMA RTs (Table 4). At the WP level, medium associations were found between the Symbol Search task and EMA RTs for all item sets except the multiple-choice items, with correlations ranging from \(r=0.29\) (\(P<.001\)) to \(r=0.40\) (\(P<.001\)); multiple-choice items had a larger correlation with the Symbol Search task (\(r=0.58, P<.001\); refer to the “within-person correlations” category in Table 4).
Table 4. Between-person (person-level) correlations between response times from different items (columns) and other variables (rows) as calculated from 3 level models.

<table>
<thead>
<tr>
<th></th>
<th>20 SS\textsuperscript{a} trials</th>
<th>16 slider items</th>
<th>4 PA\textsuperscript{b} slider items</th>
<th>4 NA\textsuperscript{c} slider items</th>
<th>3 activity slider items</th>
<th>3 Stress slider items</th>
<th>3 MC\textsuperscript{d} items</th>
<th>3 check items</th>
<th>22 slider, MC, check</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Between-person correlations</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td><strong>SS</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>( r )</td>
<td>1.00</td>
<td>0.55</td>
<td>0.54</td>
<td>0.54</td>
<td>0.49</td>
<td>0.52</td>
<td>0.57</td>
<td>0.55</td>
<td>0.58</td>
</tr>
<tr>
<td>( P ) value</td>
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<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
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<tr>
<td><strong>Fatigue</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( r )</td>
<td>−0.07</td>
<td>−0.03</td>
<td>−0.10</td>
<td>0.00</td>
<td>−0.03</td>
<td>−0.01</td>
<td>0.00</td>
<td>0.00</td>
<td>−0.03</td>
</tr>
<tr>
<td>( P ) value</td>
<td>.18</td>
<td>.28</td>
<td>.08</td>
<td>.47</td>
<td>.37</td>
<td>.46</td>
<td>.49</td>
<td>.50</td>
<td>.37</td>
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<tr>
<td><strong>Depression</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>( r )</td>
<td>0.06</td>
<td>0.05</td>
<td>0.02</td>
<td>0.05</td>
<td>0.06</td>
<td>0.03</td>
<td>0.10</td>
<td>0.07</td>
<td>0.05</td>
</tr>
<tr>
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<td>.26</td>
<td>.38</td>
<td>.23</td>
<td>.23</td>
<td>.32</td>
<td>.08</td>
<td>.17</td>
<td>.29</td>
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<tr>
<td><strong>Age</strong></td>
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</tr>
<tr>
<td>( r )</td>
<td>0.42</td>
<td>0.52</td>
<td>0.49</td>
<td>0.53</td>
<td>0.47</td>
<td>0.54</td>
<td>0.52</td>
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<tr>
<td>( P ) value</td>
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<tr>
<td><strong>GNG\textsuperscript{e}</strong></td>
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<tr>
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<td>0.1</td>
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<td>−0.08</td>
<td>−0.03</td>
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<tr>
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<td>.02</td>
<td>&lt;.001</td>
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<td>.16</td>
<td>.33</td>
<td>.04</td>
<td></td>
</tr>
<tr>
<td><strong>Within-person correlations</strong></td>
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<td></td>
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<td>&lt;.001</td>
<td>&lt;.001</td>
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<tr>
<td><strong>Fatigue</strong></td>
<td></td>
<td></td>
<td></td>
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<td>0.05</td>
<td>0.07</td>
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<td>&lt;.001</td>
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<td>.11</td>
<td>&lt;.001</td>
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<td><strong>GNG</strong></td>
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<tr>
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<td>0</td>
<td>−0.01</td>
<td>−0.03</td>
<td>0.01</td>
<td>0.02</td>
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<td>−0.03</td>
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<td>( P ) value</td>
<td>&lt;.001</td>
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<td>.18</td>
<td>.08</td>
<td>.29</td>
<td>.06</td>
<td>.41</td>
</tr>
</tbody>
</table>

\textsuperscript{a}SS: Symbol Search (higher values indicate worse processing speed).

\textsuperscript{b}PA: positive affect.

\textsuperscript{c}NA: negative affect.

\textsuperscript{d}MC: multiple-choice.

\textsuperscript{e}GNG: Go-No Go (higher values indicate better sustained attention ability).

The WP and BP correlations between EMA RTs from single items and the Symbol Search task are presented in Table S3 in Multimedia Appendix 1. To summarize, BP correlations with the Symbol Search task ranged from 0.43 to 0.58, close in magnitude to the BP correlations with RTs from the larger EMA item sets. The WP correlations ranged from 0.09 to 0.21.

**Secondary Convergent Validity and Divergent Validity Tests**

At the BP level, neither the EMA RTs from different sets of items nor the Symbol Search task were significantly associated with average fatigue (\( P=.18 \)) or depression ratings (\( P=.20 \), contrary to our hypothesis (Table 4). Older age was significantly positively correlated with worse Symbol Search RTs (\( r=0.42; P<.001 \)); and age was similarly correlated with EMA RTs, with magnitudes ranging from 0.47 to 0.54 (\( P<.001 \)). Consistent with our hypothesis, EMA RTs were more highly correlated with the Symbol Search scores (\( r \) values ranging from 0.49 to 0.58; \( P<.001 \)) than with the Go-No Go scores (\( r \) values ranging from −0.08 to 0.20; 4 of 8 nonsignificant \( P \) values of .08, .07, .16, and .33).

At the WP level, the correlations were overall consistent with our hypotheses (Table 4). Worse Symbol Search RTs were significantly associated with greater momentary fatigue levels (\( r=0.14; P<.001 \)). Slower RTs for EMA items were similarly...
associated with greater momentary fatigue, and this relationship was significant for RTs from all sets of EMA items (\(r\) values ranging from 0.05 to 0.08; \(P<.001\)), except for those from multiple-choice items (\(P=.11\)). EMA RTs were again more highly correlated with the Symbol Search scores (\(r\) values ranging from 0.29 to 0.58; \(P<.001\)) than with the Go-No Go scores (\(r\) values ranging from −0.03 to 0.02; 7 of 8 nonsignificant \(P\) values of .45, .14, .18, .08, .29, .06, and .41).

Tables S4 and S5 in Multimedia Appendix 1 show the BP and WP correlations among the study measures, as calculated from 2-level models instead of the 3-level models presented earlier. The greatest difference is that WP correlations between the Symbol Search task and EMA RTs were somewhat lower in the 2-level models (eg, \(r=0.27\) in a 2-level model vs \(r=0.35\) in a 3-level model for the 16 EMA slider items). RTs from multiple-choice EMA items showed the biggest difference in WP correlation with the Symbol Search task when comparing 2-level and 3-level models (\(r=0.18\) in a 2-level model vs \(r=0.58\) in a 3-level model).

The diurnal cycle of EMA RTs was examined and compared with that of the Symbol Search RTs. As shown in Figure 4, the average Symbol Search RTs were lowest around 3 PM to 4 PM and highest in the morning and evening. The standardized amplitude of the diurnal cycle was 0.34 \(z\) scores (SE 0.03; \(P<.001\)), which translated to RT fluctuations of 0.34 \(\times\) 2 = 0.68 SDs within a day, corresponding to a medium to large effect size [53]. EMA RTs had a similar but less pronounced diurnal cycle (Figure 5). RTs to the 16 slider EMA items were, on average, slowest during the early morning and evening and fastest from 2 PM to 4 PM. The standardized amplitude of the diurnal cycle was 0.16 (SE 0.02; \(P<.001\)), meaning that RTs fluctuated by approximately 0.16 \(\times\) 2 = 0.32 SDs (\(z\) scores) within a day, corresponding to a small effect size [53]. Diurnal plots for the other EMA item sets demonstrated similar trends (not shown here).

Figure 4. The mean Symbol Search response times (RTs) during typical waking hours (6 AM-12 AM), the period during which most surveys were completed. The black line is the predicted Symbol Search RT from the cosinor model, the band is the 95% CI of the predicted RTs, and the red dots are the observed averages of the Symbol Search RTs.

Figure 5. The mean response times (RTs) to 16 slider scale items during typical waking hours (6 AM-12 AM), the period during which most surveys were completed. The black line is the slider scale RT from the cosinor model, the band is the 95% CI of the predicted RTs, and the red dots are the observed averages of the slider scale RTs.
**Overview**

Overall, our results suggest that EMA RTs can serve as approximate indicators of both momentary and average processing speeds. The EMA RTs for the items analyzed in this study were better indicators of average, as compared with momentary, processing speed. A formal processing speed test (Symbol Search) and EMA RTs had correlations of approximately 0.5 at the BP level and 0.3 at the WP level. These correlation sizes may be acceptable in research contexts in which investigators do not have the resources for administering formal cognitive testing. Correlations of these magnitudes may be sufficient to detect strong associations with processing speed, although weaker associations may be missed. The findings of the reliability and validity tests are described in greater detail in the subsequent sections.

**Reliability**

Overall, EMA RTs showed acceptable reliability under conditions (ie, number of items and measurement occasions) typical of many EMA studies. Furthermore, BP reliability for EMA RTs were similar to that for Symbol Search RTs, and WP reliability for RTs to the 16 EMA slider items slightly exceeded that for the Symbol Search task.

The BP reliability of EMA RTs from various item sets differed largely as a function of the number of EMA measurement occasions. With just 3 EMA measurement occasions, BP reliability was acceptable (approximately 0.70), except for RTs from the 3 multiple-choice and 3 checkbox items. The lower BP reliability in these item sets may have been due to their greater heterogeneity (eg, different item content and number of response options), leading to greater variability (ie, more error variance) in mean RTs. For single items, except for multiple-choice questions, the average RTs had a reliability of at least 0.70 with 7 EMA measurement occasions. This suggests that with a relatively small number of EMA measurement occasions, even RTs from single EMA items will likely have acceptable BP reliability. For 16 slider items, the completion of just 2 EMA surveys was sufficient to cross the threshold of 0.70 BP reliability, likely because it was a larger set of items that shared the same type of response options. With more than 16 items sharing similar response options, it would perhaps be possible to obtain a reliable assessment of EMA survey RTs from just 1 measurement occasion.

In terms of the WP reliability of EMA RTs (consistency of RTs within a single EMA measurement occasion), the number of EMA questions and the type of response options appeared to be major contributing factors. The RTs to the 16 slider items had a WP reliability of 0.82, considerably higher than the WP reliability of the RTs to the item sets with only 3 or 4 items. These smaller item sets had reliability values between 0.08 and 0.60, limiting their precision for capturing WP changes in processing speed with 2-level (and not 3-level) modeling. Of the item sets with 3 or 4 items, the more homogenous sets (slider items by topic) had much greater WP reliability than the heterogeneous sets (multiple-choice and checkbox questions with differing numbers of response options). WP reliability improved after combining RTs from various slider items, suggesting that item content was not as important to reliability as the response option type. When considering RTs from the heterogeneous response option item sets, in addition to the 16 slider items, the WP reliability was similar to that found for the 16 slider items alone. Thus, for the WP reliability of EMA RTs, considering RTs from more items may not always be beneficial, specifically when the additional items have different response options.

**Validity**

Although some findings were contrary to our hypotheses (ie, no relationship between EMA RTs and depression or fatigue), the results appeared overall supportive of the validity of EMA item RTs as an approximate measure of processing speed. In our primary convergent validity test at the BP level, EMA RTs had moderate to large correlations with the Symbol Search task, a magnitude expected if EMA RTs were indicators of processing speed. In terms of secondary convergent validity tests at the BP level, observed relationships with EMA RTs were sometimes contrary to our hypotheses but were typically very similar to the associations seen with the Symbol Search task. At the BP level, we hypothesized that slower EMA RTs would be associated with greater average fatigue and greater depressive symptoms. Neither of these relationships was confirmed. For fatigue, this may have been because previous research found associations between slower processing speed and chronic fatigue syndrome (more severe than typical fatigue) [33], but the mean level of fatigue reported in the EMA in our sample may have been less severe (mean 42.70, SD 18.60; scale of 0 to 100). In terms of depression, the proportion of people in our sample with any severity of depression (ie, PHQ-8 scores of >9) was 15.7% (31/198), which was greater than the 8.58% (17,040/198,678) found in a previous study on the general population [44]. Associations between depressive symptoms and EMA RTs were trending in the theoretically expected direction (ie, more depressive symptoms were associated with slower processing speed), but our sample may have been underpowered to detect small BP relationships. Symbol Search RTs did not show significant relationships with either fatigue (P=.18) or depression (P=.20). Significant BP correlations were found between age and both RTs to EMA items (P<.001) and the Symbol Search task (P<.001). Consistent with our hypothesis, EMA RTs had a greater BP association with the Symbol Search task than with the Go-No Go task. Overall, we interpret the BP correlations as being supportive of the validity of EMA item RTs as approximate measures of processing speed. At the BP level, higher sustained attention ability was correlated with greater processing speed as measured by the Symbol Search task and was generally weakly associated with EMA RTs. Interestingly, at the BP level, better sustained attention ability was associated with faster Symbol Search RTs but with slower EMA RTs for 4 of the 8 EMA RT item sets. We can only speculate why this might be the case. Perhaps participants with greater sustained attention ability were better able to process information quickly when they were explicitly instructed to respond as fast as possible (in the Symbol Search task), whereas they may have more deliberately read the EMA items and more...
carefully considered their responses, leading to slower RTs in EMA.

At the WP level, the results were also overall supportive of the validity of EMA item RTs as measures of processing speed. Most importantly, moderate or larger correlations between different sets of EMA RTs and the Symbol Search task were observed. The diurnal cycle of EMA RTs roughly approximated the daily pattern for Symbol Search RTs. Slower EMA RTs were associated with greater fatigue for all item sets, except for multiple-choice questions. Notably, fatigue was associated with processing speed and EMA RTs at the WP level but not at the BP level. It is possible that participants in our sample did at times experience fatigue (within level) but not frequently enough that the average level of fatigue experienced was associated with decrements in processing speed on average (between level). Consistent with our hypothesis, EMA RTs had greater WP associations with the Symbol Search task than with the Go-No-Go task.

Although associations between EMA RTs and the Symbol Search task were observed, the relationships were not strong enough to argue that they provided identical measures. From the outset, we did not advocate for RTs of EMA items to serve as a replacement for formal cognitive testing; rather, we sought to examine whether they can serve as rough processing speed indicators when formal tests are not available. The tasks of completing a formal processing speed test and completing EMA items differ in several aspects. For instance, one common formal processing speed test is searching for a figure that matches a given image. In this task, RTs conceptually capture perceptual speed [5], a component of processing speed [31]. RTs in EMA may be more likely to capture decisional speed when faced with a moderately complex task (eg, answering survey items), a conceptually related but different processing speed indicator [31]. As another example, formal processing speed tests often have explicit performance and speed expectations, whereas EMA surveys do not, particularly if participants are not aware that their time to answer questions is being measured. EMA RTs may, therefore, be more affected by distractions because participants may assume that they can attend to distractors and then return to answering EMA questions at their own pace. Given the differences between formal processing speed tests and EMA surveys, their RTs and, by extension, their measures of processing speed were unlikely to correspond exactly with one another. However, because perceptual speed and decision speed both fall under the umbrella of processing speed [31], some associations were expected.

Validities of EMA RTs With Low Reliabilities

The RTs to single EMA items appeared to lack WP validity, as evidenced by low WP correlations with the Symbol Search task, but they may have some degree of BP validity with sufficient EMA measurement occasions. With an average of 70 EMA surveys completed, the BP association between the RTs to single EMA items and RTs to the Symbol Search task ranged from 0.43 to 0.58. The results of reliability analyses suggested that slightly more than 7 EMAs may result in a BP reliability of at least 0.7, indicating that a relatively small number of EMA instances (eg, 2 days with 4 EMA surveys daily) is sufficient to recover high BP associations with the Symbol Search task.

The RTs to the 3 multiple-choice items notably had the highest WP correlation with the Symbol Search task (r=0.58) but also a WP reliability much lower than other item sets. Three-level modeling helped to compensate for this low reliability by removing the errors from item-level RT variance, and the result was a much higher correlation compared with when a 2-level model was used (r=0.18). The practical implication may be that EMA RTs with low WP reliability, such as those from a few multiple-choice items differing in content and the number of response options, would not be useful to model with the 2-level approach and requires 3-level modeling. However, with a greater number of parameters specified, 3-level versions of 2-level models require larger sample sizes.

Another implication of the relatively high WP correlation between the RTs to the multiple-choice items and the Symbol Search task may be that multiple-choice question RTs deserve further investigation as potential processing speed indicators, even with the low WP reliability found here. The 3 multiple-choice items asked about activity done before the EMA (from 10 choices), where the activity was done (from 5 choices), and the perceived level of blood glucose (from 4 choices). In a future study, it may be useful to more formally investigate the extent to which item content and the number of response options in multiple-choice questions affect relationships with a formal processing speed test.

Limitations

The RTs from only a small subset of possible question types were investigated here. For multiple-choice and checkbox items, there were not enough items to investigate the effect of the number of response choices or the topics covered by these response option types. Although the effect of question topic did not appear to exert a large impact on EMA RTs for the slider items in this study, we cannot say whether the content of EMA items influences the reliability or validity of RTs to multiple-choice and checkbox items.

Data from standard laboratory-administered cognitive assessments were not collected. Therefore, we could not examine the convergent validity of individual differences in EMA item RTs using a full-length laboratory assessment of processing speed. Although a previous study found a high correlation between standard laboratory and ambulatory assessments of processing speed [5], whether EMA item RTs are associated with laboratory-based processing speed tests needs to be examined.

The recommended outcome measure for the Symbol Search task, the median reaction time in accurate trials [5], was not used here. This median RT score provides only 1 processing speed measure per Symbol Search session, which does not allow for modeling the Symbol Search scores as a 3-level multilevel model (with items nested in survey sessions nested in people). To allow such modeling, the log-transformed RT for each Symbol Search trial was computed. In preliminary 3-level multilevel model analyses, the mean of the logged RTs of accurate trials (modeled at all levels) correlated with the median
RT of accurate trials (modeled at levels 2 and 3), $r=0.99$ ($P<.001$) at the BP level (level 3) and $r=0.97$ ($P<.001$) at the survey session level (level 2). The close correspondence between the 2 appeared to justify the use of mean RTs for accurate trials, instead of the median, to enable the modeling of the Symbol Search task at 3 levels.

This study was conducted with a sample of adults with T1D experiencing various stages of the COVID-19 pandemic, which may limit the generalizability of the results. For instance, study participants were more likely to complete EMA surveys at home during times of stricter social distancing requirements. The completion of EMA surveys at home may have less potential for exposure to environmental distractors, which may have reduced the variability in item RTs. As we only examined EMA RTs as processing speed indicators in adults with T1D, further research may be needed to investigate whether findings can be replicated in other populations. For instance, the causes of processing speed fluctuations are often chronic condition specific. In adults with T1D, acute hypoglycemia has been associated with decreased processing speed [28,29]. In adults with fibromyalgia, greater momentary experiences of pain has been associated with decreased processing speed [54]. The different causes of processing speed fluctuations may also impact the relationship between EMA RTs and scores on formal processing speed tests.

Conclusions

Overall, EMA RTs appeared to be reliable and valid indicators of average and momentary processing speeds. They were not correlated to the extent that EMA survey RTs can replace formal processing speed tests. Rather, EMA survey RTs may be serviceable as rough processing speed indicators when formal processing speed testing is not feasible and when the magnitude of associations with processing speed is large. The reliability and validity of EMA survey RTs as measures of processing speed differed according to the sets of items from which the RTs were extracted, implying that EMA items can potentially be intentionally crafted to have greater associations with processing speed. For instance, in a future study, factorial analyses or machine learning models could be used to identify the specific combinations of EMA items for which the pattern of RTs is the most predictive of scores from a formal processing speed test. Analysis of RTs from EMA items may be a method of assessing average and momentary processing speeds in people’s natural environments, which does not require participants to complete additional tasks beyond answering EMA survey questions. RTs to noncognitive EMA items may be important to facilitate research on the impacts of processing speed on daily functioning, especially for populations with chronic conditions.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Results of supplementary analyses.
[DOCX File, 30 KB - mhealth_v11i1e45203_app1.docx ]

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38. ilumivu homepage. ilumivu. URL: https://ilumivu.com/ [accessed 2023-05-12]


Abbreviations

BP: between-person  
EMA: ecological momentary assessment  
ICC: intraclass correlation coefficient  
PHQ-8: Patient Health Questionnaire-8  
REDCap: Research Electronic Data Capture  
RT: response time  
T1D: type 1 diabetes  
WP: within-person

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Research Letter

The Effects of Providing a Connected Scale in an App-Based Digital Health Program: Cross-sectional Examination

Lisa A Auster-Gussman¹, PhD; Mohit Rikhy¹, MS; Kimberly G Lockwood¹, PhD; OraLee H Branch¹, PhD; Sarah A Graham¹, PhD

Lark Health, Mountain View, CA, United States

Corresponding Author:
Sarah A Graham, PhD
Lark Health
2570 El Camino Real
Mountain View, CA, 94040
United States
Phone: 1 650 300 1755
Email: sarah.graham@lark.com

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KEYWORDS
engagement; retention; scales; self-monitoring; mobile app; digital health; AI; smartphone; platform; app; application; health program; program

Introduction

Self-monitoring technologies (eg, digital scales) have been shown to improve health outcomes [1,2], such as weight loss, when combined with additional interventions such as coaching [3]. This may be because they facilitate increased self-weighing, which has been shown to be related to better health outcomes [4,5]. The purpose of this study was to examine whether the provision of a digital body weight scale as part of one’s digital health program was related to increased self-weighing and longer retention. The primary hypothesis was that members provided with a scale would weigh more frequently and remain in the program for longer than those not provided with a scale.

Methods

Study Design

We conducted an observational study of members enrolled in an artificial intelligence (AI)–powered digital health program available via smartphone on a platform called Lark. Information about Lark is published elsewhere [5,6]. We examined differences in self-weighing and retention between members with and without scales provided by their commercial insurance provider. Members received their scales immediately after the completion of enrollment.

Ethical Considerations

The study received exemption status from Advarra Institutional Review Board (protocol #Pro00047181) for retrospective analyses of previously collected and deidentified data.

Participants, Program Description, and Inclusion Criteria

We conducted an analysis of 3488 members enrolled from 2019 to 2021 in a yearlong digital program focused on general health and well-being; weight loss was not a specific target. The program included automated personalized coaching via in-app messaging using conversational AI, weekly lessons related to healthy lifestyle choices, meal logging, and weekly weight logging. The inclusion criteria were age ≥ 18 years, ≥ 1 full year has passed since enrollment date, completion of ≥ 1 educational lesson in the first 6 months, and ≥ 1 weigh-in during the first 6 months.

Outcome Measures

We examined two key outcome variables. Weigh-ins included the total number of days with recorded weigh-ins during each member’s first 6 months in the program. This included both weigh-ins from the provided scales that sync with the app automatically and manually entered weights. Scales not provided by Lark do not pair directly with the app, so weigh-ins on non-Lark scales would need to be entered manually in the app. We analyzed the first 6 months because this is the active weight loss phase of the program for members who set a goal to lose weight. The second 6 months is the maintenance phase. Active retention was the total number of days from the day the individual enrolled to the last day that they used in-app functions, such as conversation or meal logging, up to 365 days.

Analysis

We calculated descriptive statistics for the overall sample and examined differences in weigh-ins and active retention between...
members provided with versus not provided with scales using analysis of covariance (ANCOVA).

**Results**

**Participants**
Participants were 68.3% (2384/3488) female with a mean age of 45.19 (SD 11.45) years. Of the 3314 members who reported a starting weight, the mean starting BMI was 31.1 (SD 6.93) kg/m², and 48.6% (1611/3314) had obesity. Race/ethnicity data were not available for more than half of the sample and therefore not reported. Approximately 43.5% (1519/3488) of members received the insurance-provided scale, and the pairing rate was 93.7% (1423/1519).

**Associations Between Provision of a Digital Scale and Descriptive Statistics**

Although the groups were similar in mean starting BMI (no scale mean 31.52, SD 7.25 kg/m²; scale mean 30.55, SD 6.44 kg/m²) and age (no scale mean 44.63, SD 11.35 years; scale mean 45.91, SD 11.55 years), the differences were statistically significant (starting BMI $t_{3312}=4.05, P<.001$; age $t_{3316}=-3.22, P=.001$). There was also a greater proportion of women among those not provided with a scale (1411/1969, 71.7%) than among those provided with a scale (973/1519, 64.1%; $\chi^2=22.93, P<.001$). Therefore, we controlled for starting BMI, age, and sex in the ANCOVAs.

**Associations Between Provision of a Digital Scale, Weigh-ins, and Active Retention**

The ANCOVAs revealed that members provided with versus not provided with a scale had significantly more days with weigh-ins and days of active retention (see Table 1); their mean last day with a weigh-in also occurred further into the program (no scale mean 72, SE 2 days; scale mean 138, SE 3 days). On average, members not provided with a scale weighed themselves 1-2 days per month and were retained for approximately 4 months, whereas members provided with a scale weighed themselves 1 day per week and were retained for almost 6 months.

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<th>Table 1. Analysis of covariance table of mean differences based on the provision of digital scale$^a$.</th>
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<td>Engagement features</td>
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<td>Days with weigh-ins during first 6 months</td>
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<td>Days of active retention in first 12 months</td>
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$^a$Analyses of covariance include age, sex, BMI, and days of active retention as control variables; 3208 members included in the analysis who had no missing data needed for analyses; 1822 members with no scale and 1386 members with scale.

**Discussion**

These findings demonstrate that members provided with a scale recorded 3 times more days with weigh-ins and were retained almost 2 months longer than those not provided with a scale. The direct digital transfer of weights from the scale to the app greatly streamlined the weigh-in process, improving the member experience, which may have led to the observed longer retention. This research was limited by the fact that the provision of the scale was not individually randomized but the result of insurance providers’ choice to provide or not provide scales. In addition, although findings from past research show that both self-weighing and retention are associated with weight loss [4,5,7], suggesting that the provision of a scale might also be related to weight loss, this question was outside the scope of this analysis. This preliminary study is timely, given the increasing importance of understanding and attenuating the high rates of attrition in digital health [8-10], and might assist insurance providers to weigh the cost of provisioning a scale to the benefits of increased retention in lifestyle behavioral programs.

**Conflicts of Interest**

MR, KGL, and SAG are employees of Lark Technologies, Inc.

**References**


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Abbreviations
- **AI:** artificial intelligence
- **ANCOVA:** analysis of covariance

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Introduction

The opportunity to provide continuous care to patients between office visits using digital technologies holds tremendous potential to improve health care quality and patient outcomes. In 2019, the Center for Medicare and Medicaid Services (CMS) launched the remote physiologic monitoring (RPM) program that provided reimbursement for using technology to monitor patients between visits [1]. RPM delivers continuous or periodic digital data to a central location. These data typically are reviewed by clinical staff (eg, nurses, medical assistants) whose time is billed “incident to” the supervising physician. RPM offers an intuitive complement to remote care delivered via telehealth. In part related to the COVID-19 public health emergency, RPM subsequently was expanded by CMS to improve coverage and reduce barriers to access.

The RPM program requires that a biosensor be used to monitor patients between visits, often but not always in conjunction with a smartphone app. For many health conditions, a biosensor device is a logical component to chronic disease management. Examples include continuous glucose monitoring (diabetes), daily weights via a smart scale (heart failure), dysrhythmia detection (cardiac conditions), and ambulatory blood pressure monitoring (hypertension). Early evidence supporting RPM use appears favorable [2]. Outside of isolated published examples that have largely been confined to a single chronic illness, the extent to which RPM has been deployed on a national scale is unknown. Using US Medicare data, we examined the uptake of RPM in the United States from 2019 (its inception year) to 2021.

Methods

We examined publicly available Medicare Part B National Summary Data File data from January 2019 to December 2021 [3]. We extracted Medicare payment amounts and the associated services allowed based on relevant Current Procedural Terminology (CPT) codes; individual patient information is not available in this data source. RPM services were grouped as setup (CPT 99453), data transmission (CPT 99454), and monitoring time, which is billed in 20-minute increments (CPT 99457, 99458). Results were stratified by calendar year and analyzed in R version 4.2.3 (R Foundation for Statistical Computing).

Results

In 2019, the total amount paid by CMS for RPM was US $5.5 million. In 2020, RPM payments increased almost 9-fold to US $41.5 million, followed by a further 2.5-fold increase in 2021, totaling more than US $101 million annually (Figure 1).
Assuming providers initiate the program and bill setup fees only once per patient, the number of new patients increased from 20,640 (2019) to 90,149 (2020) and further increased to 123,476 (2021). The total payments made by CMS for the technical service (data transmission) were comparable to the payment for the time spent monitoring. Most (69%) monthly reimbursement for patient monitoring was for 20 minutes; only 31% was for monitoring beyond 20 minutes.

**Discussion**

Based on national data from the Medicare program, RPM grew approximately 19-fold over 3 years, suggesting rapid uptake. However, some have raised concerns about the potential for overuse of RPM without clinical benefit [3]. Moreover, the use of RPM appears to be confined to a small group of physicians, predominantly primary care providers focused on hypertension or diabetes management [4]. In addition to Medicare, both commercial insurance programs and many states’ Medicaid programs also cover RPM services [4,5]. Importantly, in 2022 CMS further expanded remote monitoring for certain medical specialties (musculoskeletal [rheumatology, orthopedics], respiratory medicine). Under this new program called remote therapeutic monitoring (RTM), a software app alone can be used for monitoring, and patients provide data through the app without a biosensor [6]. The software itself is the medical device and would be registered and cleared by the US Food and Drug Administration as a class 1 (or higher) device.

Thus beginning in 2022, RTM widens the spectrum of health domains available for monitoring, since any patient-reported outcome (eg, disease activity) or clinically relevant information (eg, medication adherence) now is reimbursable. We eagerly await the evaluation of the impact on patient outcomes offered by RPM and RTM, recognizing that much work to optimize their use remains.

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**Data Availability**

Data can be shared and are publicly available (see manuscript for source).

**Authors’ Contributions**

JRC contributed toward the concept and design of the study; drafting the manuscript; statistical analysis; administrative, technical, or material support; and supervision. JW made critical revisions to the manuscript for important intellectual content. JRC and JW contributed toward the acquisition, analysis, or interpretation of data and obtained funding for the study.

**Conflicts of Interest**

JRC receives consulting fees from and owns stock in TNacity Blue Ocean. JRC is a part-time employee of Illumination Health (a health care research organization). JW has no conflicts of interest.

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Abbreviations

CMS: Center for Medicare and Medicaid Services
RPM: remote physiologic monitoring
RTM: remote therapeutic monitoring

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