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Contents

Review

Assessing the Acceptability and Effectiveness of Mobile-Based Physical Activity Interventions for Midlife Women During Menopause: Systematic Review of the Literature

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Abstract

Background: Midlife women with menopausal symptoms are less likely to meet the recommended level of physical activity (PA). Promoting PA among women in midlife could reduce their risk of cardiovascular diseases and perhaps improve menopausal symptoms. Mobile PA interventions in the form of smartphone apps and wearable activity trackers can potentially encourage users to increase PA levels and address time and resource barriers to PA. However, evidence on the acceptability and effectiveness of these interventions among midlife women is unclear.

Objective: This systematic review evaluated the effectiveness, acceptability, and active behavior change techniques (BCTs) of mobile PA technologies among midlife menopausal women.

Methods: A mixed methods systematic review of qualitative and quantitative studies was conducted. MEDLINE (Ovid), Embase, Scopus, CINAHL, Web of Science, SPORTDiscus, CENTRAL, PsycINFO, and the ProQuest Sports Medicine and Education Index were systematically searched. Studies were selected and screened according to predetermined eligibility criteria. In total, 2 reviewers independently assessed the risk of bias using the Mixed Methods Appraisal Tool and completed BCT mapping of the included interventions using the BCT Taxonomy v1.

Results: A total of 12 studies were included in this review. Overall risk of bias was "Moderate to high" in 58% (7/12) of the included studies and "low" in 42% (5/12) of the studies. Of the 12 studies, 7 (58%) assessed changes in PA levels. The pooled effect size of 2 randomized controlled trials resulted in a small to moderate increase in moderate to vigorous PA of approximately 61.36 weekly minutes among midlife women, at least in the short term (95% CI 17.70-105.01; P=.006). Although a meta-analysis was not feasible because of heterogeneity, positive improvements were also found in a range of menopause-related outcomes such as weight reduction, anxiety management, sleep quality, and menopause-related quality of life. Midlife women perceived mobile PA interventions to be acceptable and potentially helpful in increasing PA and daily steps. The average number of BCTs per mobile PA intervention was 8.8 (range 4-13) according to the BCT Taxonomy v1. "Self-monitoring of behaviour," "Biofeedback," and "Goal setting (behaviour)" were the most frequently described BCTs across the included interventions.

Conclusions: This review demonstrated that mobile PA interventions in the form of smartphone apps and wearable trackers are potentially effective for small to moderate increases in moderate to vigorous PA among midlife women with menopausal symptoms. Although menopause is a natural condition affecting half the population worldwide, there is a substantial lack of evidence to support the acceptability and effectiveness of mobile PA interventions on menopause-related outcomes, which needs further investigation.

Trial Registration: PROSPERO CRD42021273062; https://www.crd.york.ac.uk/prospero/display_record.php?RecordID=273062

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Introduction

Background

Participation in regular physical activity (PA) confers clinically significant improvements in musculoskeletal, functional, and mental health–related outcomes, with an extensive evidence base on maintaining energy balance, lowering the risk of cardiovascular and metabolic diseases, and improving overall quality of life (QoL) [1-4].

Midlife women undergoing menopause tend to have a more noticeable decline in PA levels, being more physically inactive than men across most countries [5,6]. In England, only 23% and 21% of women aged 45 to 54 years and 55 to 64 years, respectively, met the National Health Service aerobic and muscle-strengthening guidelines recommended for adults (aged 19-64 years) [7,8]. The UK National Health Service guidelines for PA recommend that adults aged 19 to 64 years take part in a minimum of 150 minutes of moderate to vigorous PA (MVPA), 75 minutes of vigorous activity per week, or an equivalent combination of both alongside muscle-strengthening activities (eg, body and weight lifting, yoga, and Pilates) twice a week [9]. Research suggests that a reduction in PA levels parallels the drop in estrogen during the menopausal transition, a factor that may contribute to decreased PA and the shift to more sedentary behavior among midlife women [10-12].

Midlife is also a period when the risk of chronic diseases increases, potentially because of the cumulative effects of unhealthy lifestyle behaviors [13] and, most directly, as a result of menopause-associated weight gain and increased risk of abdominal obesity [14-16]. During the menopause transition, women may experience an array of bothersome symptoms that may overlap or have a cascade effect, with hot flushes, night sweats, and vaginal dryness most frequently reported [17]. Other psychosocial and physical complaints include weight gain, sleep disturbances, mood swings, anxiety, fatigue, joint aches, sexual dysfunction, heart palpitations, and deterioration of QoL [18]. Increasing PA levels may reduce menopausal symptoms and improve QoL [19-22]. Evidence is currently mixed [23-25], but there are plausible biological mechanisms by which PA can alleviate vasomotor symptoms, for instance, by releasing neuroendocrine substances (eg, cortisol) that are involved in stress and thermoregulatory body responses. PA may also attenuate weight gain influenced by menopausal transition and aging, as well as other physical and psychological symptoms such as body pain, fatigue, poor sleep, and depression [5].

The use of mobile phone–based interventions may potentially encourage midlife women to increase PA. Mobile PA technology is defined as the use of wireless devices such as smartphones, tablets, wearable activity trackers (WATs), and PDAs to promote PA and provide a means for real-time monitoring [26,27]. Apps that run on mobile platforms typically form part of these interventions. In this review, we adopted an operating definition of mobile-based PA interventions by referring to *the use of mobile app technology delivered through smartphones or WATs connected to partnering phone apps (eg, smartwatches or Fitbit) that can gather data and track progress remotely, with the aim of increasing PA participation in any form: aerobic (cardiovascular), resistance, endurance, or stretching exercise.*

Compared with men, women are more likely to use smartphones and health apps daily [28], and 83% of adults aged 55 to 64 years owned a smartphone in 2021 [29]. Moreover, women may particularly favor mobile-based interventions that use flexible delivery modes as a motivator to overcome the risk of not allocating sufficient time to be physically active [30-32]. Unlike in-person training programs, mobile PA interventions may encourage women to overcome physical barriers (ie, lack of time because of multiple responsibilities [33-36]) and feelings of stigma, social discomfort, and self-consciousness linked with participation in group-based PA programs and gym attendance [35,37], for example, a fear of being judged for decreasing abilities [37].

The global market of PA apps was valued at US $1.1 billion in 2021, with a 46% increase since May 2020 in global downloads of fitness and health apps [38]. In 2017, there were >325,000 commercially available health and fitness apps on the market [39]; approximately 30% of them targeted PA [38]. Emerging evidence indicates the potential of these apps to promote PA uptake [40] even among older adults, contributing to healthy aging [41-43]. However, despite the popularity of PA apps, the published evidence of their effectiveness from recent systematic reviews in adults shows positive but mostly nonsignificant effects [44-47].

Incorporating behavior change techniques (BCTs) and theories in developing and implementing such mobile-based interventions is an essential ingredient to ensure their acceptability and effectiveness. Goal-Setting Theory and Social Cognitive Theory (SCT) argue that, for a behavior change to occur, goals should be specific, learning-orientated, attainable in the short term but sufficiently challenging, and linked to a longer-term goal [48,49]. Regardless, many PA apps on the market have limited BCTs, for example, the ability to be tailored to users' needs and characteristics [40,50]. Recently, several content analyses have been conducted to determine the active ingredients of commercially available consumer-facing PA apps using the comprehensive BCT Taxonomy v1 (BCTTv1) [51]. Of the 93 BCTs in the taxonomy, Middelweerd et al [52] and Bondaronek et al [53] found that, on average, only 5 and 7 BCTs were used among 64 and 65 commercially available PA apps reviewed, respectively.

Furthermore, the key to successful digital behavior change interventions is potentially determined by the acceptability of the intervention and the level of motivation and user engagement [54,55]. Acceptability is a multifaceted construct that reflects how individuals consider an intervention to be appropriate based on anticipated and experienced responses to it.

Gaps in the Current Knowledge

Although the literature on the impact of mobile PA apps and WATs on adult and older adult populations is growing, to date, midlife women are largely neglected. In total, 2 pretest-posttest studies indicate that app- and web-based interventions may increase PA in this population [56,57] and may have advantages over conventional PA interventions [58]. However, to our knowledge, no review has synthesized current evidence on the contribution of mobile PA technology to changes in PA and menopause-related health outcomes among midlife women.

Aim

This mixed methods systematic review aimed to investigate and consolidate the existing evidence on the effectiveness, acceptability, and active behavior change components of mobile technologies for PA in midlife menopausal women. The following review questions were addressed: (1) How effective are mobile PA interventions in increasing PA levels in midlife women? (2) How effective are mobile PA interventions in improving menopause-related symptoms in midlife women? (3) How acceptable are mobile PA interventions for midlife women with menopausal symptoms? (4) Which BCTs are used across mobile PA interventions for midlife women during menopause?

Methods

Design

A mixed methods systematic review of qualitative and quantitative studies was conducted following the 2020 PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [59]. The protocol was registered in PROSPERO (CRD42021273062).

Information Sources and Search Strategy

Nine electronic databases—MEDLINE (Ovid), Embase, Scopus, CINAHL, Web of Science, SPORTDiscus, CENTRAL, PsycINFO, and the ProQuest Sports Medicine and Education Index—were systematically searched from January 1, 2007 (the year the first mobile app emerged on the market), to August 2021, updated in February 2022. Subsequently, a further forward and backward citation search and screening of reference lists of the included papers were used to detect any additional relevant studies. If the full text could not be found through searches, the corresponding authors of potentially relevant studies were contacted via email to request access to full-text papers or inquire about ongoing trial protocols.

The search strategy was developed and refined iteratively based on expert consultation with a systematic search librarian at University College London. The search strategy combined three key terms—"mobile digital interventions" AND "physical activity" AND "menopausal women"—including synonyms and components (eg, "mHealth," "wearables," "mobile apps," "Fitbit," and "smartwatch"). The search strategy was adapted for each database using tailored syntax, Boolean operators, and Medical Subject Heading terms. The full details of the search strategy can be found in Multimedia Appendix 1.

Systematic database searching was supplemented with gray literature searches using the Google Scholar and Google search engines. Search results were sorted by relevance, and the first 20 pages (approximately 200 results) were reviewed. However, no additional papers that met the eligibility criteria were identified through this process, and so gray literature was excluded.

Eligibility Criteria

The inclusion criteria were developed based on the Participant, Intervention, Control, and Outcome structure (Textbox 1). Studies of any design comprising quantitative (randomized, nonrandomized, and pretest-posttest studies), qualitative, and mixed methods primary research were all included. Studies that assessed the measurement properties or algorithm performance of digital interventions with no health or behavior change outcomes measured were excluded. Commentaries, conference abstracts, editorials, reviews, registered protocols with no results published, theses, books, and studies not providing an explicit research methodology were excluded.

Textbox 1. Inclusion and exclusion criteria (Participant, Intervention, Control, and Outcome structure).

Participant

- Inclusion criteria:

  - Midlife women either defined by age range (40-64 years) or menopause stage (perimenopause, menopause, and postmenopause) and experiencing at least one menopausal symptom such as hot flushes, night sweats, weight gain, sleep problems, vaginal dryness, mood swings, or anxiety

  - No restrictions on geographical location, ethnicity, or presence of comorbidities or risk factors, including studies targeting survivors of breast cancer in menopause age (40-64 years) owing to the general age-related needs and preferences

- Exclusion criteria:

  - Older or late postmenopausal women (aged >65 years) as they may have different views and concerns with regard to mobile physical activity (PA) technologies

  - Studies targeting men or the middle-aged population in general if extracting gender-specific outcomes is not possible

  - Midlife women undergoing hormonal replacement therapy (HRT), which can act as an active treatment for menopausal symptoms

  - Women with premature ovarian insufficiency as HRT is likely to be prescribed to inhibit the development of osteoporosis, atherosclerosis, cardiovascular diseases, dementia, and mortality in younger ages [60,61]

Intervention

- Inclusion criteria:

  - Mobile-based PA interventions functioning as workout fitness programs, step count, self-monitors, walking-route trackers, or social networking site fitness interventions

  - Either stand-alone mobile apps or apps paired with wearable activity trackers (WATs)

  - No restriction on the dose or duration of app use or length of the intervention and whether the interventions were supervised or self-delivered

  - Apps targeting multiple lifestyle behaviors only if PA outcome data were extracted independently

- Exclusion criteria:

  - Interventions based on traditional prompts (eg, email, phone calls, or SMS text messaging)

  - Traditional or electronic activity trackers (ie, pedometers or ActiGraph accelerometer–based interventions) unless used in conjunction with an app or as an objective measure of PA outcomes for an app

  - Passive mobile interventions where users did not have to log in, engage, or monitor PA themselves, such as software to be accessible only by clinicians and researchers

Control

- Inclusion criteria:

  - If applicable, control groups administering either no intervention or no mobile-based intervention, such as printed materials or traditional pedometers where users could not interact or receive instant feedback

- Exclusion criteria:

  - Any app-based controls

Outcome

- Inclusion criteria:

  - Changes in the frequency, intensity, or duration of PA reported in any form (eg, weekly minutes of moderate to vigorous PA, daily steps, or energy expenditure) measured using either self-reported or objective measures (ie, accelerometers)

  - Changes in the frequency or severity of any common menopause-related symptoms (eg, vasomotor, sleep disturbance, weight gain, and depression) measured using validated scales and generic or menopause-specific quality of life measured using validated scales (eg, the bothersome scale, the Greene Climacteric Scale, or generic or menopause-specific scales such as the Menopause-Specific Quality of Life Questionnaire)

  - Acceptability data through qualitative methods with respect to user satisfaction and experiences, perceived usefulness, usability, and intention to use [62] as well as engagement and interaction with the app, including quantitative data on app or WAT use and compliance

- Exclusion criteria:

- Studies that did not report the measurement of at least one of the primary or secondary outcomes of interest specified in the review protocol (eg, measurement of cancer-specific outcomes only)

Screening and Selection Procedure

After removing duplicates using EndNote (version 20; Clarivate Analytics) [63], the first reviewer (GS) screened all titles and abstracts in the first round and then reviewed the full text of potentially relevant or unclear articles against the eligibility criteria using Rayyan (Rayyan Systems, Inc) [64]. A second reviewer (HG) independently reviewed the first 20.83% (215/1032) of the retrieved records, alphabetically sorted by title, and tested them against the eligibility criteria. The percentage of agreement between the reviewers (GS and HG) was 92%, showing substantial interrater reliability (Multimedia Appendix 2). Disagreements between the reviewers were resolved through discussion and, where necessary, consultation with FH and RF.

Data Extraction

GS and HG independently extracted data using an adapted data extraction form following the Cochrane Collaboration standardized data extraction templates for quantitative and qualitative studies [65]. The following data were extracted: study characteristics (publication year, authors, and country); study type and aims; participant characteristics and context (sample size, mean age, and menopause stage if available); a description of the interventions as recommended by the Template for Intervention Description and Replication checklist [66], including content, mode of delivery, features, duration, intensity, and theoretical contribution; outcomes measured on the overall effectiveness of mobile PA technology on any menopause-relevant outcomes and PA outcomes as well as the acceptability, user engagement, and adherence to the intervention; and control group treatment (if applicable). In the case of registered or ongoing trials and protocols, we attempted to contact the corresponding authors via email to seek additional unpublished information where applicable (4 were contacted and 2 responded).

Quality Assessment

Two authors (GS and HG) assessed the methodological quality of each included study independently using the Mixed Methods Appraisal Tool [67] and discussed their assessments to achieve consensus. In this review, we used a star rating system as the Mixed Methods Appraisal Tool has no established quality threshold for inclusion and classification of overall risk of bias [68]. Studies were rated as "low risk of bias" if they obtained stars in up to four domains and as "moderate-to-high risk of bias" when they were awarded stars on ≤3 domains. Studies were not excluded based on critical appraisal given the infancy of research in this area. However, studies with moderate to high risk of bias were reported with caution.

BCT Coding

For the included studies with actual mobile PA technology (9/12, 75%), 2 reviewers trained in BCT coding (GS and TR) independently coded all PA interventions in both the intervention and (active) control groups using the BCTTv1 [51]. Published descriptions and supplementary materials, if available, were reviewed in full. All discrepancies between the 2 initial coders were resolved through discussion until agreement was achieved. If necessary, the third and fourth reviewers (FH and RF) were also consulted to mediate an agreement. The average number and type of BCTs used were mapped for each studied intervention.

Data Synthesis

Narrative synthesis following the guidelines by Popay et al [69] was used for this review because of the heterogeneity of interventions, populations, and outcomes measured. The approach by Popay et al [70] allows for transparency of narrative synthesis by interpreting evidence from different methodologies.

Quantitative data were tabulated, with textual descriptions applied to draw a preliminary synthesis of the findings. Qualitative data were coded inductively in NVivo (version 12; QSR International) using thematic synthesis [71], and analytical themes were generated. In this review, we drew on the technology acceptance model (TAM) [72] to guide the analysis of qualitative data. The TAM suggests that an individual's intention to use technology is based on two key factors: perceived usefulness, which refers to a user's beliefs that engaging with the app improves their PA performance, and perceived ease of use, which refers to the perception that using the app requires minimal effort [72]. Although the TAM assumes that acceptability does not change over the life cycle of a digital intervention, it is widely used and has been shown to be robust in several empirical studies [73].

Meta-analysis

A meta-analysis was conducted for randomized controlled trials (RCTs) only using RevMan (The Cochrane Collaboration) [74] where sufficient studies were available for an outcome. Pooling change scores within and between groups is not recommended [65]; therefore, pre-post studies were not meta-analyzed. Effect sizes were calculated using the absolute mean difference and associated 95% CI between the final values observed for the experimental and control groups. A random-effects model was used to allow for between-study variability. Heterogeneity was quantified using I^2. Owing to the small number of included studies, tests for asymmetry and publication bias could not be conducted.

## *Results*

Study Selection

The study selection process is summarized in Figure 1 using the PRISMA flow diagram. Of 1627 records identified in addition to 27 potentially relevant records, citation tracking, and reference list screening, 12 studies (0.73%) published in 14 papers were included in the final review synthesis [56,75-85]. Reasons for exclusion are presented in Multimedia Appendix

3, mainly the absence of mobile PA technology, followed by irrelevant age groups.

Figure 1. Study selection flow diagram based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement. PA: physical activity.
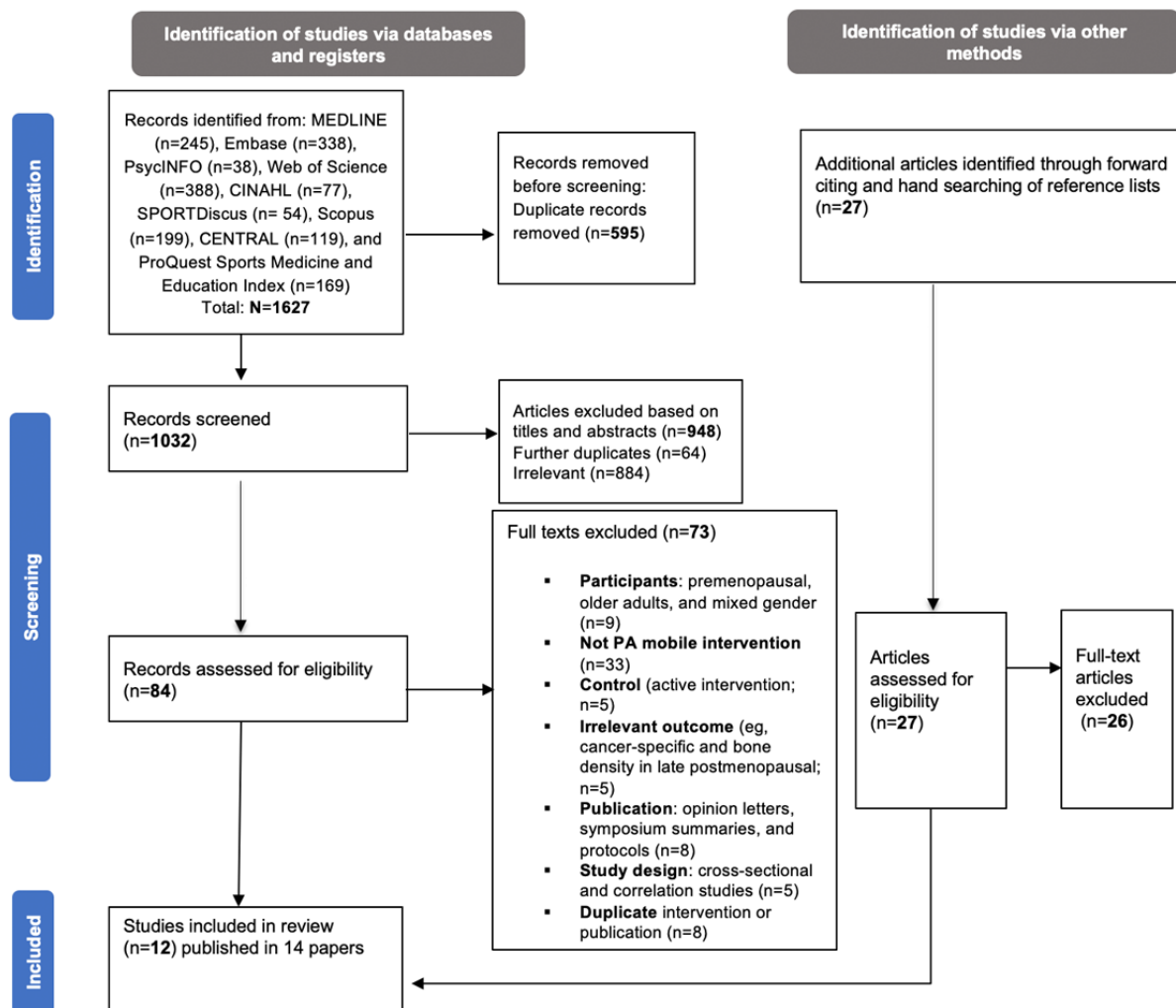
Characteristics of the Included Studies

See Table 1 for characteristics of the included studies (N=12). The studies reflected cross-disciplinary research and different stages of intervention development and evaluation. The studies were conducted in the United States (6/12, 50%), Australia (2/12, 17%), South Korea (2/12, 17%), Italy (1/12, 8%), and Iran (1/12, 8%). In total, 75% (9/12) of the studies were published in the last 5 years.

The included studies were a mix of quantitative (7/12, 58%), qualitative (4/12, 33%), and mixed methods (1/12, 8%) studies. The sample sizes ranged from 8 [77] to 83 participants [83]. Of the 12 studies, 4 (33%) were pilot RCTs, of which 1 (25%) had an active control arm [78] and 3 (75%) had waitlist or no-intervention control groups [76,81,83]. In total, 25% (3/12) of the studies were pretest-posttest studies [56,79,84]. The quantitative study duration varied from 1 [76] to 6 months [83]. Qualitative studies (4/12, 33%) included a semistructured focus group (1/4, 25%), semistructured interviews (1/4, 25%), and participatory design (2/4, 50%).

The participants were midlife women with an average age of 57.6 (SD 4.026) years. Most of the included studies (10/12, 83%) recruited women based on age range, followed by menopause stage, with only 17% (2/12) of the studies [75,77] identifying participants based on the experience of menopausal symptoms. The studied women were culturally diverse; 17% (2/12) of the studies [56,81] targeted African American women, and 8% (1/12) targeted [85] Korean-Chinese migrants. The included participants were heterogeneous concerning health conditions and the presence of chronic diseases. A total of 42% (5/12) of the studies limited recruitment to inactive (ie, ≤60 minutes per week of MVPA) and overweight (mean BMI 29.2, SD 3.5 kg/m^2) or obese (mean BMI 33.9, SD 5.9 kg/m^2) women [56,78,79,82,83]. In total, 25% (3/12) of the studies were based on midlife women diagnosed with breast cancer [80,81,83], and 8% (1/12) recruited postmenopausal women from cardiology clinics [84].

Table 1. Characteristics of all the included quantitative and qualitative studies and studied populations (N=12).

Author, year	Country	Study design (duration)	Sample size, N	Retention rate at follow-up	Age (years)	Menopausal stage	Experience of menopausal symptoms	Eligibility for recruitment	Overall risk of bias
Cadmus-Bertram et al [78], 2016	United States	RCT[a] (16 weeks)	51	96% (49/51)	Mean 60 (SD 7.1)	Post-menopausal	Not given	Inactive, overweight (mean BMI 29.2, SD 3.5 kg/m^2)	Low risk
Valle et al [81], 2017	United States	RCT (6 months)	35	94.3% (33/35)	Mean 53 (SD 9.1)	80% post-menopausal	Not given	African American, obese (mean BMI 33.9, SD 5.9 kg/m^2); diagnosed with breast cancer in the last 10 years	Low risk
Lynch et al [83], 2019	Australia	RCT (12 weeks)	83	96% (80/83)	Mean 61.6 (SD 76.4)	Post-menopausal	Not given	Inactive, overweight (mean BMI 29, SD 6.0 kg/m^2); diagnosed with breast cancer and had completed treatment	Low risk
Kashfi et al [76], 2021	Iran	RCT (1 month)	54	Not reported	Mean 53.9 (SD 4.03)	Menopausal and post-menopausal	Not given	Aged between 45 and 60 years and at least 1 year after the last menstruation; no hormone therapy over the past 6 months	Moderate to high risk
Butryn et al [79], 2016	United States	Pre-post (6 months)	36	78% (28/36)	Mean 54 (SD 7.18)	Not identified	Not given	Inactive, aged between 40 and 65 years	Moderate to high risk
Sengupta et al [84], 2020	United States	Pre-post (12 weeks)	10	80% (8/10)	Mean 64 (SD 6.0)	Not identified	Not given	Aged ≥50 years, recruited from cardiology clinics	Moderate to high risk
Joseph et al [56], 2021	United States	Pre-post (4 months)	20	80% (16/20)	Mean 56.2 (SD 4.3)	Not identified	Not given	African American, aged 50 to 65 years, inactive (≤60 minutes per week of MVPA[b]), and BMI of 40.0 (SD 8.6) kg/m^2	Moderate to high risk
Lee et al [75], 2015[c]	South Korea	Qualitative; semistructured interviews	9	N/A[d]	Range 45 to 60	Peri-menopausal	Experiencing menopause symptoms	Aged between 45 and 60 years, experiencing or having experienced menopausal symptoms within the last 5 years	Low risk
Nguyen et al [80], 2017	Australia	Qualitative; focus group	14	N/A	Mean 58.6	Post-menopausal	Not given	Active and inactive; diagnosed with breast cancer	Low risk
Senette et al [82], 2018[c]	Italy	Qualitative; participatory design focus group	26	N/A	Range 45 to 60	Peri-menopausal	Not given	Aged between 45 and 60 years, 18.5<BMI<30, and absence of chronic diseases	Moderate to high risk
Backonja et al [77], 2021[c]	United States	Qualitative; participatory design focus group	8	N/A	Range 40 to 64	Peri-menopausal and early post-menopausal	Experiencing menopause symptoms	Aged 40 to 64 years	Moderate to high risk
Kim et al [85], 2020	South Korea	Mixed methods; focus group and validity pilot test	Focus group: 16; pilot study: 12	N/A	Range 40 to 65	Not given	Not given	Korean-Chinese; aged 40 to 65 years; full-time workers for the last 6 months	Moderate to high risk

[a]RCT: randomized controlled trial.

[b]MVPA: moderate to vigorous physical activity.

[c]Preclinical studies of IT research (menopause informatics).

[d]N/A: not applicable.

Quality Assessment of the Included Studies

The overall risk of bias was "Moderate to high" in 58% (7/12) of the included studies and "low" in 42% (5/12) of the studies. All RCT groups (4/12, 33%) were comparable at baseline, whereas randomization was adequately performed and sufficiently reported in 75% (3/4) of these studies. Owing to the nature of mobile PA interventions, participant and assessor blinding could not be achieved in any study. There was poor reporting of a WhatsApp-based intervention and PA outcomes [76].

None of the 25% (3/12) of pre-post studies [56,79,84] accounted for confounders in the design and analysis, reducing the confidence in the observed effects (poor quality overall with high risk of bias). The included pre-post studies (3/12, 25%) had very small sample sizes and low recruitment rates; for instance, Sengupta et al [84] recruited 10 midlife women, and only 8 completed the 12-week follow-up. Similarly, Joseph et al [56] reported a low recruitment rate of 22% with a small sample size of 20.

There was better reporting across the qualitative studies except for reflexivity and the authors' positions. A lack of data reporting and integration was observed in the mixed methods study design by Kim et al [85]. The risk of bias scoring system is presented in Tables 2-5.

Table 2. Summary of Mixed Methods Appraisal Tool quality assessment—risk of bias of the included randomized controlled trials (RCTs).

RCT, year	Randomization appropriately performed	Groups comparable at baseline	Complete outcome data	Outcome assessors blinded to the intervention	Participants adhered to the assigned intervention	Risk of bias score[a]
Cadmus-Bertram et al [78], 2016	★[b]	★	★	0[c]	★	Low
Valle et al [81], 2017	★	★	★	0	★	Low
Lynch et al [83], 2019	★	★	★	0	★	Low
Kashfi et al [76], 2021	0	★	★	0	__[d]	Moderate to high

[a]Overall risk of bias scores were assessed by 2 independent reviewers and classified into low risk and moderate to high risk. Low risk of bias: ≥4 stars; moderate to high risk of bias: ≤3 stars.

[b]Met the criterion.

[c]Failed to meet the criterion.

[d]Insufficient information given to decide.

Table 3. Summary of Mixed Methods Appraisal Tool quality assessment—risk of bias of the included pre-post studies.

Pre-post study, year	Representativeness of the target population	Measurements appropriate for outcome and intervention	Complete outcome data	Confounders accounted for in the design and analysis	Intervention and exposure happened as intended	Risk of bias score[a]
Butryn et al [79], 2016	0[b]	★[c]	★	0	★	Moderate to high
Sengupta et al [84], 2020	0	★	★	0	★	Moderate to high
Joseph et al [56], 2021	0	★	★	0	★	Moderate to high

[a]Overall risk of bias scores were assessed by 2 independent reviewers and classified into low risk and moderate to high risk. Low risk of bias: ≥4 stars; moderate to high risk of bias: ≤3 stars.

[b]Failed to meet the criterion.

[c]Met the criterion.

Table 4. Summary of Mixed Methods Appraisal Tool quality assessment—risk of bias of the included mixed methods study.

Mixed methods study, year	Adequate rationale for using a mixed methods design	Integration of different components of the study	Adequate interpretation of outputs of the integration	Inconsistencies between qualitative and quantitative data	Different components adhered to the quality criteria of the methods involved	Risk of bias score[a]
Kim et al [85], 2020	__[b]	★[c]	★	0[d]	★	Moderate to high

[a]Overall risk of bias scores were assessed by 2 independent reviewers and classified into low risk and moderate to high risk. Low risk of bias: ≥4 stars; moderate to high risk of bias: ≤3 stars.

[b]Insufficient information given to decide.

[c]Met the criterion.

[d]Failed to meet the criterion.

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Table 5. Summary of Mixed Methods Appraisal Tool quality assessment—risk of bias of the included qualitative and mixed-methods studies.

Qualitative study, year	Appropriate to answer the research question	Adequate qualitative data collection methods used	Findings adequately derived from the data	Sufficient interpretation of results	Coherence in data collection, analysis, and interpretation	Risk of bias score[a]
Lee et al [75], 2015	★[b]	★	★	★	__[c]	Low
Nguyen et al [80], 2017	★	★	★	★	★	Low
Senette et al [82], 2018	★	★	—	★	—	Moderate to high
Backonja et al [77], 2021	★	★	—	—	—	Moderate to high

[a]Overall risk of bias scores were assessed by 2 independent reviewers and classified into low risk and moderate to high risk. Low risk of bias: ≥4 stars; moderate to high risk of bias: ≤3 stars.

[b]Met the criterion.

[c]Insufficient information given to decide.

Characteristics of the Included Interventions

All 12 studies included at least one form of mobile-enabled PA intervention, either as solo mobile apps or web-based applications or paired apps with other sensor-based activity trackers (ie, wearables). The intervention components included in-person training and behavior modification sessions [79,81,83], traditional SMS text messaging or follow-up calls [78,81,83,85], and educational pamphlets [76,83].

See Table 6 for the characteristics of the intervention types, embedded BCTs, and outcomes measured for the interventional studies (9/12, 75%). In total, 78% (7/9) used wearable devices to track activity paired with an app, including Fitbit (4/9, 44%) [56,78-80] and Garmin (2/9, 22%) trackers [80,83] and a tailored smartwatch paired with the HerBeat app (1/9, 11%) [84]. All studies were based on apps designed to promote PA except for 11% (1/9) of the studies [76], which used a WhatsApp-based PA intervention. Control groups included a basic step-counting pedometer without feedback [78] and a waitlist [81,83].

Table 6. Characteristics of the included mobile physical activity (PA) interventions, coded behavior change techniques (BCTs), and outcomes measured (N=9).

Author, year	Mobile PA technology	Control group (if applicable)	Duration	BCTs	Theoretical contribution	Outcomes measured
Cadmus-Bertram et al [78], 2016	Fitbit-based PA intervention	Basic step-counting pedometer+printed materials	16 weeks	Intervention group: • 1.1 Goal setting (behavior) • 1.4 Action planning • 1.5 Review behavior goals • 2.2 Feedback on behavior • 2.3 Self-monitoring of behavior • 2.6 Biofeedback Control group: • 1.1 Goal setting (behavior) • 1.2 Problem solving • 1.4 Action planning • 2.3 Self-monitoring of behavior	The CALO-RE[a] framework, known as a comprehensive and standardized protocol for the identification, reporting, and appraisal of behavior change interventions for health behaviors, including PA [86]	• MVPA[b] (minutes per week) and increased steps per day using ActiGraph GT3X+ accelerometerc • Height and weight measured using standard procedures and BMI[c]
Valle et al [81], 2017	Self-weighing and activity tracker mobile intervention	Waiting list	6 months	• 2.6 Biofeedback • 2.3 Self-monitoring of behavior • 1.2 Problem solving • 2.2 Feedback on behavior • 2.4 Self-monitoring of outcome of behavior • 1.6 Discrepancy between behavior and goal • 3.1 Social support (unspecified) • 4.1 Instruction on how to perform the behavior • 5.1 Information about health consequences • 7.1 Prompts and cues • 8.3 Habit formation • 12.5 Adding objects to the environment	SRT[d], a set of psychological subfunctions that must be mobilized for self-directed change [87]	• Weight change, measured using BMI and waist circumferencec • Energy expenditure (kcal per week), measured using the PAQ[e,c]
Lynch et al [83], 2019	Wearable activity monitor and app (Garmin)	Waiting list	12 weeks	• 2.6 Biofeedback • 1.1 Goal setting (behavior) • 1.2 Problem solving • 1.5 Review behavior goals • 2.3 Self-monitoring of behavior • 2.2 Feedback on behavior • 3.1 Social support (unspecified) • 4.1 Instruction on how to perform the behavior • 5.3 Information about social and environmental consequences • 7.1 Prompts and cues	None	• MVPA (minutes per week) using ActiGraph GT3X+[f] • Sedentary time, measured using an activPAL[f] • Sleep disturbance, measured by actigraphy and self-reported PSQI[g,f]

Author, year	Mobile PA technology	Control group (if applicable)	Duration	BCTs	Theoretical contribution	Outcomes measured
Kashfi et al [76], 2021	WhatsApp-based mobile intervention	No intervention	1 month	• 1.1 Goal setting (behavior) • 1.2 Problem solving • 1.4 Action planning • 3.1 Social support (unspecified) • 5.1 Information about health consequences • 4.1 Instruction on how to perform the behavior • 6.1 Demonstration of the behavior • 7.1 Prompts and cues	None	QoL[h] measured using self-reported MENQOL[i,f]
Butryn et al [79], 2016	Fitbit-based, blended PA intervention	Baseline	6 months	• 1.1 Goal setting (behavior) • 1.2 Problem solving • 1.6 Discrepancy between behavior and goal • 2.2 Feedback on behavior • 2.3 Self-monitoring of behavior • 2.5 Monitoring of outcome of behavior without feedback • 2.6 Biofeedback • 3.1 Social support (unspecified) • 6.2 Social comparison • 9.1 Credible source	None	• MVPA (minutes per week), measured using ActiGraph GT3X+[j] • Sedentary time[j] • Weight loss, measured using a standardized scale[j]
Sengupta et al [84], 2020	Smartwatch and smartphone app (HerBeat)	Baseline	12 weeks	• 1.1 Goal setting • 1.4 Action planning • 1.6 Discrepancy between behavior and goal • 2.1 Monitoring of behavior by others without feedback • 2.3 Self-monitoring of behavior • 2.6 Biofeedback • 5.3 Information about health consequences • 7.1 Prompts and cues • 10.4 Social reward	None	• Change in PA using IPAQ-SF[k,l] • Exercise and dietary self-efficacy using the Exercise Condensed Survey[l] • Weight circumference and BMI[j] • Depressive symptoms, measured using the PHQ-9[m,j] • Perceived stress[l]
Joseph et al [56], 2021	Smart walk app and Fitbit	Baseline	4 months	• 1.1 Goal setting (behavior) • 1.2 Problem solving • 2.3 Self-monitoring of behavior • 2.6 Biofeedback • 3.1 Social support (unspecified) • 4.1 Instruction on how to perform the behavior • 5.3 Information about social and environmental consequences • 6.1 Demonstration of the behavior	SCT[n], proposes that people are driven not by inner forces but by external factors [88]	• MVPA (minutes per week) using the 2-item Exercise Vital Sign Questionnaire[j] • Weekly estimated energy expenditure[j] • Changes in SCT mediators measured using self-reported questionnaires[j], with unexpected decrease in self-efficacy for PA
Nguyen et al [80], 2017	WATs[o] and paired apps: Fitbit One, Jawbone UP24, Garmin, Vivofit 2, Garmin Vivosmart, Garmin Vivoactive, and Polar A300	N/A[p]	4 weeks	• 2.3 Self-monitoring of behavior • 2.6 Biofeedback • 4.1 Instruction on how to perform the behavior • 7.1 Prompts and cues	None	Preferences and experience of WATs to promote PA behavior change among postmenopausal women (generated themes)

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Author, year	Mobile PA technology	Control group (if applicable)	Duration	BCTs	Theoretical contribution	Outcomes measured
Kim et al [85], 2020	• Mobile-based living laboratory intervention • Fitbit and mobile app	N/A	24 weeks	• 1.1 Goal setting (behavior) • 1.2 Problem solving • 1.5 Review behavior goals • 2.3 Self-monitoring of behavior • 2.6 Biofeedback • 3.1 Social support (unspecified) • 3.3 Social support (emotional) • 5.1 Information about health consequences • 6.1 Demonstration of the behavior • 4.1 Instruction on how to perform the behavior • 7.1 Prompts and cues • 10.4 Social reward • 15.1 Verbal persuasion about capability	SCT [88]	• Involvement of middle-aged, migrant women in the development of a culturally appropriate, mobile intervention to promote PA • Validity testing of the developed app based on content, interface design, and technology criteria using a 23-item self-reported smartphone app evaluation tool for health care

[a]CALO-RE: Coventry, Aberdeen, and London-Refined.

[b]MVPA: moderate to vigorous physical activity.

[c]No statistically significant difference between the groups (no evidence).

[d]SRT: self-regulation theory.

[e]PAQ: Paffenbarger Physical Activity Questionnaire.

[f]Statistically significant difference between the groups (significant evidence).

[g]PSQI: Pittsburgh Sleep Quality Index.

[h]QoL: quality of life.

[i]MENQOL: Menopause-Specific Quality of Life Questionnaire.

[j]Statistically significant difference from baseline (some supporting evidence).

[k]IPAQ-SF: International Physical Activity Questionnaire-Short Form.

[l]No statistically significant difference from baseline (no evidence).

[m]PHQ-9: Patient Health Questionnaire-9.

[n]SCT: Social Cognitive Theory.

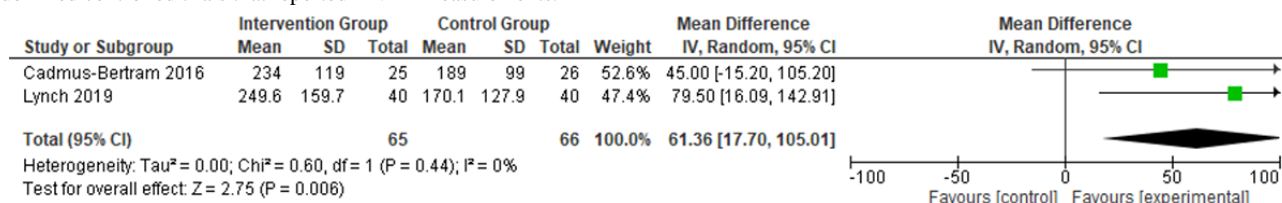[o]WAT: wearable activity tracker.

[p]N/A: not applicable.

Effectiveness of Mobile PA Technologies in Menopausal Women

PA Behavior Change

Change in PA was measured in 86% (6/7) of the included quantitative studies using MVPA (minutes per week), energy expenditure (kcal per week), or a number of daily steps. In total, 50% (2/4) of the RCTs (n=131) reported changes in MVPA (minutes per week) between the groups [78,83]. Compared with the control groups, the use of mobile-based PA interventions (wearables and their paired apps) significantly improved MVPA by 61.36 minutes per week (95% CI 17.70-105.01; P=.006) after 16 weeks of intervention. There was no evidence of statistical heterogeneity (I^2=0%; P=.44); however, the CIs were very wide, and the sample sizes were small, suggesting that this should be interpreted with caution (Figure 2).

The findings of other studies were mixed. The RCT by Valle et al [81] used the self-reported Paffenbarger Physical Activity Questionnaire (PPAQ) to measure energy expenditure (kcal per week) as a secondary outcome and found no statistical difference between the groups in PA over 6 months of follow-up. There was no reporting of quantitative analysis, and the authors did not respond to queries. In the 25% (3/12) of pre-post studies, MVPA (minutes per week) was measured using objective ActiGraph GT3X+ accelerometers, the International Physical Activity Questionnaire-Short Form (IPAQ-SF), and Exercise Vital Sign self-reported questionnaires [56,79,84]. Butryn et al [79] found a significant modest increase in MVPA from 63 minutes per week at baseline to 135 minutes per week after 6 months (P=.01). Similarly, Joseph et al [56] self-reported a significant increase in MVPA from 20 minutes per week at baseline to 50 minutes per week after 1 month of intervention (P<.001). Sengupta et al [84] found a moderate increase in PA from 35.6 minutes per day at baseline to 63.1 minutes per day at 3 months; however, this did not reach statistical significance.

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Figure 2. Meta-analysis results of between-group difference in moderate to vigorous physical activity (MVPA; mins per week) of the 2 included randomized controlled trials that reported MVPA measurements.

Study or Subgroup	Intervention Group			Control Group			Weight	Mean Difference IV, Random, 95% CI	Mean Difference IV, Random, 95% CI
	Mean	SD	Total	Mean	SD	Total			
Cadmus-Bertram 2016	234	119	25	189	99	26	52.6%	45.00 [-15.20, 105.20]	
Lynch 2019	249.6	159.7	40	170.1	127.9	40	47.4%	79.50 [16.09, 142.91]	
Total (95% CI)			65			66	100.0%	61.36 [17.70, 105.01]	

Heterogeneity: Tau² = 0.00; Chi² = 0.60, df = 1 (P = 0.44); I² = 0%
Test for overall effect: Z = 2.75 (P = 0.006)

Favours [control] Favours [experimental]

Sedentary Time

Only 17% (2/12) of the studies [79,83] assessed the impact of mobile PA interventions on sedentary time. Lynch et al [83] measured sedentary behavior using an activPAL and found a moderate significant decrease of −36.6 minutes per day (95% CI −71.7 to −1.6) between the groups after 12 weeks of intervention (P=.01). Butryn et al [79] found a nonclinically significant decrease in sedentary time from 75.6 (SD 5.72) minutes per day to 73.2 (SD 5.81) minutes per day at the 6-month follow-up (P<.05).

Self-efficacy

Self-efficacy (SE) to exercise was measured in 67% (2/3) of the pre-post studies [56,84]. Neither found a significant positive effect on SE. Joseph et al [56] also measured other social cognitive mediators—self-regulation, behavioral capability, expectations, and social support—using self-reported questionnaires. Over the 4-month mobile PA intervention, the results showed significant improvements in other social cognitive mediators such as behavioral capability for PA (r=0.440; P=.004). However, unexpectedly, they found a decreased negative trend in exercise SE for PA (r=−0.364; P=.02) after 4 months of intervention [56]. The authors did not report any explanation for this unexpected decrease in SE.

Menopause-Related Outcomes

The measures included were weight loss, sleep disturbance, mental health (perceived stress and depressive symptoms), and menopause-specific QoL.

Weight Loss

Changes in weight were assessed in 33% (4/12) of the studies [78,79,81,84]. BMI was measured by one 3-arm RCT [81]. Valle et al [81] reported a borderline significant marginal decrease in BMI of −0.4 kg/m^2 (95% CI −1.7 to −0.1) over 6 months (P=.046) between the mobile-based technology intervention and control groups.

The findings for weight change were mixed, with nonclinically meaningful effects. Both RCTs [78,81] found no statistically significant difference between the intervention and control groups for weight, measured in kilograms, and median percent weight change (IQR). Cadmus-Bertram et al [78] found a nonstatistical difference of 0.06 between the web-based intervention and pedometer control groups after 16 weeks of intervention (P=.61). Similarly, Valle et al [81] reported nonstatistically significant weight loss over 6 months favoring the interventional group of both the PA tracker and self-weighing mobile intervention (P=.07) but not the self-weighing only intervention group (P=.36) compared with the control group. Owing to high heterogeneity and different reported outcomes of the 2 RCTs [78,81], a meta-analysis did not seem to be appropriate.

In total, 67% (2/3) of the pre-post studies measured change from baseline [79,84]. Butryn et al [79] found a statistically significant weight loss of 1.86 kg from baseline to the 6-month follow-up (P=.01). Similarly, Sengupta et al [84] reported that midlife women showed statistically significant improvement in waist circumference (P=.048), weight (P=.02), and BMI (P=.01) from baseline.

Sleep Disturbance

The impact of a mobile-based PA intervention (Garmin Vivofit 2 wearable and its paired app) on sleep quality measured by ActiGraph and the Pittsburgh Sleep Quality Index was reported as a secondary analysis of the Activity and Technology (ACTIVATE) RCT on menopausal survivors of breast cancer [83]. At 12 weeks of intervention, a significant reduction in both actigraphy-based awake time after sleep and number of awakenings equivalent to −5.7 minutes (95% CI −11.7 to −0.2) and −2.0 minutes (95% CI −3.6 to −0.4) was observed, respectively, compared with the control arm. The changes in Pittsburgh Sleep Quality Index scores and actigraphy sleep efficiency favored the intervention arm, although there was no statistically significant difference between the groups [83].

QoL Measure

The study by Kashifi et al [76] measured the impact of a mobile-based PA intervention using WhatsApp on the QoL of menopausal women in Iran using the self-reported Menopause-Specific Quality of Life Questionnaire at baseline and the 1-month intervention follow-up. The study showed significant improvements in vasomotor, physical, and psychosocial dimensions between the intervention and control groups 1 month after the intervention. The mean difference in total QoL between the 2 groups was −10.52 (P<.001). Within the intervention group, the total QoL dimension changed significantly from 72.70 (SD 5.33) at baseline to 63.81 (SD 6.81), with lower scores indicating better QoL [76].

Psychosocial Outcomes

The impact on perceived stress and depressive symptoms was assessed in 8% (1/12) of the studies [84] using the adapted rating scores of the Perceived Stress Scale and the Patient Health Questionnaire-9. Sengupta et al [84] showed nonsignificant improvements in perceived stress scores, possibly because of the limited functionality of the prototype, with a significant reduction in depressive symptoms observed by the end of the 12-week intervention.

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Experienced Acceptability: Quantitative Data

The usability and acceptance of the interventions were examined quantitatively in 42% (5/12) of the studies using surveys [56,78,79,81,84] (Table 7). Acceptability was most frequently assessed in terms of satisfaction and the users' experience of using mobile apps, WATs, or the overall program. There were high levels of satisfaction and acceptability, favoring the use of mobile apps and Fitbit activity trackers. For instance,

Cadmus-Bertram et al [78] compared a Fitbit-based intervention with a traditional pedometer without feedback received in a control group and found significantly higher satisfaction levels in the Fitbit group—96% (24/25) rated Fitbit as "somewhat or very helpful" compared with only 32% (8/26) in the pedometer control group. Similarly, 67% (2/3) of the pre-post studies [56,79] found that midlife women favored Fitbit (combined use of the Fitbit app and activity tracker) and reported that using Fitbit was "motivational to PA."

Table 7. Acceptability ratings across the included quantitative studies.

Author, year, intervention type	Acceptability measurements informed by the TAM2[a] model [72]	Acceptability rating
Cadmus-Bertram et al [78], 2016, Fitbit-based intervention (activity tracker and app-based website)	• User experience and satisfaction survey • Perceived ease of use • Perceived usefulness • Intention and likelihood of future use	• A total of 96% (24/25) of midlife women liked the Fitbit app-based website. • There were lower perceived barriers associated with the use of Fitbit; 80% (20/25) reported no technical issues or difficulty with the trackers. • A total of 96% (24/25) rated Fitbit as "somewhat or very helpful" for increasing PA[b] compared with only 32% in the pedometer control group. • A total of 76% (19/25) reported that they would recommend Fitbit to a friend.
Valle et al [81], 2017, weight loss mobile intervention (tracker and app)	• Program acceptability and satisfaction survey	• Almost all the intervention group (11/11) was satisfied and rated the tracker as "extremely helpful" on a 4-point scale at 6 months.
Butryn et al [79], 2016, Fitbit-based intervention (tracker and app)	• Satisfaction survey • Perceived confidence • Intention and likelihood of future use	• At 6 months, 89% (25/28) of the participants rated the whole program as favorable for increasing PA on a 5-point Likert scale (mean 4.11 out of 5, SD 1.14). The Fitbit was reported as the "best part." • After the intervention ended, 88% (24/28) reported confidence in the ability to maintain PA over the next 3 months. • At 6 months, 77% (22/28) reported that they had purchased or intended to purchase a device. • In total, 88% (24/28) agreed to recommend the program to others.
Sengupta et al [84], 2020, Her-Beat mobile app and smartwatch	• User satisfaction using the SUS[c] • Perceived usefulness and ease of use	• Midlife women found the app features to be easy to use and well integrated (mean score on the SUS was 83.60, SD 16.4). • Participants somehow felt confident in using the app. • The most frequent technical complaints were regarding the short battery life of the smartwatch. • Participants had no adverse events or privacy concerns.
Joseph et al [56], 2021, Fitbit-based intervention (tracker and app)	• Consumer satisfaction survey	• Treatment acceptance was measured using an adapted consumer satisfaction survey to assess users' perceptions of the intervention's content, app usability, and preferences. • A total of 87% (13/15) of the women found the combined use of the Fitbit app and activity tracker helpful and "motivational to exercise."

[a]TAM2: technology acceptance model 2.

[b]PA: physical activity.

[c]SUS: System Usability Scale.

The perceived usefulness and ease of use, where measured, were often limited to whether users experienced technical issues associated with the use of mobile apps and activity trackers. Cadmus-Bertram et al [78] found that 80% (20/25) of midlife women had no technical difficulties with the Fitbit trackers and reported technical issues that were easy to resolve. Furthermore, participants reported that more hands-on training could improve their satisfaction and engagement with the app-based website functions. Sengupta et al [84] reported on the acceptability and usability of the HerBeat smartwatch and paired app. In this pilot study, midlife women with cardiovascular diseases found the

app features to be easy to use but complained about the short battery life of the HerBeat smartwatch [84].

Across the included studies, no adverse events were reported by the participants themselves or by the research team to be related to the use of mobile apps or trackers.

Anticipated Acceptability: Qualitative Data

We identified three main themes from 33% (4/12) of high-quality studies related to perceived usefulness, readiness to use, and ease of using mobile PA technologies [75,77,79,82].

A summary description of the themes with some corresponding excerpts can be found in Multimedia Appendix 4 [75,77,79,82].

Theme 1: Perceived Usefulness to Increase Self-awareness of PA and Menopause Experience

Mobile apps were viewed as an opportunity to track self-management behaviors such as exercise, dietary intake, and regular health checkups that could support the management of menopausal symptoms [75,77,79,82]. Promoting and tracking PA during menopause was perceived as a critical feature of a mobile-based intervention to increase self-awareness of PA and sedentary time, particularly in working women who were less aware of their sitting time [80].

Similarly, Lee et al [75] reported the need for an app to encourage exercise and contain personalized health management information as most participants wanted self-management strategies to facilitate lifestyle changes other than receiving medical treatments, as well as a space where menopausal women could share common experiences.

Theme 2: Perceived Readiness and Ease of Using Mobile Apps and Activity Trackers

Midlife women appeared to have some level of hesitancy and lack of readiness to adopt and engage with mobile PA technologies that were rooted in their perceived low confidence with technology and limited knowledge and technological capabilities regarding how to use the devices and in the complexity of WATs that could intimidate midlife women into ending up not using the technologies [77,80].

There were mixed views among midlife women on perceived ease of use of WATs and their paired apps. Most midlife women from the focus group by Nguyen et al [80] had no trouble using commercially available trackers and their apps (eg, *Garmin Vivofit 2*, *Fitbit*, and *Polar A300*), yet most of them relied on basic features of activity trackers, such as the step-counting function. By contrast, some women had limited use of functions as they found it challenging to set up wearables and synchronize them with their phones [80]. Hands-on training could support midlife women in setting up and ensuring ease of use of mobile PA technologies. Simplicity of content, clear communication and navigation, and appropriate use of colors and text were considered important to ensure user-friendliness [80,82]. A participant highlighted the importance of ensuring that positive language is used when referring to menopause to empower midlife women through their menopause journey [77].

However, midlife women experienced challenges associated with the practicality of activity trackers that discouraged their motivation and intention to wear and sustain the use of PA trackers over time. These challenges included discomfort of wearables, particularly regarding size or buzzing; inability to record light-intensity PA and strength training; and concerns about accuracy. Subsequently, some participants reported disuse of wearables over time as they were not enough to maintain PA or reported that they ignored alarms because of frustration [80].

Midlife women also emphasized the significant value of the esthetics of wearables to determine their preferences and likelihood of using PA trackers. Midlife women preferred smaller activity trackers such as *Fitbit* and *Garmin* Vivofit 2 [80]. However, some participants reported that trackers with larger screens and text would be easier to see and push buttons in [80].

Theme 3: Midlife Women's Favored Features of PA Apps

Step Count

Step counting was the most favored feature of mobile apps and activity trackers, with little use of other advanced features of mobile apps or WATs [80]. Menopausal women found that calculating and viewing the number of steps was helpful in hitting 10,000 steps a day.

Setting Goals and Monitoring Progress

Midlife women expressed their desire to use a PA app that allowed for goal setting and daily step-count monitoring to guide behavior changes to eventually help minimize burdensome menopausal symptoms in their busy lives [77,80,84] as this was seen as motivational [80]. However, most participants found that a feature that automatically adjusted the user's step goal based on previous activity levels was less motivational compared with fixed or manually adjusted goals [80].

Real-time Feedback of PA

Receiving notifications on smartphones to encourage PA was perceived as acceptable to nudge women to exercise. Apps with personalized notifications were felt to be more effective based on how motivational and nonrepetitive the prompts were [75]. Midlife women also liked the idea of receiving real-time feedback on PA behavior on the apps. Some participants also acknowledged the additional positive reinforcement via emails, SMS text messages, or peer support via social media sites [80].

BCT Identification

The average number of BCTs per mobile PA intervention was 8.8 (range 4-13; Figure 3). BCTs were mapped out for all actual interventions included (9/12, 75%) and the one active control (1/12, 8%) in the study by Cadmus-Bertram et al [78] (Table 6).

Collectively, 22 different BCTs from 9 different clusters of the BCTTv1 were identified across the 75% (9/12) of coded interventions. A total of 8% (7/93) of the BCTs were used in more than half of the interventions—"Self-monitoring of behaviour" (8/9, 89%), "Biofeedback" (8/9, 89%), and "Goal setting (behaviour)" (7/9, 78%) were the most frequently described BCTs. "Problem solving," "Social support (unspecified)," "Prompts and cues," and "Information on health consequences" were identified in 67% (6/9) of the interventions each. All the included interventions (9/9, 100%) used at least one BCT from cluster 1 "Goals and planning" or cluster 2 "Feedback and monitoring" of the BCTTv1.

There were no clear patterns between the type and total number of BCTs used and the effectiveness of the included interventions. In total, 50% (2/4) of the RCTs [76,83] reported significant evidence on PA, sedentary time, sleep disturbance, and QoL outcomes and used a total of 10 and 8 BCTs. By contrast, the RCTs by Cadmus-Bertram et al [78] and Valle et al [81] used

6 and 12 BCTs, respectively, yet found no evidence of effectiveness. In the RCT by Cadmus-Bertram et al [78], the distinction in BCTs between the intervention (Fitbit-based) and active control (pedometer-based) groups was feedback on behavior, biofeedback, and review behavior goals, which were only present in the intervention group. Both groups involved the common BCTs "Goal setting (behaviour)," "Action planning," and "Self-monitoring of behaviour" [78].

In total, 67% (2/3) of the pre-post studies [56,79] found some supporting evidence of significant changes in PA, sedentary time, and weight loss from baseline and used 10 and 8 BCTs. However, Sengupta et al [84] used 9 BCTs and reported no evidence of the effectiveness of mobile apps on PA, perceived stress, and depressive symptoms (see Multimedia Appendix 5 [56,76,78-81,83-85] for the full coding process of BCTs of each intervention studied).

Figure 3. The frequency of coded behavior change techniques (BCTs) across the included interventions (n=9). mHealth: mobile health; PA: physical activity.
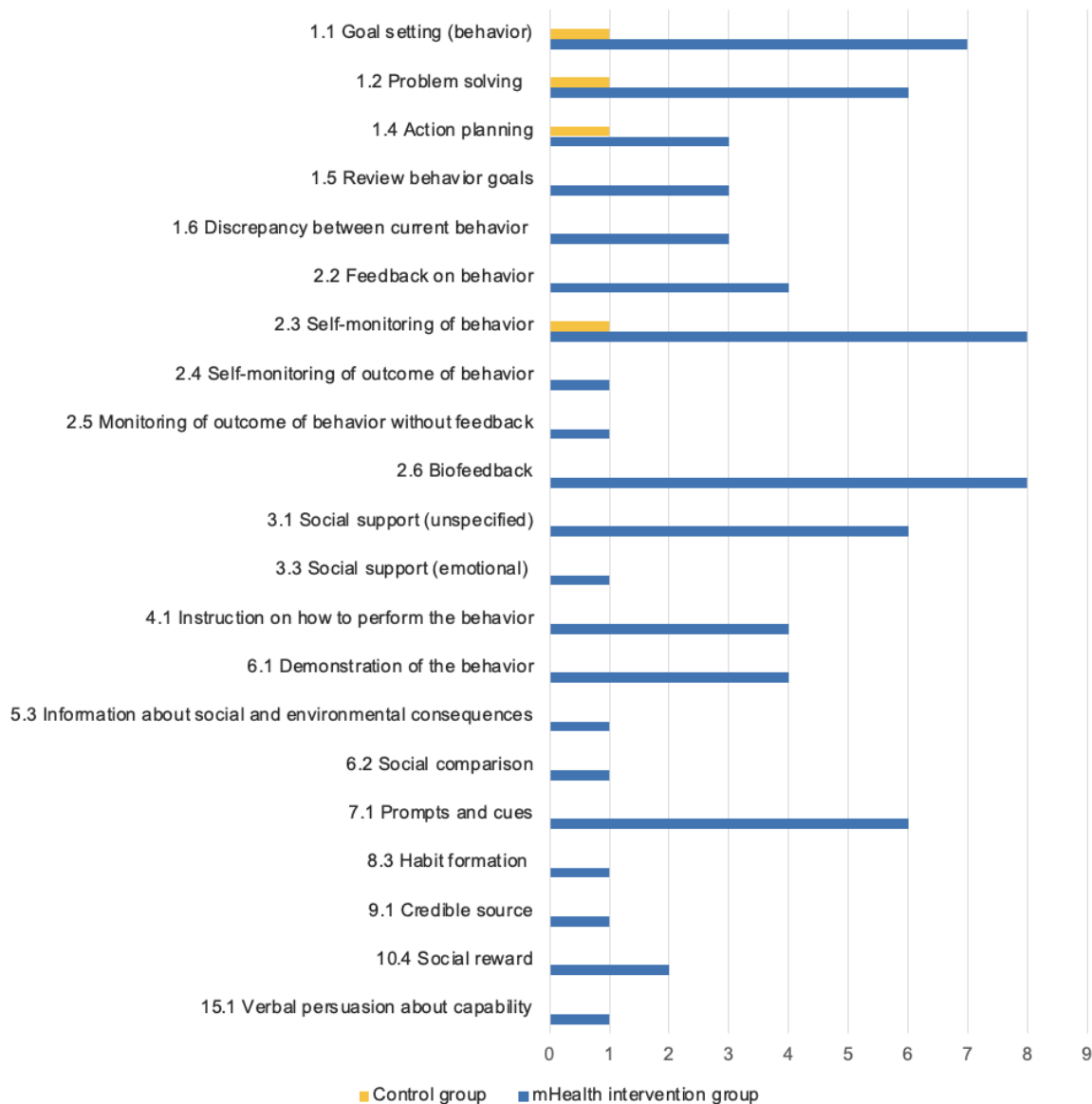
Theoretical Consideration

A total of 42% (5/12) of the studies mentioned the contribution of behavioral theories to inform the design and development of the mobile PA technology. Four specific theories were referenced: the Coventry, Aberdeen, and London-Refined (CALOR-E) [78]; Behavior Change Support Systems [82]; self-regulation theory [81]; and SCT [56,85]. Of these 5 theory-informed studies, 2 (40%) were qualitative and had no evaluation outcomes [82,85]. In total, 40% (2/5) of comparator studies reported no significant evidence on both PA and weight outcomes. Only the trial by Joseph et al [56] was based on SCT and found some supporting evidence of a significant increase in PA of 30 minutes per week over 4 weeks (P<.001). The reporting of theoretical underpinnings in the development and implementation of interventions was generally poor.

Discussion

Principal Findings

This review of 12 studies found that mobile PA interventions in the form of stand-alone apps or WATs resulted in a small to moderate increase in objectively measured MVPA of approximately 61.36 minutes per week among midlife women, at least in the short term (≤16 weeks). However, precision decreases with a reduced sample size and, thus, the pooled effect size should be interpreted with caution. Although a meta-analysis was not possible for other menopause-related outcomes, moderate- to high-risk evidence suggests significant, positive effects on weight reduction, managing anxiety and sleep disturbance, and enhancing menopause-specific QoL domains in midlife women. Quantitative studies were mostly uncontrolled with small sample sizes. We also found from high-quality qualitative exploratory research that most midlife women perceived mobile technologies as acceptable and potentially helpful in motivating them to increase PA levels. Daily step count was seen as an acceptable and clear outcome to monitor.

To our knowledge, this is the first systematic review to synthesize the current evidence with regard to the effectiveness and acceptability of mobile apps and WATs targeting PA in midlife women. An increase of 61.36 minutes per week, at least in the short term, among both healthy and clinical midlife women is promising. PA apps and WATs tend to be effective in comparison with no intervention or traditional pedometer-based interventions with no mobile technology component. The estimated increase in weekly MVPA represents 40.9% (61/150) of the recommended weekly MVPA for adults aged 19 to 64 years [89]. However, certainty in the pooled effect estimate was downgraded because of small study bias. Although all other individual effect estimates favored mobile PA interventions, not all studies reached statistical significance.

This review was consistent with the recently published meta-analysis of 63 studies (N=8250 participants) of digital and mechanical wearables providing PA feedback showing a small pooled effect for MVPA equivalent to 48.5 minutes per week (95% CI 33.8-63.3) among adult populations [90]. Similarly, the meta-analysis by Laranjo et al [91] found that mobile apps and WATs caused small to moderate increases in PA (equivalent to 1850 steps per day) among healthy adult populations. The meta-analysis by Yerrakalva et al [92] also found a modest increase of 753 steps per day among older adults after using app-based interventions for ≤3 months. Owing to substantial physical inactivity among midlife women compared with the general adult population [5,7], even small increases in MVPA are likely to be beneficial. The effects of mobile PA interventions on sedentary behavior in this population as sedentary time were inconclusive, highlighting a need for more research to assess the impact of mobile apps on sedentary behavior outcomes in midlife women [79,83].

Few studies (6/12, 50%) evaluated menopause-related outcomes. We found mixed evidence of the effect on weight loss [78,79,81]. Single studies found positive effects on sleep disturbance [83], menopause-specific QoL [76], and depressive symptoms but not on perceived stress [84]. None of the included studies assessed the effect of mobile PA interventions on vasomotor symptoms such as hot flushes and night sweats.

Design of Acceptable, Potentially Effective Mobile PA Interventions for Midlife Women

In alignment with the key constructs of the TAM [72], findings from the qualitative synthesis suggest that perceived usefulness was grounded in women's beliefs about the extent to which mobile apps or WATs could increase self-awareness of PA and improve the overall menopause experience by exchanging reliable health information and promoting behavior change. There was a tendency to favor a holistic approach when designing apps for midlife women by focusing on menopause as a whole experience and on lifestyle behaviors rather than on the limited functions of menopausal symptom trackers [77].

In this review, midlife women showed a desire for PA mobile technology that required only limited technical abilities and met their needs and preferences without imposing further burdens on their busy lives [77,80,82]. Echoing previous studies in older populations [93-96], women aged 40 to 64 years showed some hesitancy toward new technology and tended to be reluctant to take up mobile apps and WATs, possibly because of low confidence and SE in using new technology [82]. This may, in turn, reduce the effect of trackers on PA behavior change [97]. However, unlike a common reluctance to learn new technology among older populations [98,99], our review findings suggest that midlife women were willing to learn how to use apps to increase PA and make better lifestyle changes [77].

One of the key findings is related to which specific features of mobile apps and WATs were preferred by midlife women. Previous research suggests that effective PA apps for the general population might need some adaptations to meet the needs and requirements of each subgroup of that population [100]. The qualitative synthesis suggests that midlife women liked simple features, namely, step goal setting, activity monitoring, real-time feedback, easy-to-read content, and a user-friendly interface, with most midlife women considering step counting as the most favored feature [82,83]. We noticed that midlife women shared similar preferences related to functionality with older populations [95,99,101,102]. For instance, using large visual screens and readable text was perceived as helpful [91,93] and, thus, may facilitate PA mobile technology use among midlife women.

Furthermore, the application of the TAM suggests that providing technical support may facilitate uptake and engagement with new technologies [72]. Access to additional telephone or face-to-face technical support may increase midlife women's confidence in technology, especially among those who were initially reluctant [78,80]. Hands-on training and easy-to-read manuals to guide the installation, synchronization of PA apps, and use of WATs were perceived as essential.

Most Frequently Reported BCTs

"Self-monitoring," "biofeedback," and "goal setting of PA behaviour" were the most frequently used BCTs across the included studies. These findings concur with previous literature on digital behavior change interventions targeting PA, which

also highlighted the role of "social support" in adults [103-105] and older adults [106]. In this review, "social support" was used in 67% (6/9) of the studies targeting both healthy [56,76,79,85] and clinical (ie, survivors of breast cancer) [81,83] midlife women. Most recently, research suggests that midlife women are ready to make positive behavior changes, yet they need social support and connectivity [107,108]. Similarly, our qualitative synthesis found that midlife women would prefer an app that offers a safe space to share common experiences and receive social support [75].

However, because of the scarcity of existing evidence and heterogeneity in intervention type (eg, smartphone apps and WATs), multicomponent interventions (eg, in-person sessions, SMS text messaging, and follow-up calls), mode of delivery, and outcomes measured, it was not possible to ascertain which intervention components or BCTs were most effective in increasing PA or improving menopause-related outcomes. Reporting of interventions and mode of delivery in the included studies was insufficient; accordingly, we could not comment on the link between the described BCTs and mechanisms of action, a problem highlighted in similar reviews. Sediva et al [103] highlighted the relevant real concern of low treatment fidelity on the delivery of content as planned across the 13 included complex interventions, including PA apps. By contrast, without adequate information reported on measurements of fidelity or ensuring that the underpinning theory is reflected in the design and implementation process, implementation failure can potentially occur and, thus, the real-world effectiveness of such interventions must be considered with caution [109,110].

Interestingly, the top identified BCTs—"self-monitoring," "goal setting," and "biofeedback"—were in parallel with the most preferred app features perceived by midlife women according to the qualitative data synthesis. Hence, to optimize the effectiveness of mobile PA interventions in midlife women, it might be beneficial for future mobile interventions to take advantage of the simple features of step counts, goal setting, and real-time feedback and pair them with a sufficient number of BCTs. Evidence suggests that incorporating more BCTs is more effective than using limited or single BCTs to obtain significant effects on PA [106,111]. Further research is needed to determine which mobile PA components or active BCTs are the most effective in increasing PA in midlife women.

Strengths, Limitations, and Future Implications

To our knowledge, this is the first systematic review evaluating the use of mobile PA interventions among midlife menopausal women. The main strengths of this review are the rigorous and inclusive methodological approach and the comprehensive and extensive literature search. The screening, data extraction, and risk-of-bias assessment processes were independently reviewed by a second researcher. BCT coding was also independently conducted by 2 trained researchers, with high agreement.

However, this review has certain limitations. It should be noted that the findings of this review were based on healthy and clinical midlife women with potentially chronic conditions as well as on survivors of breast cancer, which may reflect special needs and, thus, different perspectives toward using mobile apps and WATs. For example, Nguyen et al [80] highlighted

that survivors of breast cancer may have higher motivation to exercise to prevent recurrence of cancer and, thus, to sustain the use of WATs than healthy women. In this review, we only identified 25% (1/4) of RCTs [78] that targeted middle-aged women from the general population. However, the results were relatively consistent across populations. Future research should focus on targeting midlife women from the general community to ensure the generalizability of the findings.

In total, 58% (7/12) of the studies were at moderate to high risk of bias, and the inclusion of lower-quality study designs (eg, pre-post studies) substantially increased the risk of bias. Moreover, the data extracted from most of the included quantitative studies did not adjust for covariates and, thus, the meta-analysis reflects an unadjusted effect. Owing to the inherent variability in mobile interventions, control groups (active or no intervention), and the methodological quality of the included studies, the effect sizes of the pooled estimate and from individual studies had large CIs and low precision. Hence, further studies with larger sample sizes are needed to measure outcomes in a consistent way as the current lack of significant results of individual studies could be attributed to either a lack of effect or underpowered studies.

Given the novelty of this research area and the scarcity of existing RCTs, the inclusion of different study designs provides valuable insights. A total of 25% (3/12) of the studies included in this review were exploratory, participatory design qualitative studies that involved midlife women to obtain their insights before developing innovative mobile solutions, which may enhance the relevance and uptake of such interventions by this population. However, further rigorous studies informed by relevant theoretical frameworks and best practices are essential to explore how midlife women and their subgroups can best participate in the design of mobile PA interventions. Furthermore, qualitative process evaluations of interventional studies might also be equipped to fill in the gaps regarding the experiences and engagement with mobile PA interventions among midlife women.

Few empirical studies looked at the effect of PA mobile technologies [19,20,23] on menopause-related outcomes. Menopause is a life transition affecting half of the population and, thus, an area requiring further research and innovative applications. Rigorous studies on menopause-related outcomes can then serve as a solid base for policies and interventions to support more inclusive workplaces for women. For instance, promoting mobile apps for PA may be a way that workplaces and health care settings could use as a scalable, cost-effective strategy to deal with menopausal symptoms.

Conclusions

The findings from this review suggest that mobile PA interventions in the form of apps and WATs are likely to be acceptable to midlife women and may potentially increase PA. Evidence was mixed for sedentary time and weight loss, with single studies suggesting positive improvements in sleep disturbance and menopause-specific QoL domains. The most frequently reported BCTs across the included studies were biofeedback, self-monitoring of behavior, and goal setting (behavior). The most acceptable components of PA apps were

manual goal setting and step trackers, whereas activity trackers needed to be comfortable and attractive. Although the approach of using mobile PA apps in midlife women appears promising, larger, high-quality studies should address the lack of evidence on effectiveness, acceptability, and feasibility of using mobile PA apps to address menopause-related outcomes and, thus, encourage midlife women to seek support to manage menopausal symptoms.

Acknowledgments

Data Availability

Data extraction and quality assessment templates can be available upon request.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Search strategy.
[[DOCX File , 14 KB](#) - [mhealth_v10i12e40271_app1.docx](#)]

Multimedia Appendix 2
Reasons for study exclusion.
[[DOCX File , 99 KB](#) - [mhealth_v10i12e40271_app2.docx](#)]

Multimedia Appendix 3
Interrater reliability between independent reviewers.
[[DOCX File , 16 KB](#) - [mhealth_v10i12e40271_app3.docx](#)]

Multimedia Appendix 4
Thematic analysis of qualitative studies and excerpts.
[[DOCX File , 20 KB](#) - [mhealth_v10i12e40271_app4.docx](#)]

Multimedia Appendix 5
Behavior change technique coding process.
[[DOCX File , 45 KB](#) - [mhealth_v10i12e40271_app5.docx](#)]

Multimedia Appendix 6
PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist.
[[DOCX File , 28 KB](#) - [mhealth_v10i12e40271_app6.docx](#)]

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Abbreviations

ACTIVATE: Activity and Technology
BCT: behavior change technique
BCTTv1: Behavior Change Technique Taxonomy v1
CALOR-E: Coventry, Aberdeen, and London-Refined
IPAQ-SF: International Physical Activity Questionnaire-Short Form
MVPA: moderate to vigorous physical activity
PA: physical activity
PPAQ: Paffenbarger Physical Activity Questionnaire
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

QoL: quality of life
RCT: randomized controlled trial
SCT: Social Cognitive Theory
SE: self-efficacy
TAM: technology acceptance model
WAT: wearable activity tracker

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Original Paper

Factors Associated With Self-reported Use of Web and Mobile Health Apps Among US Military Veterans: Cross-sectional Survey

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Abstract

Background: Despite their prevalence and reported patient interest in their use, uptake of health-related apps is limited. The Veterans Health Administration (VHA) has developed a variety of apps to support veterans; however, uptake remains low nationally.

Objective: We examined the prevalence of VHA health-related app use and how veterans learned about these apps in order to identify factors associated with their use.

Methods: As part of a VHA quality improvement initiative, we recruited a national cohort of veterans to obtain feedback on their use of technology for health and collected data from them via a cross-sectional survey. The survey data were supplemented with VHA administrative data. We used descriptive statistics to examine demographic and health characteristics, health-related technology use, and how veterans learned about apps. We assessed factors associated with app use using bivariate analyses and multiple logistic regression models.

Results: We had complete data on 1259 veterans. A majority of the sample was male (1069/1259, 84.9%), aged older than 65 years (740/1259, 58.8%), White (1086/1259, 86.3%), and non-Hispanic (1218/1259, 96.7%). Most respondents (1125/1259, 89.4%) reported being very comfortable and confident using computers, over half (675/1259, 53.6%) reported being an early adopter of technology, and almost half (595/1259, 47.3%) reported having used a VHA health-related app. Just over one-third (435/1259, 34.6%) reported that their VHA care team members encouraged them to use health-related apps. Respondents reported learning about available VHA health-related apps by reading about them on the VHA's patient portal (468/1259, 37.2%), being told about them by their VHA health care team (316/1259, 25.1%), and reading about them on the VHA's website (139/1259, 11%). Veterans who self-reported having used VHA health-related apps were more likely to receive care at the VHA (OR [odds ratio] 1.3, 95% CI 1.0-1.7), be in worse health (as assessed by Hierarchical Condition Community score; OR 1.1, 95% CI 1.0-1.2),

report owning a desktop or laptop computer (OR 1.8, 95% CI 1.1-3.1), have posttraumatic stress disorder (OR 1.4, 95% CI 1.1-1.9), and report having VHA health care team members encourage them to use the apps (OR 2.7, 95% CI 2.1-3.4).

Conclusions: We found strong associations between self-reported use by veterans of VHA health-related apps and multiple variables in our survey. The strongest association was observed between a veteran self-reporting app use and having received encouragement from their VHA health care team to use the apps. Veterans who reported receiving encouragement from their VHA care team members had nearly 3 times higher odds of using VHA apps than veterans who did not report receiving such encouragement. Our results add to growing evidence suggesting that endorsement of apps by a health care system or health care team can positively impact patient uptake and use.

Introduction

There is an expanding number of apps available to help patients manage specific health conditions and promote overall well-being [1]. Evidence suggests use of health-related apps is associated with improved management of chronic health conditions [2] and mental health disorders [3,4], desirable health behavior change [5], and better medication adherence [6] and perceptions of health [7]. Studies have also shown that individuals are interested in using health-related apps to support self-management and to improve health [8]. Despite their prevalence and reported patient interest in using them, however, uptake of such apps remains limited [7,9,10].

A variety of barriers to health-related app adoption have been identified in previous work, including concerns about privacy and security [11-14], app usability issues [12,15], and limited proficiency with technology [14]. Recent literature also indicates that lack of awareness or knowledge of health-related apps is also a common barrier to adoption [14,16,17], highlighting the need to clarify how individuals who use health-related apps learn about them. Use of health-related apps has also been associated with certain patient demographic characteristics [18] and factors including positive perceptions of usefulness, motivation to change health behaviors or pursue a health goal, the availability of data visualization within the app, and the app not having any associated costs [9,11,14,16,18]. Importantly, research has also shown that the adoption of specific health-related apps may be bolstered if the app is recommended by a source that the target user trusts and finds credible [19].

US military veterans are an ideal population in which to examine the adoption of health-related apps. In comparison to the general US adult population, veterans often face significant health-related challenges, including disproportionate rates of physical and behavioral health diagnoses [20,21], and they commonly experience multiple comorbidities that require them to have frequent interaction with the health care system [22]. Some of these health concerns can be directly related to military service and difficulties with postservice community reintegration, while others represent common comorbidities experienced by US adults (eg, diabetes, heart disease, and chronic pain). For these reasons, US military veterans, like the broader population, stand to benefit from health-related apps and the support they offer for self-management and enhanced connection with health care providers and resources.

In recent years, studies have indicated that integrating apps into care for veterans may improve outcomes [23]. The effectiveness of multiple health-related apps targeted toward veterans has been demonstrated in randomized controlled trials, including use of the Virtual Hope Box app to support coping with negative emotions among veterans who experience suicidal ideation [24] and use of the PTSD Coach app to manage posttraumatic stress disorder (PTSD) symptom severity and increase PTSD treatment seeking [25]. As part of the Veterans Health Administration (VHA)'s digital health strategy, the VHA Office of Connected Care maintains a VHA app store, which contains a variety of mobile and web-based apps intended to support veterans in the management of their health. These apps are designed to address some of the unique needs of the veteran population, promote wellness and healthy behaviors, provide condition-specific self-management support, inform clinical management, and facilitate other transactions with the health care system that may be relevant to all veterans.

Despite the evolving evidence for their effectiveness, as well as recent literature indicating that many veterans are interested in using health-related apps [26,27] and have a device with which they can access them [28], uptake of VHA apps remains low nationally, and factors associated with veteran use of such apps are not well understood. Given that veterans represent a large patient population that could substantially benefit from the use of health-related apps, the objectives of this analysis were to examine the prevalence of VHA health-related app use, determine how veterans learned about these apps, and identify factors associated with their use.

Methods

Design

The VHA Office of Connected Care, in cooperation with investigators from the VHA Quality Enhancement Research Initiative program, developed the Veterans Engagement with Technology Collaborative (VET-C) cohort in 2017, the purpose of which was to engage veterans in the evaluation of VHA technologies that are intended to increase access, enhance coordination, and support self-management [28]. The VET-C cohort is a quality improvement resource that includes longitudinal survey data. Veterans who are part of the VET-C cohort are invited to provide feedback on their use of technologies for health, including VHA technologies, and this

feedback is used in turn to inform usability and broader uptake. We used the VET-C cohort to examine how veterans learned about VHA health-related apps and factors associated with their adoption.

Recruitment

To be eligible to join the VET-C cohort, veterans had to be users of VHA health care services, have a mobile phone, and be active users of the secure messaging feature of the VHA's online patient portal, My HealtheVet, a feature that is available to veterans who have a premium portal account. The secure messaging use requirement was intended as a proxy for receptivity to and use of VHA patient-facing technologies more generally. Active use of secure messaging was defined as having sent at least 5 secure messages to VHA clinical team members through the portal in the 12 months prior to cohort recruitment. Veterans who met these inclusion criteria were recruited from VHA facilities across the United States. VHA facilities were chosen as VET-C recruitment sites because they (1) had high rates of secure messaging, (2) served as field test sites for other new VHA patient-facing technologies, (3) were known to serve significant populations of women veterans and veterans from diverse ethnic and minority groups, and (4) had active research and evaluation programs.

Procedures

Recruitment lists to support development of the VET-C cohort were created by querying data from the VHA Corporate Data Warehouse (CDW). Veterans were called once by the evaluation team, and those who answered were told about the purpose of the VET-C cohort and invited to join. Veterans who were interested then completed the cohort baseline telephone survey, and evaluation team members entered their responses directly into an online REDCap database. During 2017 and 2018, 2727 veterans from 14 VHA facilities joined the VET-C cohort and completed the baseline survey. From March 2019 to March 2020, we administered a second survey to all veterans in the VET-C cohort who completed the baseline survey. This follow-up survey was completed by 1418 veterans in the cohort. Both our baseline and second surveys included validated question items, questions used in other studies, and new question items developed specifically for these surveys. They were developed in close consultation with leadership from the VHA Office of Connected Care, which is responsible for the health care system's digital health strategy. After we excluded veterans for whom there were missing data for the variables used in the analyses, we included a total of 1259 veterans in the current analyses.

Measures

For this paper, constructs of interest from the surveys included veteran demographics, health and health care use variables, technology ownership and use, VHA care team member encouragement to use VHA apps, and use of VHA health-related apps.

We asked all participants to respond to demographic questions on age, gender, race, ethnicity, relationship status, and education; report their perceived health status [29]; report where they normally received their medical care (the response options were

"mostly at the VHA," "mostly outside the VHA," "about half in the VHA, half outside the VHA," and "nowhere"); and indicate the amount of time it typically took them to travel to their VHA primary care doctor from their home. We also asked participants about their technology ownership (ie, whether they owned a desktop computer, tablet computer, or mobile phone), whether they considered themselves to be early adopters of technology (ie, whether they liked to be among the first to get a new device, tech gadget, or app when it comes out), and how comfortable or confident they felt using computers (responses ranged from 0, "not at all," to 5, "very") [30].

Additionally, we asked participants to report whether they used VHA health-related apps and how they learned about the VHA health-related apps that are available. We also asked participants to report the perceived extent to which their VHA care team members encouraged them to use health-related apps (responses ranged from 1, "strongly disagree," to 7, "strongly agree").

We calculated the participants' prior-year comorbidity index as the Hierarchical Condition Community (HCC) score based on information in the VHA CDW [31,32]. The CDW was also used to identify diagnosed health conditions in the prior 5 years among our sample, and to fill in missing demographic data (eg, for age and gender).

Analyses

We used descriptive statistics (mean, range, and SD, or proportion, as appropriate) to characterize the demographics of the sample, as well as their reported health and health care use, technology ownership and use, VHA health-related app use, how they learned about VHA health-related apps, and their perceptions of VHA care team member encouragement to use health-related apps. We used bivariate analyses (the chi-square test and the t test) to examine differences among veterans who reported using (vs not using) VHA health-related apps. We then assessed factors associated with VHA health-related app use using unadjusted and adjusted multiple logistic regression models. We selected variables for inclusion in the unadjusted model based on significant bivariate associations with the outcome variables and known associations from the existing literature; we selected variables for inclusion in the adjusted model based on significant unadjusted associations at the $P<.1$ level and known associations from the existing literature. Statistical analyses were performed with Stata MP (version 14.2; StataCorp).

Ethics Approval

This work was reviewed by the institutional review boards of the VHA Bedford Healthcare System in Bedford, Massachusetts, and the Edward Hines Jr VHA Hospital in Hines, Illinois. The study was designated as a program evaluation for quality improvement purposes, exempting it from further oversight (VHA Handbook 1058.05).

Results

Sample Characteristics

Descriptive statistics and results of bivariate analyses are presented in Table 1. Overall, a majority of the sample was male

(1069/1259, 84.9%), aged over 65 years (740/1259, 58.8%), White (1086/1259, 86.3%), and non-Hispanic (1218/1259, 96.7%). Most (1125/1259, 89.4%) reported being very comfortable and confident using computers, and over half (675/1259, 53.6%) reported being an early adopter of technology. Almost half (595/1259, 47.3%) reported using VHA health-related apps. Just over one-third (435/1259, 34.6%) reported that their VHA care team members encouraged them to use health-related apps.

Respondents reported having learned about VHA apps through the VHA's patient portal (468/1259, 37.2%), their VHA health care team (316/1259, 25.1%), the VHA's government website (139/1259, 11%), veteran service organizations (102/1259, 8.1%), newsletters (66/1259, 5%), other veterans (64/1259, 5%), public app stores (64/1259, 5%), and the VHA mobile app store (58/1259, 5%). These results are presented in Table 2.

Table 1. Comparison of demographic characteristics of veterans who were self-reported users or nonusers of health-related apps (N=1259).

Variable	Overall	Self-reported VHA[a] app users (595/1259; 47.3%)	Self-reported VHA app nonusers (664/1259; 52.7%)	*P* value
Demographics, n (%)				
Age older than 65 years	740 (58.8)	359 (60.3)	381 (57.4)	.29
Male	1069 (84.9)	505 (84.9)	564 (84.9)	.97
Race				.85
White	1086 (86.3)	512 (86.1)	574 (86.5)	
Black	118 (9.4)	55 (9)	63 (10)	
Other	55 (4)	28 (5)	27 (4)	
Hispanic ethnicity	41 (3)	24 (4)	17 (3)	.14
Relationship status: in a relationship[b]	906 (72)	426 (71.6)	480 (72.3)	.79
Education status: at least some college or vocational school[c]	1115 (88.6)	524 (88.1)	591 (89)	.60
Socioeconomic status[d]: "not very hard to pay for basics"	897 (71.3)	413 (69.4)	484 (72.9)	.17
Mostly receiving medical care at the VHA, n (%)	955 (75.9)	471 (79.2)	484 (72.9)	.009
Travel time to VHA[e]: more than 60 minutes, n (%)	198 (15.7)	82 (14)	116 (17.5)	.07
Perceived health status (fair/poor), n (%)	421 (33.4)	208 (35)	213 (32.1)	.28
Hierarchical Condition Community score, mean (SD)	1.6 (1.2)	1.7 (1.3)	1.5 (1.1)	.047
Technology use, n (%)				
Desktop or laptop computer	1184 (94)	571 (96)	613 (92.3)	.006
Tablet computer	721 (57.3)	356 (59.8)	365 (55)	.08
Smartphone	1123 (89.2)	541 (90.9)	582 (87.7)	.06
Early technology adopter	675 (53.6)	327 (55)	348 (52.4)	.37
Very comfortable or confident using computers	1125 (89.4)	540 (90.8)	585 (88.1)	.13
VHA health care team encouragement to use apps	435 (34.6)	276 (46.4)	159 (24)	<.001
Health conditions[f], n (%)				
Hypertension	726 (57.7)	345 (58)	381 (57.4)	.83
Osteoarthritis	716 (56.9)	347 (58.3)	369 (55.6)	.33
Diabetes	522 (41.5)	243 (40.8)	279 (42)	.67
Depression	515 (40.9)	252 (42.4)	263 (39.6)	.32
Chronic kidney disease	363 (28.8)	160 (26.9)	203 (30.6)	.15
Ischemic heart disease	340 (27)	165 (27.7)	175 (26.4)	.58
Asthma	302 (24)	140 (23.5)	162 (24.4)	.72
Posttraumatic stress disorder	269 (21.4)	148 (24.9)	121 (18.2)	.004
Peripheral vascular disease	202 (16)	103 (17.3)	99 (15)	.25
Anxiety disorders	201 (16)	102 (17.1)	99 (15)	.28
Atrial fibrillation	155 (12.3)	69 (12)	86 (13)	.47
Heart failure	118 (9.4)	62 (10)	56 (8)	.23
Acute myocardial infarction	115 (9.1)	48 (8)	67 (10)	.21
Stroke	90 (7)	45 (8)	45 (7)	.59
Prostate cancer	68 (5)	35 (6)	33 (5)	.48
Traumatic brain injury	63 (5)	33 (6)	30 (5)	.40
Chronic obstructive pulmonary disease	53 (4)	25 (4)	28 (4)	.99

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Variable	Overall	Self-reported VHA[a] app users (595/1259; 47.3%)	Self-reported VHA app nonusers (664/1259; 52.7%)	*P* value
Colorectal cancer	20 (2)	9 (2)	11 (2)	.84
Lung cancer	17 (1)	7 (1)	10 (2)	.61

[a]VHA: Veterans Health Administration.

[b]Defined as married, in a civil union, or engaged; not being in a relationship was defined as being single, separated, divorced, or widowed.

[c]Defined as 1 to 4 years of college or vocational school or a master's, professional, or doctoral degree.

[d]Defined by the listed response to the question "How hard is it for you (and your family) to pay for the very basics like food and heating/cooling?"

[e]Response to the question "How many minutes does it usually take you to get to your healthcare practitioners office (your VHA primary care doctor's office)?"

[f]In the prior five years.

Table 2. Ways veterans reported having learned about Veterans Health Administration health-related apps. Respondents checked all options that applied to them.

Venue	Respondents (N=1259), n (%)
VHA[a] patient portal	468 (37.2)
VHA health care team members	316 (25.1)
VHA website	139 (11)
Veteran service organizations	102 (8.1)
Newsletters	66 (5)
Other veterans	64 (5)
Public app stores	64 (5)
VHA mobile app store	58 (5)
Other	17 (1)
Do not remember	12 (1)
At the hospital	12 (1)
VHA employee	7 (1)
Phone	6 (1)
Television	2 (0.2)

[a]VHA: Veterans Health Administration.

Bivariate Comparisons of VHA Health-Related App Users and Nonusers

Bivariate analyses comparing respondents who reported using (vs not using) VHA health-related apps revealed that the former included greater proportions of veterans with PTSD (148/595, 24.9% vs 121/664, 18.2%; *P*=.004) and veterans who reported owning a desktop or laptop computer (571/595, 96% vs 613/664, 92.3%, *P*=.006), mostly receiving their medical care at the VHA (471/595, 79.2% vs. 484/664, 72.9.%; *P*=.009), and being encouraged by their VHA care team to use the apps (276/595, 46.4% vs 159/664, 24%; *P*<.001). In addition, veterans who self-reported using VHA health-related apps had a higher average HCC score than those who did not (mean HCC score 1.7 vs 1.5, respectively; *P*=.05).

Factors Associated with VHA Health-Related App Use

Results from the unadjusted and adjusted multiple logistic regression models assessing factors associated with self-reported VHA health-related app use are presented in Table 3. These analyses indicated that veterans who reported mostly receiving care at the VHA (OR 1.3, 95% CI 1.0-1.7), were in worse health (as assessed by HCC score; OR 1.1, 95% CI 1.0-1.2), reported owning a desktop or laptop computer (OR 1.8, 95% CI 1.1-3.1), had PTSD (OR 1.4, 95% CI 1.1-1.9), and reported having VHA health care team members encourage them to use the apps (OR 2.7, 95% CI 2.1-3.4) were more likely to self-report having used VHA health-related apps.

Table 3. Results of multiple logistic regression analysis of factors associated with Veterans Health Administration health-related app use (N=1259). *P<.05, **P<.01, ***P<.001.

Variable	Unadjusted odds ratio (95% CI)	Adjusted odds ratio (95% CI)
Age older than 65 years (reference: age younger than 65 years)	1.1 (0.9-1.4)	N/A[a]
Male (reference: female)	1.0 (0.7-1.4)	N/A
Race (reference: White)		
Black	1.0 (0.7-1.4)	N/A
Other	1.2 (0.7-2.0)	N/A
Hispanic ethnicity (reference: non-Hispanic ethnicity)	1.6 (0.9 -3.0)	N/A
Relationship status: in a relationship[b] (reference: not in a relationship)	0.97 (0.8-1.2)	N/A
Education status: at least some college or vocational school (reference: less than some college education)	0.9 (0.6-1.3)	N/A
Socioeconomic status: "not very hard to pay for basics" (reference: "some hardship paying for basics")	0.8 (0.7-1.1)	N/A
Mostly receives medical care in the VHA[c] (reference: mostly receives medical care outside the VHA)	1.4** (1.1 -1.8)	1.3* (1.0 -1.7)
Travel time to VHA: >60 minutes (reference: ≤60 minutes)	0.8 (0.6 -1.0)	0.8 (0.6-1.1)
Perceived health status fair or poor (reference: good, very good, or excellent perceived health status)	1.1 (0.9-1.4)	N/A
Hierarchical Condition Community score (continuous)	1.1* (1.0-1.2)	1.1* (1.0-1.2)
Technology ownership (reference: does not own a device)		
Desktop or laptop computer	2.0* (1.2-3.3)	1.8* (1.1-3.1)
Tablet computer	1.2 (1.0-1.5)	1.2 (0.9-1.5)
Smartphone	1.4 (1.0-2.0)	1.2 (0.9-1.8)
Early technology adopter (reference: not an early technology adopter)	1.1 (0.9-1.4)	N/A
Very comfortable or confident using computers (reference: not very comfortable or confident using computers)	1.3 (0.9-1.9)	N/A
VHA health care team encouragement to use apps (reference: no health care team encouragement)	2.8*** (2.2-3.5)	2.7*** (2.1-3.4)
Health conditions[d]		
Hypertension	1.0 (0.8-1.3)	N/A
Osteoarthritis	1.1 (0.9-1.4)	N/A
Diabetes	1.0 (0.8-1.2)	N/A
Depression	1.1 (0.9-1.4)	N/A
Chronic kidney disease	0.8 (0.7-1.1)	N/A
Ischemic heart disease	1.1 (0.8-1.4)	N/A
Asthma	1.0 (0.7-1.2)	N/A
Posttraumatic stress disorder	1.5** (1.1-2.0)	1.4* (1.1-1.9)
Peripheral vascular disease	1.2 (0.9-1.6)	N/A
Anxiety disorders	1.2 (0.9-1.6)	N/A
Atrial fibrillation	0.9 (0.6-1.2)	N/A
Heart failure	1.3 (0.9-1.9)	N/A
Acute myocardial infarction	0.8 (0.5-1.2)	N/A
Stroke	1.1 (0.7-1.7)	N/A
Prostate cancer	1.2 (0.7-2.0)	N/A
Traumatic brain injury	1.2 (0.7-2.0)	N/A

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Variable	Unadjusted odds ratio (95% CI)	Adjusted odds ratio (95% CI)
Chronic obstructive pulmonary disease	1.0 (0.6-1.7)	N/A
Colorectal cancer	0.9 (0.4-2.2)	N/A
Lung cancer	0.8 (0.3-2.1)	N/A

[a]N/A: not applicable.

[b]Defined as married, in a civil union, or engaged; not being in a relationship was defined as being single, separated, divorced, or widowed.

[c]VHA: Veterans Health Administration.

[d]In the prior five years.

Discussion

Principal Findings

Our analyses suggest that veterans had greater odds of self-reporting use of VHA health-related apps if they mostly received their health care from the VHA, were in worse health, owned a desktop or laptop computer, and had a PTSD diagnosis. Perhaps most importantly, our analyses also showed that health care team member encouragement to use the apps was strongly associated with self-reported use. Veterans who reported receiving encouragement from their VHA care team members had nearly 3 times higher odds of using VHA apps to manage their health than veterans who did not report receiving such encouragement.

This finding confirms results from previous surveys of veterans demonstrating a positive association between health care team member recommendations to use an app and veteran interest in app use [26]. This finding is also aligned with research that extends beyond the veteran population suggesting that health-related app adoption may be bolstered if it is recommended by a source that the target user trusts and finds credible [19], such as the target user's health care providers [14,17,33]. Taken together, our findings, along with these related studies, contribute to growing evidence regarding the importance of the role health care providers need to play to achieve widespread adoption of health-related apps. Based on this evidence, we recommend that health care systems committed to increasing the use of health-related apps in their patient populations consider how best to prepare their frontline clinical staff to engage with patients about apps that may be relevant to them. Such preparation could include, but is not limited to, educating health care team members about apps that are available for patients and evidence regarding their effectiveness, creating tools (eg, prescription pads for health-related apps or reminders and decision aids in the electronic health record) that can be used to cue action and remind patients about health care team member recommendations, and training health care team members on how best to have these conversations with patients or creating pathways for them to refer patients to other local experts who can talk with them about health-related apps.

Our analyses also revealed that certain patient demographics and health conditions were positively associated with app adoption. Prior research conducted outside the veteran population has shown that app adoption is associated with specific sociodemographic characteristics, including female sex, younger age, more education, higher socioeconomic status

(SES), and better health status [9,18]. Our results differ, however, in that we did not find associations based on age, gender, education, or SES, and found an opposite association between health status and app use, namely, we found that veterans who were in worse health had greater odds of using VHA health-related apps. This may be related to our findings on encouragement; veterans who are in poorer health and those who report mostly receiving their health care from the VHA might have more frequent interactions with their providers and the health care system, which might drive increased app use. Additional research on how patients can best integrate the health-related apps they adopt into their self-management practices and sustain their use over time is also needed, as are studies of how clinical team members can best integrate the data from these apps into their clinical decision-making and workflows.

In interpreting these findings, it is important to note that our sample consisted of veterans who were established health-technology users and, as such, they may have had higher levels of technology literacy. It is possible that removing technology literacy as a barrier would affect the relationship between health status and app adoption. This is particularly important because patients who have more chronic conditions may benefit more from using health-related apps and because technology literacy is a modifiable factor [34], as it can be taught. Recent systematic reviews have underscored the importance of technology literacy as a factor in the use of consumer health informatics applications [35].

Similarly, the veterans in our sample reported having learned about VHA health-related apps from a variety of sources, the most frequently reported of which were directly tied to the VHA health care system. Sources included the VHA's online patient portal, VHA health care team members, and the VHA's government website. Of note, the VHA understands the importance of its online patient portal in driving adoption of other VHA health-related apps, and leverages the system to promote, market, and direct veterans to these resources in an effort to increase engagement in care and self-management. In this way, use of one patient-facing technology can beget the use of others, suggesting the importance of interventions to support the use of other technologies (as reported by Grossman et al [36]) and their potential to indirectly impact further technology adoption. Lack of awareness or knowledge of health-related apps among patients has already been recognized as a barrier to their adoption [14,16,17,37]. Our findings suggest that, at least in the case of veterans, interactions with and resources

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from the health care system might present effective opportunities for patients to learn about health-related apps and, in turn, overcome these barriers. While the VHA has demonstrated success using its online patient portal for this purpose, we recommend that health care systems also consider the potential of other patient-facing technologies available to their patient populations as potential platforms for promoting use of other health-related apps. For example, health care systems that are already using automated text-messaging systems to reach and remind patients could consider creating specific text messages designed to market the availability of other apps.

Of note, we also found that veterans with PTSD had greater odds of self-reporting use of VHA health-related apps. Interestingly, the results of our unadjusted analyses did not suggest that there were differences in app use among veterans with other diagnosed health conditions. While our data cannot speak to the specific reasons for this finding, we suspect that it may be driven in part by the fact that the VHA has more available and established apps relevant to PTSD, as well as conditions highly comorbid with PTSD, including depression, anxiety disorders, and insomnia, and these apps may thus be promoted more frequently than others.

Relatedly, a recent systematic review of available VHA and Department of Defense mental health–related apps found that while efficacy data for many such apps were emerging, research did indicate the efficacy of the PTSD Coach and Virtual Hope Box apps [23]. In addition, the VHA has several apps available to support behavioral health treatments commonly received by veterans with PTSD (ie, CPT Coach, PE Coach, and CBTi Coach), which behavioral health care providers may be encouraging veterans to use in tandem with treatment, thus bolstering adoption. Industry data also suggests that this trend is not specific to the VHA. In general, digital health products focused on psychiatric concerns have experienced more growth over the past decade than products focused on other health concerns [38]. We recommend health care systems see use of mental health–related apps as a potential opportunity to suggest other health-related apps to patients that may be valuable for addressing their other health and well-being needs.

Limitations

We cannot infer causal relationships from our analyses, and self-reported survey data are subject to biases. The veterans who compose the VET-C cohort were also intentionally sampled because they were users of another VHA patient-facing technology, the health care system's patient portal. In addition

to potentially being more likely to use technology, previous research has indicated that veterans who use the VHA's portal are more educated, younger, and have higher income than the overall veteran population [39,40], which could limit the generalizability of our findings to the overall veteran population. It is important to note, however, that to ensure the privacy and security of user's health data, many of the VHA's mobile apps require veterans to sign in through a secure sign-in partner, the options for which include a DS Logon Level 2 (Premium), ID.me, or My HealtheVet Premium account. In this way, the VET-C cohort, which comprises veterans who have a My HealtheVet Premium account, may more broadly reflect veterans who use the VHA's mobile health apps. In addition, we acknowledge that the health-related apps the VHA offers are evolving, and those available at the time we completed this project may have had differing levels of relevance to the needs of different segments of the veteran population. The VET-C cohort is also characterized by more homogeneity in important demographic factors, including education and SES levels, than the overall veteran population, which may further limit generalizability. The limited number of female veterans in our sample may have further curtailed our ability to detect differences associated with gender. Finally, as with any effort to collect longitudinal data, there was attrition between the administration of our baseline survey and our second-round survey, which could have introduced response bias.

Conclusions

In this survey of veterans, we found that nearly half of respondents self-reported use of VHA health-related apps and that encouragement from a veteran's health care team was a critical factor associated with self-reported app use. Veterans predominantly reported learning about available health-related apps through other VHA technologies or their VHA health care team members. These results add to growing evidence suggesting that endorsement of apps by a health care system or health care providers can positively impact patient uptake and use. Future work should examine approaches to supporting efforts by health care team members to engage with patients about apps that may be most beneficial to their health, as well as ways to support shared decision-making regarding which apps to use and how best to integrate them as components of care and self-management. Such approaches could be included as part of multicomponent implementation strategies and tested to determine their impacts on the adoption of health-related apps by patients.

Disclaimer

The views expressed in this article are those of the authors and do not necessarily reflect the position and/or policy of the Department of Veterans Affairs or the United States Government.

All evaluation procedures described in this manuscript were completed in accordance with the ethical standards of the responsible committee on human experimentation (institutional or regional) and with the Helsinki Declaration.

Conflicts of Interest

None declared.

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Abbreviations

CDW: corporate data warehouse
HCC: Hierarchical Condition Community
OR: odds ratio
PTSD: posttraumatic stress disorder
SES: socioeconomic status
VET-C: Veterans Engagement with Technology Collaborative
VHA: Veterans Health Administration

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<u>Original Paper</u>

Preliminary Use and Outcome Data of a Digital Home Exercise Program for Back, Hip, and Knee Pain: Retrospective Observational Study With a Time Series and Matched Analysis

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Abstract

Background: Musculoskeletal conditions are among the main contributors to the global burden of disease. International guidelines consider patient education and movement exercises as the preferred therapeutic option for unspecific and degenerative musculoskeletal conditions. Innovative and decentralized therapeutic means are required to provide access to and availability of such care to meet the increasing therapeutic demand for this spectrum of conditions.

Objective: This retrospective observational study of preliminary use and outcome data explores the clinical outcomes of Vivira (hereafter referred to as "program"), a smartphone-based program for unspecific and degenerative pain in the back, hip, and knee before it received regulatory approval for use in the German statutory health insurance system.

Methods: An incomplete matched block design was employed to assess pain score changes over the intended 12-week duration of the program. Post hoc analyses were performed. In addition, a matched comparison of self-reported functional scores and adherence rates is presented.

Results: A total of 2517 participants met the inclusion criteria and provided sufficient data to be included in the analyses. Overall, initial self-reported pain scores decreased significantly from an average of 5.19 out of 10 (SD 1.96) to an average of 3.35 out of 10 (SD 2.38) after 12 weeks. Post hoc analyses indicate a particularly emphasized pain score reduction over the early use phases. Additionally, participants with back pain showed significant improvements in strength and mobility scores, whereas participants with hip or knee pain demonstrated significant improvements in their coordination scores. Across all pain areas and pain durations, a high yet expected attrition rate could be observed.

Conclusions: This observational study provides the first insights into the clinical outcomes of an exercise program for unspecific and degenerative back, hip, and knee pain. Furthermore, it demonstrates a potential secondary benefit of improved functionality (ie, strength, mobility, coordination). However, as this study lacks confirmatory power, further research is required to substantiate the clinical outcomes of the program assessed.

Trial Registration: German Clinical Trials Register DRKS00021785; https://drks.de/search/en/trial/DRKS00021785

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Introduction

Musculoskeletal conditions (MSCs) are among the most important contributors to the global burden of disease [1]. As the most prevalent disorders among working populations, they not only contribute greatly to direct but also to indirect health care costs [2]. At the same time, the access to and availability of adequate therapeutic means for the MSC spectrum remain challenging [3]. Yet, it has repeatedly been shown that different kinds of physical activity (PA), especially structured exercise programs, effectively address certain kinds of MSCs. This particularly applies to unspecific and degenerative musculoskeletal pain (MSP) [4-6].

PA has been studied in numerous digital health intervention studies far beyond the clinical spectrum of MSC. A recent meta-analysis by Mönninghoff et al [7] showed that PA (measured as walking standardized mean difference, moderate-to-vigorous physical activity standardized mean difference, total physical activity standardized mean difference, and energy expenditure standardized mean difference) could be improved at the end of the intervention. Nevertheless, effect sizes decreased over time in the 33 studies reporting short-term and in the 8 studies reporting long-term (ie, postintervention) follow-up. Additionally, effect sizes were moderated by the study population, with higher effect sizes in sick and at-risk populations (ie, sedentary, older, overweight), indicating the higher impact of digital health interventions for such populations and the necessity to evaluate digital health interventions in respective clinical settings thoroughly.

Focusing on PA changes in patients with chronic MSP, a meta-analysis by Oliveira et al [8] found that PA interventions compared to no or minimal interventions in patients with chronic muscular pain showed no significant improvement over short-term, intermediate, or long-term follow-up. Most of these studies delivered their intervention in a nondigital blended approach consisting of an instructional part in a face-to-face setting and an exercise part to be completed independently at home. In comparison to the review by Mönninghoff et al [7], only 1 study included in the review by Oliveira et al [8] used a digital component (web-based PA intervention over 9 weeks that incorporated a baseline test; goal setting, time-contingent physical activity objectives; and text messaging to promote physical activity). However, the relatively low number of studies included (8 randomized controlled trials) in Olivera et al [8] may substantially limit this finding and highlights the need for further studies investigating the effect of interventions on PA in MSC patients and the added effect of using digital components in interventions.

To address the outlined challenge, this study presents preliminary use data of Vivira, a smartphone-based program for unspecific and degenerative pain in the back, hip, and knee. It also demonstrates early data on self-reported pain score reductions and functional improvements, as well as data on adherence to the program.

Methods

Study Design

This study presents observational data on the primary outcome of overall pain score reduction and the secondary outcomes of reporting interval-specific and stratum-specific pain score reductions, functional improvement, and retention to the program. Clinical outcomes are collected with self-reported pain scores, assessed with a verbal-numerical rating scale (VNRS), which has been established to be a reliable [9] and valid instrument [10] to capture pain score intensity as a participant-reported outcome measure. The primary hypothesis test for assessing pain score changes is a nonparametric, 2-sided Skillings-Mack test, outlined elsewhere in detail [11]. In brief, it allows the analysis of an unbalanced and incomplete block design with relevant missing data by design or random. The functional assessment is developed based on established orthopedic functional tests and employs the principles of functional regional interdependence [12-15]. To enable a participant-directed self-assessment, these tests are presented with audiovisual guidance. Results are entered on a binary scale (ie, the test could be completed, or the test could not be completed). In this study, through expert consensus of a panel of orthopedic surgeons and physical therapists, the weighted transformation of the functional tests was performed to compute discrete functional scores. A Wilcoxon signed-rank test, a Kruskal-Wallis test, and a 1-way ANOVA were used for secondary analyses of pain and functional scores. Distributions were assessed using the Bartlett test.

Corrections for familywise errors were performed using the Bonferroni procedure. Retention was assessed based on whether participants started to use the program (ie, completed at least 1 exercise) and submitted a complete pain assessment at predefined thresholds (2 weeks, 4 weeks, 8 weeks, and 12 weeks). Participants were enrolled through a self-selection process of voucher-based mass campaigns and early self-pay subscriptions between January 9, 2018, and June 15, 2020. Inclusion criteria are outlined in Textbox 1. Additional data on the pain duration (ie, acute, <6 weeks; subacute, 6-12 weeks; chronic, ≥12 weeks [16]) were collected to allow stratum-specific analyses.

Textbox 1. Inclusion criteria for this study.

- Age ≥18 years
- Report of any applicable pain area (ie, upper back, lower back, hip, or knee)
- Initial pain score assessed with the verbal-numerical rating scale (VNRS) >0/10
- Completion of at least 1 exercise during the study period

Ethics Approval

This study received approval from the ethics committee of the Landesärztekammer Baden-Württemberg (state physician chamber of Baden-Württemberg) under the reference F-2020-075 and is registered with the German Clinical Trials Register DRKS under the reference DRKS00021785.

Exercise Program and Composition of Exercise Regimes

The program investigated was a smartphone-based application that is Conformité Européenne (CE) marked and approved as a medical device directive (MDD) class I medical device. It consists of a series of specific exercises that include a multidimensional progression module. In brief, participants were guided through a pain and functional assessment at baseline and were prompted to provide multiloop feedback (ie, after each exercise, as well as on a weekly and monthly basis) as to whether they could complete the individual exercises presented and whether these exercises caused any complaints. If a complaint, primarily any pain sensation, was reported, the progression module was paused, and the intensity of the exercise program was reassessed. Overall pain score assessments were collected every week, and a follow-up functional assessment was prompted every month. Figure 1 presents a schematic illustration of the baseline assessment (A-C) and the progression module (D-G).

Figure 1. Examples of the baseline assessment and the progression module. A. Patients are prompted to perform certain exercises with visual and text-based aids. B. Pain and movement limitations are assessed. C. A baseline functional score is computed and used as the intraindividual benchmark for further assessments. D. After the completion of any exercise, patients are required to report any pain sensations. E. If pain is reported, a warning is issued. F. Patients can select whether they want to exclude the exercise from their training program, or whether they want to regress to an easier version of the same exercise. G. The exercise program proceeds to the next exercise. "(...)" indicates that not all screens of the dialogue are shown.
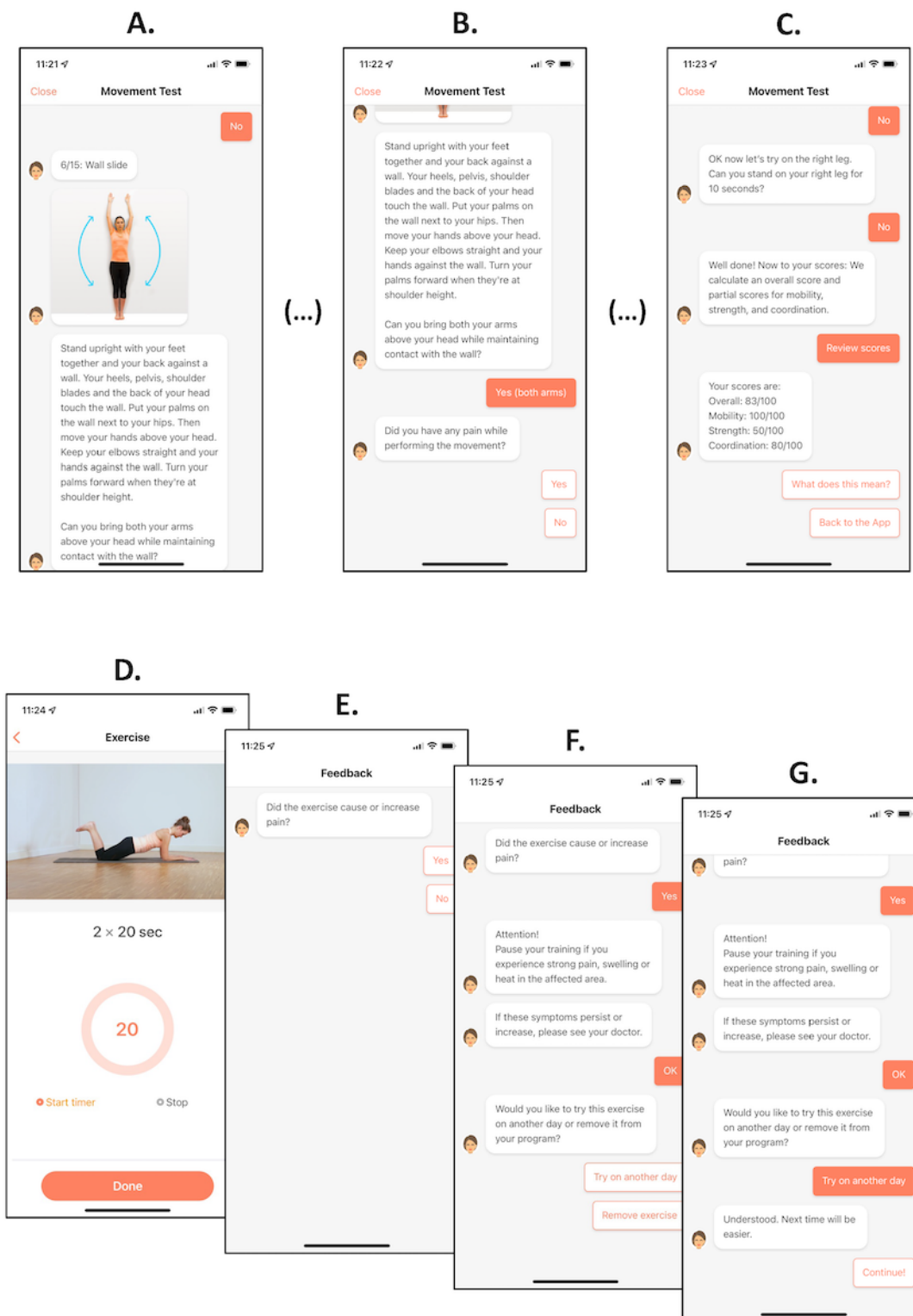
Statistical Analysis

Tests for Pain Reduction

The primary hypothesis test for assessing pain score changes is a nonparametric, 2-sided Skillings-Mack test, which is particularly useful for an unbalanced and incomplete block design or in the presence of missing data due to design or missing at random. For self-reported pain scores, the number of observations for the block, the median of the measurement, and the standard deviation were reported for each Skillings-Mack. We used the Bonferroni correction to control

familywise errors and reported corrected alpha levels. A Wilcoxon signed-rank test, a Kruskal-Wallis test, and a 1-way ANOVA were employed for secondary analyses of pain and functional scores. Distributions were assessed using the Bartlett test. Corrections for familywise errors were again performed by using Bonferroni correction.

Tests for Functional Scores

A time analysis was not feasible for functional scores, and matched pairs were calculated. Based on a Shapiro-Wilk test, a normal distribution could not be assumed. We used a nonparametric method to analyze the functional scores shown. Consequently, the hypothesis test used was a Wilcoxon signed-rank test, and the IQR is reported. After adjustment for familywise errors using Bonferroni correction, statistical significance was assumed when the probability of a type I error was $P<.0167$.

Assessment of Retention

Retention was assessed based on whether participants completed at least 1 exercise and submitted a full pain assessment at predefined thresholds (2 weeks, 4 weeks, 8 weeks, and 12 weeks). We hence report the proportions of the initially included study population.

Results

Study Population

As the study population at hand was enrolled prior to the program being subject to a prescription by physicians and other authorized health care providers, the enrollment was primarily based on self-selection through out-of-pocket pay or the use of voucher codes, which were handed out through marketing campaigns over the period of the data collection to evaluate the program at hand. A total of 2517 participants (63% female, mean age 47.08, SD 14.61 years) met the inclusion criteria and provided at least 2 data points necessary for the intraindividual control over 12 weeks. Measurements were collected after 2, 4, 8, and 12 weeks of use. Demographic characteristics on age and sex were collected to investigate differences of age groups in pain duration (ie, acute, subacute, chronic, not specified) and pain area (ie, lower back, upper back, hip, knee). Baseline demographics are displayed in Table 1. At baseline, 1864 (74.06%) patients did not receive physiotherapy in addition to Vivira, while 653 (25.94%) received physiotherapy in addition to Vivira. Moreover, 2023 (80.37%) patients reported at baseline that they did not take any pain medication, while 494 (19.63%) reported that they took pain medication.

Table 1. Baseline characteristics of the study population.

Characteristics	Reported pain area				Reported pain duration			
	Lower back, n (%)	Upper back, n (%)	Hip, n (%)	Knee, n (%)	Acute, n (%)	Subacute, n (%)	Chronic, n (%)	Not speci-fied, n (%)
Age								
18-35	312 (24.4)	196, (42.8)	58 (18.6)	148 (31.6)	110 (37.9)	85 (36.3)	243 (26.2)	276 (25.9)
36-45	255 (20)	71 (15.5)	52 (16.7)	58 (12.4)	59 (20.3)	46 (19.7)	145 (15.6)	186 (17.5)
46-55	340 (26.6)	118 (25.8)	94 (30.1)	87 (18.6)	69 (23.8)	48 (20.5)	236 (25.4)	286 (26.9)
56-65	268 (21)	46 (10)	82 (26.3)	126 (26.9)	38 (13.1)	36 (15.4)	230 (24.8)	218 (20.5)
66-75	82 (6.4)	23 (5)	22 (7.1)	45 (9.6)	13 (4.5)	18 (7.7)	68 (7.3)	73 (6.9)
75+	15 (1.2)	2 (0.4)	4 (1.3)	4 (0.9)	1 (0.3)	1 (0.4)	6 (0.6)	17 (1.6)
Not available[a]	6 (0.5)	2 (0.4)	__[b]	1 (0.2)	—	—	—	9 (0.8)
Sex								
Female	770 (57)	318 (69.4)	211 (67.6)	287 (61.2)	182 (62.8)	138 (59)	638 (68.8)	628 (59)
Male	580 (43)	140 (30.6)	101 (32.4)	182 (38.8)	108 (37.2)	96 (41)	290 (31.3)	437 (41)

[a]Not available because some patients did not provide their age when asked in the initial interaction.

[b]No patients in the population with this specification existed.

Overall Pain Reduction

We saw a substantial reduction in self-reported pain scores across 2, 4, 8, and 12 weeks ($t_{2516}=2728.27$, $P=.03$). Self-reported pain scores at the start were, on average, 5.19 (SD 1.96) out of 10; after 2 weeks, 3.72 (SD 2.06) out of 10; after 4 weeks, 3.39 (SD 2.35) out of 10, after 8 weeks, 3.19 (SD 2.44) out of 10; and after 12 weeks, 3.35 (SD 2.38) out of 10. These differences are illustrated in Figure 2 and described in Tables 2 and 3.

Figure 2. Average self-reported pain score for each retention period for all pain areas. Centerline (green), median; boxplot limits, upper and lower quartiles; whiskers, 1.5x IQR; points, outliers; $P<.05 =$* for the Skillings-Mack Test. Skillings-Mack Test for Initial, Week 2, Week 4, Week 8, Week 12. $T_{2516}=2728.27$, $T<.05$
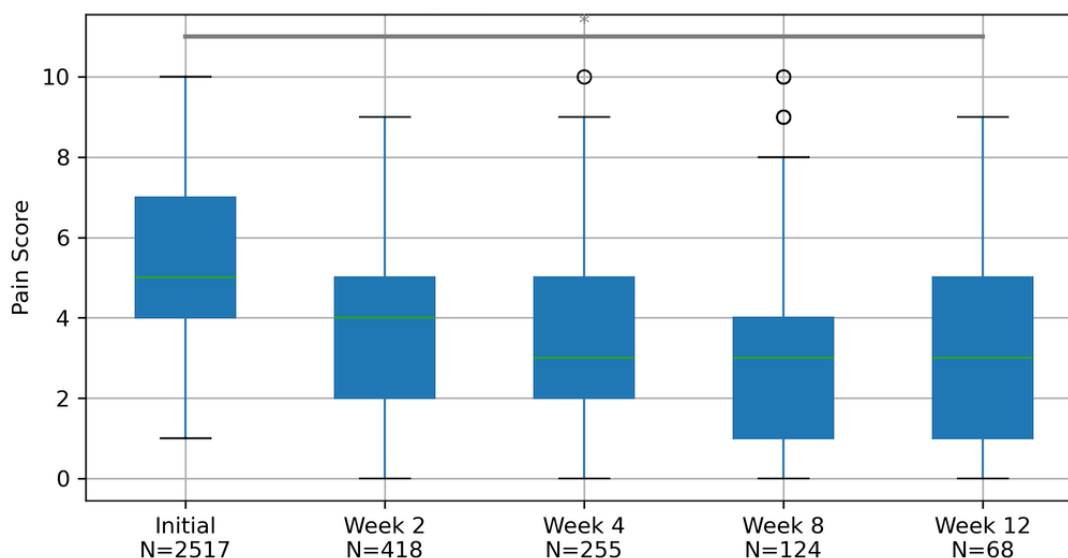

Table 2. Self-reported pain scores and changes across indication subsets and reported pain duration by retained days.

Pain Area	Lower back	Lower back	Lower back	Lower back	Lower back	Upper back	Upper back	Upper back	Upper back	Upper back
Pain duration	All	Acute	Subacute	Chronic	Not specified	All	Acute	Subacute	Chronic	Not specified
Initial, n (%)	1278 (37)	144 (4)	107 (3)	443 (13)	584 (17)	458 (13)	74 (2)	50 (1)	170 (5)	164 (5)
Initial, mean (SD)	5.33 (1.98)	4.47 (1.76)	5 (1.54)	5.37 (1.84)	5.57 (2.13)	5.19 (1.84)	4.57 (1.76)	4.96 (1.74)	5.15 (1.73)	5.57 (1.93)
Week 2, n (%)	202 (36)	30 (5)	26 (5)	120 (21)	26 (5)	81 (14)	15 (3)	15 (3)	47 (8)	4 (1)
Week 2, mean (SD)	3.97 (2.04)	3.23 (2.1)	3.54 (1.73)	4.2 (2.05)	4.19 (2.02)	3.65 (2.11)	3.13 (2.53)	4.27 (2.22)	3.57 (1.93)	__[a]
Week 4, n (%)	119 (36)	16 (5)	17 (5)	69 (21)	17 (5)	46 (14)	11 (3)	4 (1)	26 (8)	5 (2)
Week 4, mean (SD)	3.63 (2.38)	2.19 (1.56)	3.71 (1.99)	4.12 (2.39)	2.94 (2.77)	2.91 (2.03)	3.18 (1.89)	—	2.81 (2)	—
Week 8, n (%)	57 (39)	10 (7)	4 (3)	39 (26)	4 (3)	17 (11)	4 (3)	2 (1)	9 (6)	2 (1)
Week 8, mean (SD)	3.58 (2.41)	2.6 (2.12)	—	4 (2.52)	—	3.65 (2.98)	—	—	3 (2.4)	9 (1.41)
Week 12, n (%)	33 (39)	5 (6)	3 (4)	23 (27)	2 (2)	9 (11)	0 (0)	0 (0)	7 (8)	2 (2)
Week 12, mean (SD)	4.12 (2.63)	2.8 (3.27)	—	4.35 (2.62)	—	3.67 (2.5)	—	—	2.86 (2.04)	—
SM[b] test value	1361.13	156.39	115.34	523.17	571.83	487.45	—	—	187.02	159.81
SM degrees of freedom	1271	143	106	439	580	457	—	—	169	163
SM adjusted values[c]	0.8	0.9	0.9	0.07	0.9	0.9	—	—	0.9	0.9

[a]No sufficient data was available to calculate the statistics.

[b]SM: Skillings-Mack.

[c]The adjusted *P* values were calculated using Bonferroni corrections.

Table 3. Self-reported pain scores and changes across indication subsets and reported pain duration by retained days.

Pain Area	Hip	Hip	Hip	Hip	Hip	Knee	Knee	Knee	Knee	Knee
Pain duration	All	Acute	Subacute	Chronic	Not specified	All	Acute	Subacute	Chronic	Not specified
Initial, n (%)	62 (23)	6 (2)	11 (4)	42 (16)	3 (1)	73 (27)	9 (3)	10 (4)	51 (19)	3 (1)
Initial, mean (SD)	3.87 (2.08)	3 (2)	4.09 (1.97)	3.93 (2.12)	—[a]	2.97 (1.91)	2.22 (1.56)	3.8 (1.32)	3.06 (2.01)	—
Week 2, n (%)	44 (24)	2 (1)	8 (4)	33 (18)	1 (1)	46 (26)	3 (2)	6 (3)	31 (17)	6 (3)
Week 2, mean (SD)	3.93 (2.43)	—	4 (1.51)	3.94 (2.73)	—	2.72 (2.33)	—	1 (0.89)	2.97 (2.24)	4 (3.03)
Week 4, n (%)	23 (23)	2 (2)	4 (4)	17 (17)	—	27 (27)	1 (1)	2 (2)	22 (22)	2 (2)
Week 4, mean (SD)	3.04 (2.46)	0.5 (0.71)	3.75 (2.99)	3.18 (2.38)	—	2.22 (1.91)	—	—	2.41 (2.02)	—
Week 8, n (%)	7 (13)	1 (2)	1 (2)	4 (8)	1 (2)	19 (37)	2 (4)	3 (6)	14 (27)	0 (0)
Week 8, mean (SD)	3.14 (2.04)	—	—	—	—	1.95 (1.18)	—	—	1.93 (1.33)	—
Week 12, n (%)	7 (13)	1 (2)	1 (2)	4 (8)	1 (2)	19 (37)	2 (4)	3 (6)	14 (27)	—
Week 12, mean (SD)	3.14 (2.04)	—	—	2.75 (2.06)	—	1.95 (1.18)	—	—	1.93 (1.33)	—
SM[b] test value	353.05	—	—	174.65	—	508.86	—	48.58	217.42	—
SM degrees of freedom	311	—	—	137	—	467	—	47	175	—
SM adjusted values[c]	0.9	—	—	0.35	—	0.9	—	0.9	0.34	—

[a]No sufficient data was available to calculate the statistics.

[b]SM: Skillings-Mack.

[c]The adjusted *P* values were calculated using Bonferroni corrections.

Post Hoc Analysis Comparison of Sequential Data Entry Points

We calculated further post hoc tests to investigate the effect of different assessment times and, consequently, different durations of exposure to the program. We used the Bonferroni method to adjust for familywise errors. First, we calculated a Wilcoxon signed-rank test to investigate to what degree a change in pain reduction occurred in participants that provided self-reported data at the initial assessment and after using the home exercise program for 2 weeks. We found a significant difference between the initial assessment (median 5) and the assessment after 2 weeks (median 4; t_{417}=8219.5, P<.001). Second, we calculated a Kruskal-Wallis test showing that the self-reported pain values differed significantly between the initial (median 5), 2-week (median 3), and 4-week assessments (median 3; t_{166}=60.56, P<.001). Third, we calculated a Kruskal-Wallis test showing that the self-reported pain values differed significantly between the initial (median 4), 2-week (median 3), 4-week (median 3),

and 8-week assessments (median 3, t_{66}=25.16, P<.001). Finally, as this subsample was normally distributed and had an equal variance as indicated by Bartlett test, we calculated a 1-way ANOVA showing a nonsignificant difference in self-reported pain for the initial (mean 4.62, SD 2.12), 2-week (mean 3.5, SD 2.39), 4-week (mean 3.2, SD 2.48), 8-week (mean 2.8, SD 2.44), and 12-week (mean 2.66, SD 2.51) assessments (F_{23}=2.51, P=.18). Figure 3 illustrates these findings and highlights that, given the retention outlined below, shorter exercise periods also showed an overall clinical outcome on pain score reduction. Finally, we investigated whether the initial pain score differed for patients completing the intervention (providing a final data point after 12 weeks) and for patients who did not complete the intervention. Using a Mann-Whitney *U* rank test, we found no significant difference between the reported initial pain of the group providing a data point after 12 weeks (n=68, median 5) and the group providing no data point after 12 weeks (n=2449, median 5; U=79470, P=.516).

Figure 3. Post hoc results for self-reported pain scores when comparing different assessment times. Centerline (green), median; boxplots limits, upper and lower quartiles; whiskers, 1.5x IQR; points, outliers; *P* values for the Wilcoxon signed-rank test (initial and 2 weeks), the Kruskal-Wallis test (initial, 2 and, 4 weeks and initial, 2, 4, and 8 weeks), and the 1-way ANOVA (initial, 2, 4, 8, and 12 weeks) are displayed on the line.
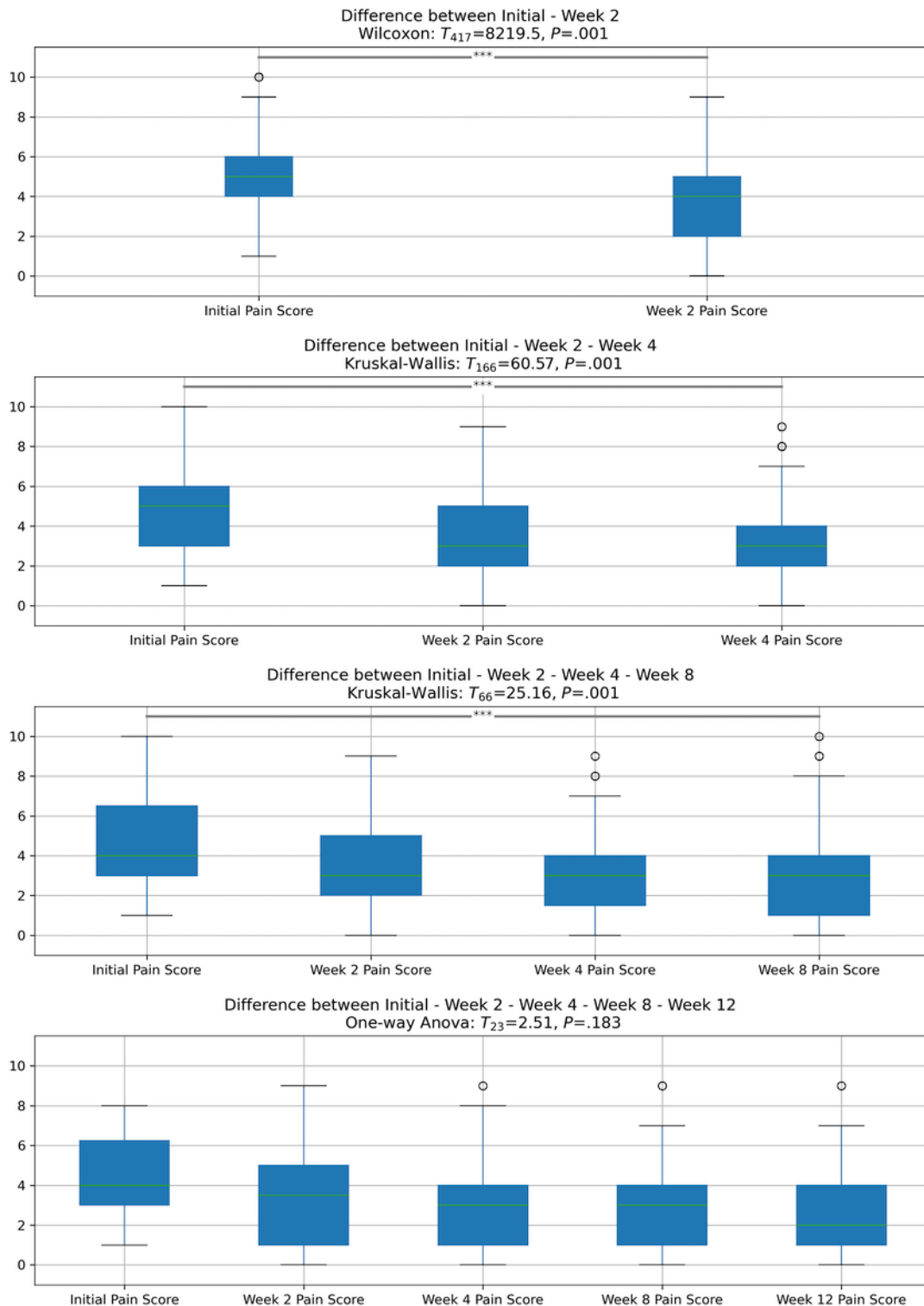
Stratum-Specific Changes in Pain Intensity

After stratifying the available data for pain area and pain duration as a secondary analysis, we saw a comparable response pattern across all pain areas. Participants with lower back pain reported a reduction in their initial pain score from 5.33 to 4.12 after 12 weeks of exercises (t_{1271}=1361.13, *P*=.80). The

subpopulation of participants with chronic lower back pain saw a marked improvement from 5.37 to 4.35 (t_{439}=523.17, *P*=.07). Similarly, participants with upper back pain reported a reduction of their pain intensity from 5.19 to 3.67 after completing the exercise program (t_{457}=478.45, *P*=.90). The pain score change in participants with hip pain was on a comparable trajectory; we saw a reduction from a baseline pain score of 5.21 to 3.14

after 12 weeks (t_{311}=353.05, P=.90). Finally, participants with knee pain saw an improvement from a baseline of 4.8 to 1.95 after completing the exercise program (t_{467}=508,86, P=.90). As the employed Skillings-Mack test cannot provide values for lacking blocks, no substratum analyses for acute and subacute upper back pain, acute, subacute, and nonspecified hip pain, and acute and nonspecified knee pain could be reported (Tables 2-3, Multimedia Appendix 1).

Functional Scores

Another secondary outcome was to assess the improvement of a set of functional scores. The lower and upper back showed significant improvement in strength and mobility and total functional score (Table 4). This finding is consistent with overall intervals of available submitted scores studied, except for the upper back, which did not have a significantly improved strength score between participants' first and fourth submissions (Table 5). For coordination, the upper back and lower back did not show significant improvement across any intervals of submitted scores studied, except for the upper back between the first and fourth submissions of functional scores, where a significant improvement in coordination score was observed (Table 6). The knee and hip showed a significant improvement in mobility (Table 5) and coordination (Table 6), as well as total functional (Table 3) score between the first and second submission of functional scores. However, they did not show a significant improvement in strength across any completed submission (Table 3). For the hip and knee, no significant improvement could be shown for mobility (Table 5), coordination (Table 6), and total functional score (Table 3) could be shown between the first and third and first and fourth submissions of functional scores.

For coordination, the upper back and lower back did not show significant improvement across any intervals of submitted scores studied, except for the upper back between the first and fourth submission of functional scores, where a significant improvement in coordination score was observed (Table 6). The knee and hip showed a significant improvement in mobility (Table 6) and coordination (Table 7), as well as total functional (Table 4) score between the first and second submission of functional scores. However, they did not show a significant improvement in strength across any completed submission (Table 4). For the hip and knee, no significant improvement was shown for mobility (Table 6), coordination (Table 7), and total functional score (Table 4) between the first and third and first and fourth submissions of functional scores.

Table 4. Total functional score for matched comparison and pain area.

Matched comparison and pain area	Pain area, n	Retained days, median (IQR)	Initial, median (IQR)	Last, median (IQR)	Test
First and second entry					
Lower back	132	29 (20.5-38.5)	60 (43-75)	71.5 (53-81.5)	P<.001
Upper back	38	29 (20.5-38.5)	65 (43-80)	71.5 (60-83)	P<.001
Hip	40	29 (20.5-38.5)	67 (43-77)	70 (55-80)	P<.05
Knee	47	29 (20.5-38.5)	70 (50-83)	80 (57-87)	P<.01
First and third entry					
Lower back	48	59 (48-80)	60 (43-75)	78.5 (60-87)	P<.001
Upper back	15	59 (48-80)	65 (43-80)	73 (63-87)	P<.05
Hip	16	59 (48-80)	67 (43-77)	60 (41.5-81.5)	P=.0525
Knee	20	59 (48-80)	70 (50-83)	80 (73-83)	P=.0348[a]
First and fourth entry					
Lower back	25	88.5 (72-112)	60 (43-75)	80 (67-87)	P<.05
Upper back	8	88.5 (72-112)	65 (43-80)	81.5 (67-96.5)	P<.05
Hip	5	88.5 (72-112)	67 (43-77)	67 (63-80)	P=.0625
Knee	13	88.5 (72-112)	70 (50-83)	80 (73-87)	P=.1592

[a]Due to adjustments to the P level (Bonferroni correction), these values are not significant.

Table 5. Strength functional score for matched comparison and pain area.

Matched comparison and pain area	Pain area, n	Retained days, median (IQR)	Initial, median (IQR)	Last, median (IQR)	Test
First and second entry					
Lower back	132	29 (20.5-38.5)	60 (30-80)	70 (40-100)	$P<.001$
Upper back	38	29 (20.5-38.5)	60 (40-80)	70 (60-100)	$P<.05$
Hip	40	29 (20.5-38.5)	60 (40-100)	80 (55-100)	$P=.0213$[a]
Knee	47	29 (20.5-38.5)	70 (50-90)	80 (60-100)	$P=.0249$[a]
First and third entry					
Lower back	48	59 (48-80)	60 (30-80)	80 (60-100)	$P<.001$
Upper back	15	59 (48-80)	60 (40-80)	80 (60-100)	$P<.05$
Hip	16	59 (48-80)	60 (40-100)	60 (45-95)	$P=.0498$[a]
Knee	20	59 (48-80)	70 (50-90)	80 (60-100)	$P=.0797$
First and fourth entry					
Lower back	25	88.5 (72-112)	60 (30-80)	80 (60-100)	$P<.05$
Upper back	8	88.5 (72-112)	60 (40-80)	80 (50-100)	$P=.1250$
Hip	5	88.5 (72-112)	60 (40-100)	60 (60-80)	$P=.3125$
Knee	13	88.5 (72-112)	70 (50-90)	90 (60-100)	$P=.0938$

[a]Due to adjustments to the P level (Bonferroni correction), these values are not significant.

Table 6. Mobility functional score for matched comparison and pain area.

Matched comparison and pain area	Pain area, n	Retained days, median (IQR)	Initial, median (IQR)	Last, median (IQR)	Test
First and second entry					
Lower back	132	29 (20.5-38.5)	60 (47.5-80)	70 (55-80)	$P<.001$
Upper back	38	29 (20.5-38.5)	62.5 (50-75)	70 (60-90)	$P<.001$
Hip	40	29 (20.5-38.5)	60 (45-77.5)	70 (50-80)	$P<.05$
Knee	47	29 (20.5-38.5)	60 (50-80)	70 (55-85)	$P<.01$
First and third entry					
Lower back	48	59 (48-80)	60 (47.5-80)	75 (60-85)	$P<.01$
Upper back	15	59 (48-80)	62.5 (50-75)	75 (60-90)	$P<.05$
Hip	16	59 (48-80)	60 (45-77.5)	65 (40-82.5)	$P=.1187$
Knee	20	59 (48-80)	60 (50-80)	80 (72.5-82.5)	$P=.1191$
First and fourth entry					
Lower back	25	88.5 (72-112)	60 (47.5-80)	70 (65-90)	$P<.05$
Upper back	8	88.5 (72-112)	62.5 (50-75)	82.5 (75-95)	$P<.05$
Hip	5	88.5 (72-112)	60 (45-77.5)	70 (65-70)	$P=.0625$
Knee	13	88.5 (72-112)	60 (50-80)	80 (70-85)	$P=.2695$

**Table 7.** Coordination functional score for matched comparison and pain area.

Matched comparison and pain area	Pain area, n	Retained days, median (IQR)	Initial, median (IQR)	Last, median (IQR)	Test
First and second entry					
Lower back	132	29 (20.5-38.5)	70 (40-80)	80 (55-80)	$P=.2806$
Upper back	38	29 (20.5-38.5)	80 (50-80)	80 (60-100)	$P=.0585$
Hip	40	29 (20.5-38.5)	60 (35-80)	80 (50-85)	$P<.05$
Knee	47	29 (20.5-38.5)	60 (40-80)	70 (50-80)	$P<.05$
First and third entry					
Lower back	48	59 (48-80)	70 (40-80)	80 (60-100)	$P=.2187$
Upper back	15	59 (48-80)	80 (50-80)	80 (60-100)	$P<.05$
Hip	16	59 (48-80)	60 (35-80)	70 (50-90)	$P=.1717$
Knee	20	59 (48-80)	60 (40-80)	80 (60-80)	$P=.0885$
First and fourth entry					
Lower back	25	88.5 (72-112)	70 (40-80)	80 (80-80)	$P=.6509$
Upper back	8	88.5 (72-112)	80 (50-80)	80 (60-100)	$P=.0938$
Hip	5	88.5 (72-112)	60 (35. 80)	80 (60-100)	$P=.0625$
Knee	13	88.5 (72-112)	60 (40-80)	80 (70-80)	$P=.2422$

Retention

As a third secondary analysis, the retention rate for the program at hand was examined. The overall retention rate was 17% after 2 weeks, 10% after 4 weeks, 4% after 8 weeks, and 3% after 12 weeks (Table S1 in Multimedia Appendix 1). This high attrition was present in all subpopulations, and no difference in the loss to follow-up patterns could be detected. However, total attrition could be observed in participants with pain in the lower back and nonspecified pain duration, upper back with acute and subacute pain durations, and knee with a nonspecified pain duration (Table S1 in Multimedia Appendix 1). Nonetheless, we noticed a tendency toward higher retention rates among participants with chronic pain (Figure 4).

Figure 4. Retention rate for different pain areas and durations.
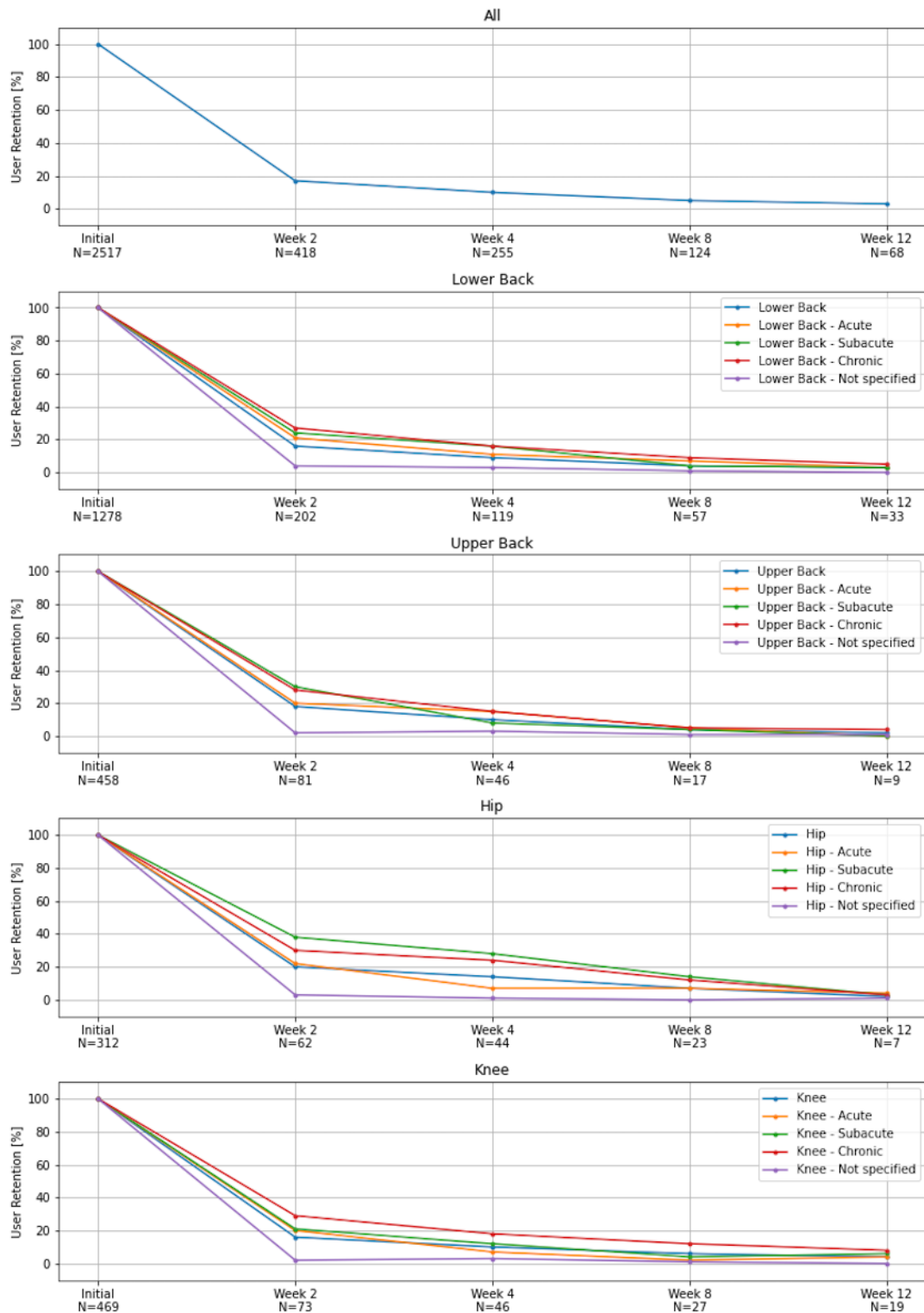
Discussion

A Digital Home Exercise Program Can Lead to Significant Improvements in Pain Scores

Because exercise is known to effectively address unspecific and degenerative musculoskeletal pain [4-6], a digitally guided home exercise program was a priori considered a practical therapeutic intervention to address this spectrum of conditions. The overall analysis of the data set supports this assumption and shows a significant improvement in self-reported pain scores based on a VNRS (Figure 2, Table 2). Although the presented observational data do not yield confirmatory power, we consider the improvement of self-reported pain scores an effect of the home exercise treatment and not an indicator of spontaneous improvement. This consideration is based on prior research demonstrating a lower-than-expected rate of spontaneous improvement for MSP in general and for back pain in particular

[17]. These findings were particularly emphasized in participants with established or chronic pain [18]. Hence, participants with chronic pain were greatly overrepresented in our study population, at 36.9% (n=928) at baseline and 70.6% (n=48) after 12 weeks of follow-up, compared to an expected prevalence of chronic back pain of 15.5% in the source population [19], so we deem this interpretation applicable. Additional post hoc analyses showed significant improvements between the initial and 2-week assessments, the initial, 2-week, and 4-week assessments, and the initial, 2-week, 4-week, and 8-week assessments. Yet, they failed to show significant improvements between all assessment time points (Figure 4). We conclude from these analyses that an indicator for an overall improvement in pain scores is given and that shorter periods of exposure to the home exercise program yielded significant pain score improvements over the abbreviated time points (ie, up until 8 weeks). Nevertheless, conclusions based on this data set warrant careful interpretation, as a high attrition rate is prone to bias.

Secondary Analyses of Subpopulations Did Not Yield Relevant Pain Score Reductions

An exploratory stratification across different pain areas (ie, upper back, lower back, hip, and knee) and different pain durations (ie, acute, subacute, and chronic pain) did not significantly improve the pain scores reported. However, repeated corrections for familywise errors were required to perform this analysis correctly. Therefore, a significantly lower alpha level had to be applied. From the insignificant improvements, however, we saw a tendency toward a relevant improvement in pain scores for lower back $(P=.039)$, hip $(P=.05)$, and knee $(P=.088)$. These data suggest a more nuanced response to a home exercise program across different pain areas. However, the available data did not provide a sufficient density to investigate this issue thoroughly.

Functional Improvements Showed a Differential Pattern

Except for hip and knee, significant improvements in strength and mobility could be detected between the first and the second assessment of the functional ability. However, participants with hip and knee pain showed a significant response in terms of increasing their coordination. This indicates a secondary benefit of the examined program. Interestingly, participants with lower back pain showed a particularly sustained response over an extended period (median follow-up of 88.5 days, IQR 72-112) in the dimensions of strength and mobility. We interpret this as an indicator of a differential functional response to the respective exercise programs. Because the transformation of the functional test results (ie, the test could be completed successfully or the test could not be completed successfully) into a discrete score (ie, mobility, strength, coordination, and total score) was solely based on expert consensus, a thorough validation of the assessment is required. Therefore, a careful interpretation of these results is warranted because of the limited data availability.

Retention Rates Were Within the Expected Range of a Digital Therapeutic

Retention rates to digital therapeutics have proven to show both high attrition to use and attrition to follow-up. For example, Baumel et al [20] reported an average adherence to mental health digital therapeutics of <10% after 30 days of use. Similarly, Fleming et al [21] presented a systematic review on the intensity of digital therapeutics use in mental health and reported a sustained use (ie, completion of a program or continuation for more than 6 weeks) between 0.5% and 28.6%. The retention rates in this study were within this spectrum; only the spectrum of hip pain reached a retention rate of 14% after 4 weeks and exceeded the expected range. After 12 weeks (ie, upon completion of the exercise program), an average retention rate of 3% was demonstrated.

The low retention to digital therapeutics demonstrates a key challenge for evaluation, as insufficiently reported outcome data limit the interpretability of the clinical outcomes obtained. This circumstance mandates further research on how participant behavior (ie, continuation or discontinuation of the exercise regime as prompted) relates to retention to a study and, consequently, the clinical value of digital therapeutics.

Limitations

Because this study was based on participant-initiated enrollment and self-reported data, a number of limitations need to be discussed. Regarding the study population, we saw an overrepresentation of female participants. Comparable studies have presented similar sex distributions when allowing for self-selection of participation but have not concluded on the potential implications of this imbalance. A potential, nonexhaustive explanation could lie in the differential awareness of health and information–seeking behavior for health-related questions, which favors women to discover and adopt offered health care services more quickly [22]. Additionally, participants with chronic pain were overrepresented in our study population. This leads to our understanding that the therapeutic effects observed were plausibly due to the program examined and not due to the natural course of the spectrum of conditions studied.

Nonetheless, the drivers and potential implications of this imbalance remain unclear. In addition, the self-assessed and self-reported outcome data are subject to a certain interindividual difference. However, the VNRS employed has been shown to be particularly applicable in a day-to-day setting [10], valid [9,23], and reliable [9]. This, however, does not apply to the functional assessments employed. Although all assessments were based on a set of validated orthopedic tests, the transformation of the binary assessment into a discrete scale, as outlined earlier in this report, has only been validated through an expert panel review and lacks quantitative validation. Overall, we see a valid indication for a therapeutic benefit of the program assessed but acknowledge that the presented data warrant a careful interpretation.

Comparison With Prior Work

The clinical outcomes of interventions in general (ie, without a key digital component) to improve PA was reviewed in a meta-analysis showing no significant short-term, intermediate,

or long-term improvements [8]. Studies focusing specifically on digital health interventions have been reviewed in different studies. One systematic review investigating the adherence to digital interventions aiming to increase PA in patients with MSP showed no significant difference in adherence to exercises between conventional and therapeutic exercises (standardized mean difference 0.23, 95% CI –0.10 to 0.57) [24]. Another systematic review focusing on digital health interventions' clinical outcomes addressing MSCs showed significantly better results for digital therapeutics than the control [25]. Two studies [26,27] included in the review had a similar focus to this work. However, these studies were randomized controlled trials and did not investigate clinical outcomes in a real-world setting.

Conclusions

Innovative therapeutic means are required to address the increasing burden of disease from MSCs. This study presents early observational use data on the clinical outcomes of a program in terms of overall self-reported pain score reduction and demonstrates significant improvement in its primary analysis. However, stratum-specific pain reductions did not reach the adjusted level of significance. Significant functional improvements, particularly in strength and mobility, could be demonstrated for upper and lower back pain but not for hip and knee pain. Nevertheless, coordination improved significantly in participants with hip and knee pain.

Interestingly, chronic back pain profited from the extended use and showed significant increases in strength and mobility scores after a median of 88.5 days. Retention was shown to be low but was within the spectrum of what the available literature allows us to expect. Further research is required to substantiate the early indicators of the examined program's therapeutic benefit and quantify the clinical relevance of the improvements achieved.

Authors' Contributions

GWT contributed to the data analysis, data visualizations, interpretations, and manuscript draft. TK provided methodological guidance and reviewed the manuscript. FPH contributed to developing the study concept, data analysis and interpretations, and manuscript composition. LB led the development of the study concept, prepared the data collection, contributed to the data analysis and the interpretation, and contributed to the manuscript draft. All authors reviewed the manuscript.

Conflicts of Interest

GWT and TK are affiliated with the Center for Digital Health Interventions, a joint initiative of the Institute for Implementation Science in Health Care, University of Zurich; the Department of Management, Technology, and Economics at Swiss Federal Institute of Technology in Zürich; and the Institute of Technology Management and School of Medicine at the University of St Gallen, which is funded in part by the Swiss health insurer CSS. CSS is not involved in any way in this study. TK is also cofounder of Pathmate Technologies, a university spin-off company that creates and delivers digital clinical pathways. However, Pathmate Technologies was not involved in this study. LB is affiliated with Vivira Health Lab GmbH, the developer of the software examined. Vivira Health Lab GmbH did not make any financial contributions to support the analysis or the publication of this manuscript. FPH has no conflicts of interest to declare.

Multimedia Appendix 1
Further figure regarding pain scores and table displaying adherence.
[DOCX File , 663 KB - mhealth_v10i12e38649_app1.docx]

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        10.1038/s41746-018-0076-7] [Medline: 31304351]

Abbreviations

CE: Conformité Européenne
MDD: medical device directive
MSC: musculoskeletal condition
MSP: musculoskeletal pain
PA: physical activity
VNRS: verbal-numerical rating scale

Review

Effectiveness of mHealth Interventions in the Control of Lifestyle and Cardiovascular Risk Factors in Patients After a Coronary Event: Systematic Review and Meta-analysis

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Abstract

Background: Coronary artery disease is the main cause of death and loss of disability-adjusted life years worldwide. Information and communication technology has become an important part of health care systems, including the innovative cardiac rehabilitation services through mobile phone and mobile health (mHealth) interventions.

Objective: In this study, we aimed to determine the effectiveness of different kinds of mHealth programs in changing lifestyle behavior, promoting adherence to treatment, and controlling modifiable cardiovascular risk factors and psychosocial outcomes in patients who have experienced a coronary event.

Methods: A systematic review of the literature was performed following PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. A thorough search of the following biomedical databases was conducted: PubMed, Embase, Web of Science, SciELO, CINAHL, Scopus, The Clinical Trial, and Cochrane. Articles that were randomized clinical trials that involved an intervention consisting of an mHealth program using a mobile app in patients after a coronary event were included. The articles analyzed some of the following variables as outcome variables: changes in lifestyle behavior, cardiovascular risk factors, and anthropometric and psychosocial variables. A meta-analysis of the variables studied was performed with the Cochrane tool. The risk of bias was assessed using the Cochrane Collaboration tool; the quality of the evidence was assessed using the Grading of Recommendations, Assessment, Development, and Evaluation tool; and heterogeneity was measured using the I^2 test.

Results: A total of 23 articles were included in the review, and 20 (87%) were included in the meta-analysis, with a total sample size of 4535 patients. Exercise capacity measured using the 6-minute walk test (mean difference=21.64, 95% CI 12.72-30.55; P<.001), physical activity (standardized mean difference [SMD]=0.42, 95% CI 0.04-0.81; P=.03), and adherence to treatment (risk difference=0.19, 95% CI 0.11-0.28; P<.001) were significantly superior in the mHealth group. Furthermore, both the physical and mental dimensions of quality of life were better in the mHealth group (SMD=0.26, 95% CI 0.09-0.44; P=.004 and SMD=0.27, 95% CI 0.06-0.47; P=.01, respectively). In addition, hospital readmissions for all causes and cardiovascular causes were statistically higher in the control group than in the mHealth group (SMD=–0.03, 95% CI –0.05 to –0.00; P=.04 vs SMD=–0.04, 95% CI –0.07 to –0.00; P=.05).

Conclusions: mHealth technology has a positive effect on patients who have experienced a coronary event in terms of their exercise capacity, physical activity, adherence to medication, and physical and mental quality of life, as well as readmissions for all causes and cardiovascular causes.

KEYWORDS

coronary disease; acute coronary syndrome; mobile health; smartphone; mobile apps; mobile phone

Introduction

Background

Cardiovascular diseases (CVDs) are the main cause of death worldwide [1] according to data from the World Health Organization. They are considered to be responsible for 17.5 million deaths every year, which is 30% of those recorded worldwide [1]. In high-income countries, approximately 70% of CVD cases are attributed to modifiable risk factors, the most common being metabolic risk factors (obesity and cholesterol) and tobacco use [2].

Among CVDs, coronary artery disease (CAD) is the main cause of death and loss of disability-adjusted life years worldwide [3]. Much of this burden falls on low-income and medium-income countries, representing nearly 7 million deaths and 129 million disability-adjusted life years per year [4].

The secondary prevention of CAD is considered essential at present [5], as it has contributed significantly to the decrease in morbidity and mortality by facilitating the adoption of and adherence to healthy behavior, promoting an active lifestyle, and increasing adherence to drug treatment [5,6].

Thanks to the advances in medicine and technology, hospital stays after myocardial infarction have been shortened in recent years, meaning that health care professionals have fewer opportunities to inform patients about their disease during their admission [7].

Information and communication technology is becoming an increasingly important part of health care systems, including the innovative cardiac rehabilitation (CR) services through mobile phone and mobile health (mHealth) interventions [8]. mHealth technology can provide evidence-based guidance in an attractive, and user-friendly format, thus decreasing health care costs [9]. A meta-analysis [10] of 30 randomized trials including 7283 patients with CAD concluded that secondary prevention with telehealth programs can be used instead of, or together with, traditional CR and is associated with greater control of cardiovascular risk factors and fewer clinical events. This study, however, used different kinds of telehealth interventions in each trial (internet, telephone calls, SMS text messages, and mobile apps).

Early secondary preventive care patients recently discharged after acute coronary syndrome was shown to promote adherence to drug treatment and facilitate the control of changes in cardiovascular risk factors. However, because of the COVID-19 pandemic, it is likely that the uptake and availability of secondary prevention strategies have been affected, as CR programs may have been suspended or patients avoided or could not go to health centers [11,12]. Therefore, innovative secondary prevention and CR strategies are needed to be implemented to increase long-term adherence to a healthy lifestyle.

Objectives

Despite the exponential growth in and availability of smartphone technology to provide a new tool to optimize the secondary prevention of heart diseases, no systematic reviews have been published that focus exclusively on the effectiveness of mHealth involving mobile apps as a way of providing digital health and its secondary prevention components to patients who have experienced a coronary event. Thus, the aim of this review was to determine the effectiveness of the different means of providing mHealth programs in changing lifestyle behavior, promoting adherence to treatment, and controlling modifiable cardiovascular risk factors and psychosocial outcomes.

Methods

Search Strategy

A systematic review of the literature was performed following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [13]. A thorough search was conducted of the following biomedical databases between June and November 2021: PubMed, Web of Science, Scopus, SciELO, CINAHL, Cochrane, and The Clinical Trial. Manual searches of the references from other reviews and meta-analyses were also performed to find more studies. The search terms included the following: *coronary syndrome, infarction, acute coronary syndrome, coronary disease, mHealth, mobile applications,* and *smartphone*, which were combined with each other using the Boolean operators (AND/NOT) and the appearance of these terms into Title or Abstract (Multimedia Appendix 1). Truncation (*) was applied when necessary to improve the search results. The search was limited to the time frame from 2015 to 2021. The search protocol was registered with PROSPERO (International Prospective Register of Systematic Reviews; registration number: CRD42022299931).

Inclusion and Exclusion Criteria: Selection of Studies

Studies were included if they complied with the inclusion criteria, namely randomized controlled trials (RCTs) in which an intervention had been performed consisting of a telehealth or mHealth program by means of a mobile app in patients with coronary heart disease and included the following outcome variables: change in lifestyle behavior (diet, physical exercise, and treatment adherence) and control of cardiovascular risk factors (tobacco, blood sugar, systolic blood pressure [SBP], diastolic blood pressure [DBP], total cholesterol, low-density lipoprotein [LDL] cholesterol, and high-density lipoprotein [HDL] cholesterol); anthropometric variables (waist

circumference and BMI); and psychosocial variables (anxiety, depression, and stress).

Studies that used SMS text messages without an app or web portal and included participants who had experienced a stroke or another CVD were excluded.

Study Selection

Two researchers independently examined the identified articles using the search strategy described in the *Search Strategy* section. First, the titles and abstracts of the articles were checked, and 58 articles were selected for the whole text to be read. A critical reading was performed, and a decision was made regarding whether the articles complied with the inclusion criteria. If there was any discrepancy regarding which articles were eligible for selection, a third reviewer intervened to resolve the problem, helping to reach a final agreement. The quality of the included RCTs was assessed using the Grading of Recommendations, Assessment, Development, and Evaluation tool [14]. This tool provides an approach to grading the quality or certainty of evidence and strength of recommendations. It is a framework for evaluating the effectiveness of systematic reviews. The Grading of Recommendations, Assessment, Development, and Evaluation tool specifies 4 categories for the quality of a body of evidence: high, moderate, low, and very low (Multimedia Appendix 2). The risk of bias was assessed using the Cochrane tool [15], which is used to assess the methodology of scientific evidence in systematic reviews for the individual analysis of included RCTs, addressing 7 specific domains: random sequence generation, allocation concealment, blinding of participants and personnel, blinding of outcome assessment, incomplete outcome data, selective reporting, and other bias. Publication bias was assessed using funnel plots (Multimedia Appendix 3).

Data Extraction Synthesis and Analysis

A total of 23 studies were included in the systematic review, of which 20 (87%) were included in the meta-analysis. The Cochrane Review Manager (RevMan 5.4; The Cochrane Collaboration) software was used for the statistical analysis. Differences in the effects of mHealth interventions and standard health care were examined by means of the inverse variance method. The difference of means was used as the statistic to analyze the effect, and the standardized difference of means was used when variables with different measurement scales were compared, and a 95% CI was given for each effect size. Risk difference was assessed for the qualitative variables. To test the hypothesis, the *P* value was set at <.05 with 2 tails. The analysis was performed in general using the random-effects model, and when heterogeneity was 0%, the fixed-effects model was used. Heterogeneity was assessed by means of the I^2 statistic, which is a useful statistic for quantifying inconsistency. It describes the percentage of the variability in effect estimates that is because of heterogeneity rather than sampling error. A value of I^2<25% was considered low heterogeneity, I^2 from 25% to 50% moderate heterogeneity, and I^2>50% high heterogeneity [16]. The sensitivity of the meta-analysis was tested [16]. Forest plots were constructed to visualize the results.

Results

Selection of Studies

The search provided a total of 1773 articles that were distributed among the following databases: Web of Science (n=598, 33.73%); PubMed (n=299, 16.86%); Scopus (n=168, 9.48%); SciELO (n=69, 3.89%); CINAHL (n=319, 17.99%); Cochrane (n=172, 9.7%); and The Clinical Trial (n=148, 8.35%). A total of 23.18% (411/1773) of articles were identified as duplicates and hence removed. First, the titles and then the abstracts were checked using the inclusion and exclusion criteria. Eventually, 8.35% (148/1773) of articles were selected for the whole text to be read, of which 15.5% (23/148) were chosen for the review and 13.5% (20/148) for the meta-analysis. Figure 1 shows a summary of the selection of studies using the PRISMA flow diagram.

Figure 1. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram of the study selection process. CVD: cardiovascular disease.
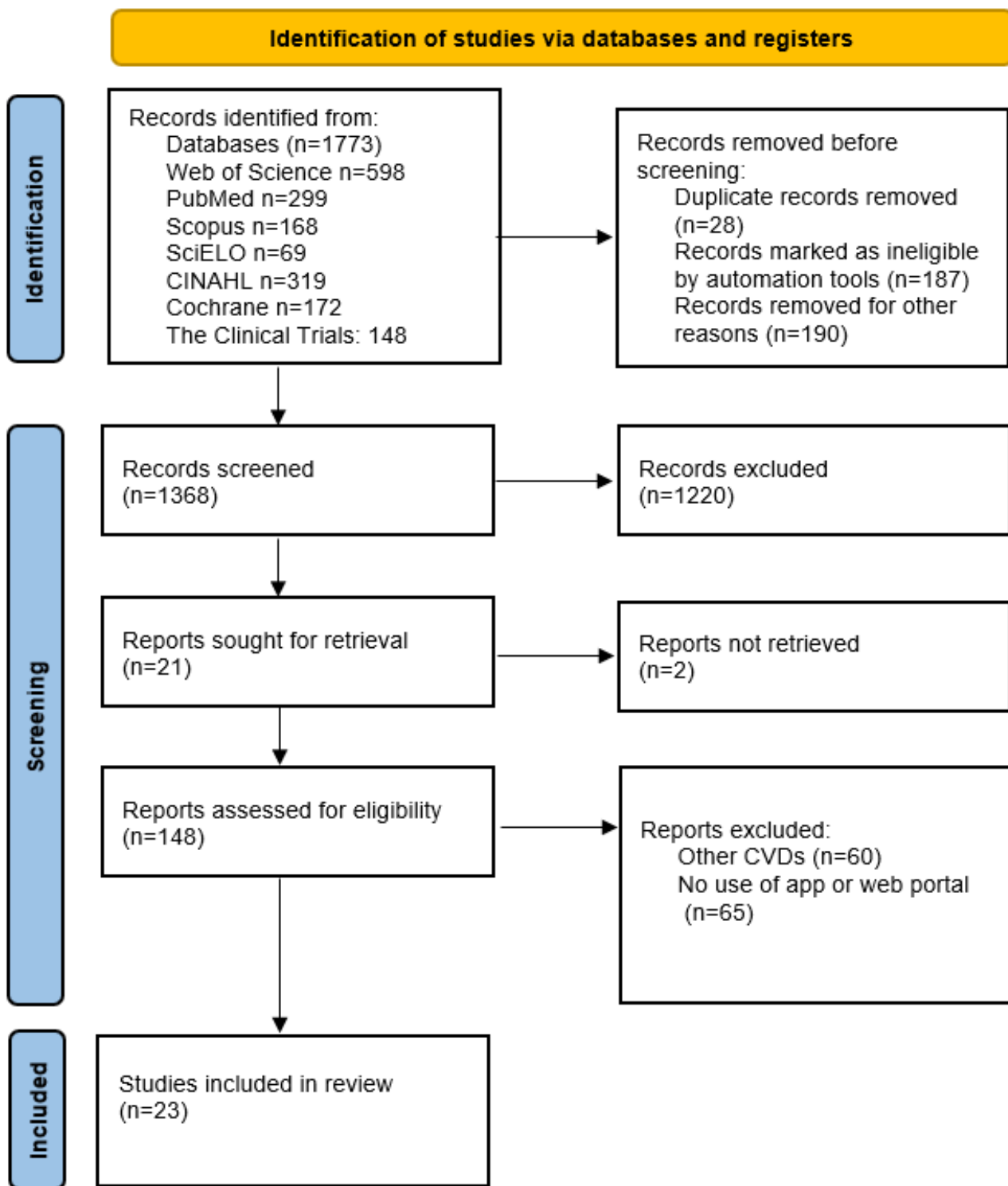
Characteristics of the Studies

All the articles that were selected to be part of the review were RCTs, with a total of 4535 patients. Among the 24 variables analyzed in the RCTs, 54% (13/24) presented evidence of high or moderate quality and 46% (11/24) of variables provided low or very low quality of evidence. The follow-up duration of the intervention ranged from 2 to 26 months, with the most frequent duration being 6 months. The age of the patients in these clinical

trials ranged from 55 to 66 years and 81.32% (3688/4535) of the patients were male.

In the included studies, the control group received "usual health care" or "standard medical care" after the coronary event. In general, the interventions were conducted by a multidisciplinary team of nurses, cardiologists, physiotherapists, nutritionists, specialists in sports medicine, and exercise physiologists.

The patient dropout rate across the studies did not exceed 20%, except in the trial by Skobel et al [17], which had a dropout rate of 65.5% in the intervention group and 34% in the control group. The main reasons for participants dropping out were the health care professionals being unable to contact the participants, the participants wishing to withdraw from the study, and health problems making it impossible for them to continue.

The most commonly studied variables were SBP, DBP, and lifestyle, whereas the least frequently analyzed were c-reactive protein, which was studied only by 2 authors [13,14]; improvement in diet, studied by Choi et al [18] using the "Mediterranean diet score" and Widmer et al [19] using the "food score"; and nicotine dependence (by means of the Fagerström Test), analyzed only in the RCT by Fang et al [20]. An economic assessment analyzing the profitability of the intervention was conducted only by Frederix et al [21] and Maddison et al [22].

Multimedia Appendix 4 [17-39] shows a summary of the design of the included studies, the components of the mHealth systems used, and the initial characteristics of the patients included.

Risk of Bias in the Included Studies

The risk of bias in the RCTs included in this review is summarized in Figure 2 [17-39] and Figure 3. The random sequence generator and the concealment of the allocation of the patients recruited to the RCT were accurately presented in most of the studies, and they had been classified as low risk. The methods used for the randomization were a computer-generated random sequence, 2-tailed *t* test, and permuted block technique. In total, 26% (6/23) of studies did not include information about the allocation concealment method used, so they were classified as presenting an unclear risk of bias because of the lack of specific information [34-39].

Owing to the nature of these RCTs (N=23), the participants, and sometimes the medical professionals, could not be blinded; therefore, all the trials were considered to present a high risk of concealment bias. The researcher assessing the results was not blinded in 17% (4/23) of studies [17,18,29,37]; in 17% (4/23) of other studies, the concealment bias was not clear, so they were categorized as having unclear risk [20,26,35,39], and in the 22% (5/23) of the remaining studies, specific details of the blinding of the assessors were given.

Regarding attrition bias, 22% (5/23) of the trials were considered high risk because of incomplete results data [19,27,36,40] and a dropout rate of >20% [17]. The study by Park et al [26] was classified as having an unclear risk of bias, as it was a pilot RCT reporting preliminary results. In contrast, 74% (17/23) of studies were considered to present a low risk of attrition bias as they provided clear and detailed descriptions, there were no missing results data, and the percentage of dropouts was <20%.

All the trials included in the review were classified as having a low risk of reporting bias because of the following reasons: the trials had study protocols that were readily available; the results studied were previously specified; or if the study protocol was not available, it was clear that all the expected results were included.

Finally, regarding other possible risks of bias, all the studies were classified as low risk, as the patients who participated in the trials provided their written, informed consent to participate in the study. All the RCTs were approved by the ethics committee of the institution where the trial was conducted, and their ethics approval statements were included in the texts.

In summary, most of the trials were assessed as having moderate risk, as it was not possible to blind all the participants because of the nature of these RCTs.

Figure 2. Risk of bias summary: authors' judgments about each risk of bias item for each included trial.

Figure 3. Risk of bias graph: authors' judgments about each risk of bias item presented as percentages across all included trials.
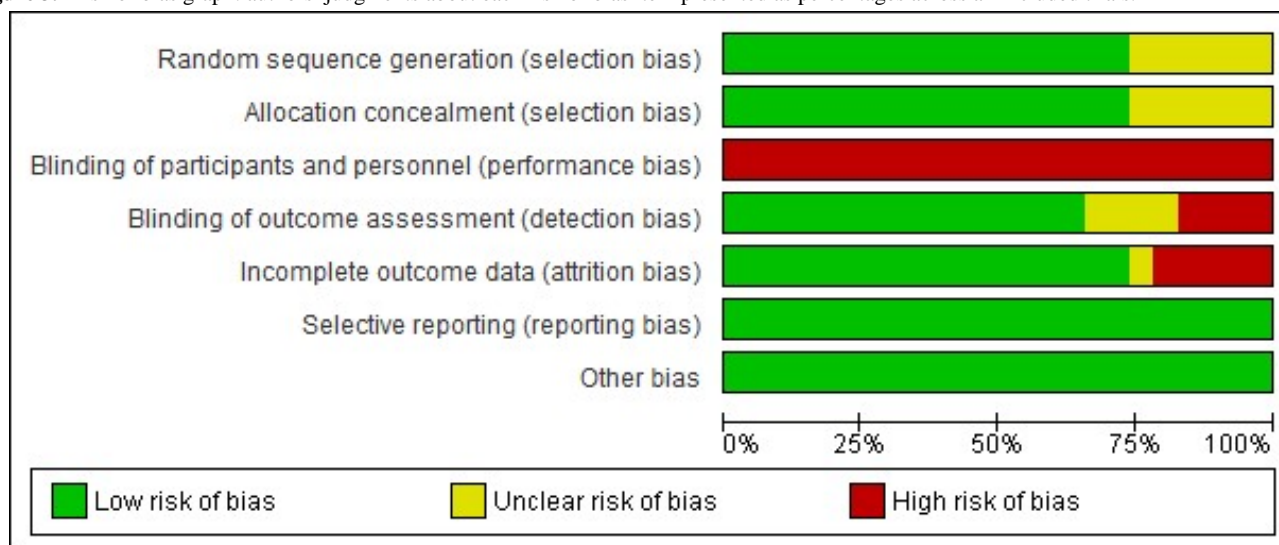
Effects of the Interventions on the Results

Blood Lipids

A total of 39% (9/23) of the trials provided data on the plasma concentrations of total cholesterol and LDLs from a total of 1211 participants. Santo et al [28] and Snoek et al [29] did not provide information about HDL cholesterol despite reporting data on LDL cholesterol, and the sample for analyzing HDL cholesterol included 943 patients. Triglycerides were evaluated in 26% (6/23) of studies, with a total sample size of 889 patients. High heterogeneity was found in the studies analyzing total and LDL cholesterol levels.

The meta-analysis of the included trials did not show significant differences in total cholesterol (*P*=.44), LDL cholesterol (*P*=.35), HDL cholesterol (*P*=.21), and triglycerides (*P*=.72), although favorable outcomes were found in the mHealth groups (Multimedia Appendix 5 [17,18,21,25,27-29,31,32]).

Blood Pressure

A total of 57% (13/23) of studies with high heterogeneity (I^2=78%) reported the SBP of 2459 included patients, and 52% (12/23) of studies, which also had high heterogeneity (I^2=66%), informed about the DBP of 2187 patients. Dorje et al [23] did not provide data about DBP, although data about SBP after the intervention were included. No differences were found in either SBP (*P*=.99) or DBP (*P*=.36) between the groups after the interventions (Multimedia Appendix 6 [17,18,21,25,27-29,31,32,34]).

Body Composition

A total of 39% (9/23) of trials with high heterogeneity (I^2=88%) studied the BMI (*P*=.97) of a total of 1986 patients. After the mHealth interventions, no significant differences in BMI were found between the groups. Neither was there a significant difference in waist circumference measurements between the 2 groups. This measurement was analyzed by 3 studies with high heterogeneity (I^2=56%) with a sample of 376 patients (Multimedia Appendix 6).

Glycated Hemoglobin and Basal Blood Glucose

A total of 13% (3/23) of studies with high heterogeneity (I^2=76%) evaluated glycated hemoglobin levels in a sample of 382 participants. Although the decrease was greater in the mHealth group, the difference was not statistically significant (glycated hemoglobin, *P*=.23 and basal blood glucose, *P*=.54). Fasting blood sugar levels were also reported in 13% (3/23) of homogeneous trials (I^2=0%), with no significant improvements being found (Multimedia Appendix 7 [17,18,21,25,27-29,31,32,34,36]).
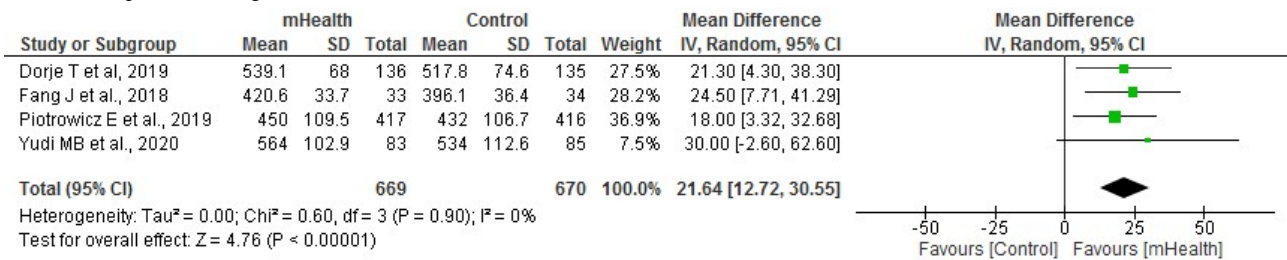
Heart Rate

Heart rate (*P*=.10) was lower in the mHealth groups, but the differences were not significant. A total of 13% (3/23) of studies with high heterogeneity (I^2=65%) evaluated this value in a sample of 494 patients (Multimedia Appendix 7).

Exercise Capacity

A total of 17% (4/23) of homogeneous studies (I^2=0%) analyzed exercise capacity by means of the 6-minute walk test (6-MWT) with a sample of 1339 patients. The results of the meta-analysis showed that exercise capacity as measured by this test was significantly higher in the mHealth groups (*P*<.001; Figure 4 [20,23,27,31]).

Another outcome measure of exercise capacity was the peak oxygen consumption, studied in 8 trials with high heterogeneity (I^2=64%) with a sample of 1512 patients, although the results were not significant (Multimedia Appendix 8 [17,21,25,27,29,32,35,37]).

Figure 4. Forest plots for changes in the 6-minute walk test. IV: instrumental variable; mHealth: mobile health.

Study or Subgroup	mHealth Mean	SD	Total	Control Mean	SD	Total	Weight	Mean Difference IV, Random, 95% CI
Dorje T et al, 2019	539.1	68	136	517.8	74.6	135	27.5%	21.30 [4.30, 38.30]
Fang J et al., 2018	420.6	33.7	33	396.1	36.4	34	28.2%	24.50 [7.71, 41.29]
Piotrowicz E et al., 2019	450	109.5	417	432	106.7	416	36.9%	18.00 [3.32, 32.68]
Yudi MB et al., 2020	564	102.9	83	534	112.6	85	7.5%	30.00 [-2.60, 62.60]
Total (95% CI)			669			670	100.0%	21.64 [12.72, 30.55]

Heterogeneity: Tau² = 0.00; Chi² = 0.60, df = 3 (P = 0.90); I² = 0%
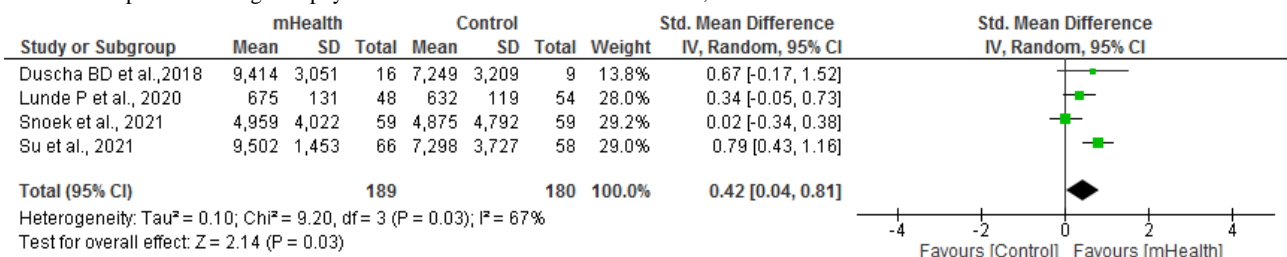Test for overall effect: Z = 4.76 (P < 0.00001)

Physical Exercise

A total of 17% (4/23) of studies with high heterogeneity (I^2=67%) analyzed physical exercise (steps/day, time until exhaustion, or the International Physical Activity Questionnaires questionnaire). The meta-analysis of the included trials showed a significant improvement in physical activity among the participants in the mHealth groups compared with those receiving standard health care (*P*=.03; Figure 5 [29,32,33,35]).

Figure 5. Forest plots for changes in physical exercise. IV: instrumental variable; mHealth: mobile health.

Study or Subgroup	mHealth Mean	SD	Total	Control Mean	SD	Total	Weight	Std. Mean Difference IV, Random, 95% CI
Duscha BD et al.,2018	9,414	3,051	16	7,249	3,209	9	13.8%	0.67 [-0.17, 1.52]
Lunde P et al., 2020	675	131	48	632	119	54	28.0%	0.34 [-0.05, 0.73]
Snoek et al., 2021	4,959	4,022	59	4,875	4,792	59	29.2%	0.02 [-0.34, 0.38]
Su et al., 2021	9,502	1,453	66	7,298	3,727	58	29.0%	0.79 [0.43, 1.16]
Total (95% CI)			189			180	100.0%	0.42 [0.04, 0.81]

Heterogeneity: Tau² = 0.10; Chi² = 9.20, df = 3 (P = 0.03); I² = 67%
Test for overall effect: Z = 2.14 (P = 0.03)

General Quality of Life

Health-related quality of life was studied in 39% (9/23) of RCTs with moderate heterogeneity (I^2=47%) with a sample of 1741 patients, using the following validated questionnaires: European Quality of Life-5 Dimension (visual analog scale and index), Partners in Health scale, 36-Item Short Form Health Survey, Quality of Life after Myocardial Infarction questionnaire, and MacNew Heart Disease Health-Related Quality of Life questionnaire. The scores on these questionnaires were higher in the mHealth groups, but the differences did not reach statistical significance (Multimedia Appendix 9 [17,20,23-25,27,29,31,32,36]).

Physical and Mental Dimensions of Quality of Life

The physical and mental dimensions of quality of life were analyzed in 22% (5/23) of studies, with a sample of 620 patients. The following validated questionnaires were used in these trials: 12-Item Short Form Health Survey, 36-Item Short Form Health Survey, Health-Related Quality of Life, and World Health Organization Quality of Life: Brief Version.

In both the physical (I^2=16%) and mental (I^2=32%) dimensions, significantly higher scores were obtained in the groups that received the mHealth intervention than in the control group (*P*=.004 and *P*=.01, respectively; Figures 6 and 7 [20,21,23,24,32]).

Figure 6. Forest plots for changes in quality of life (physical dimension or physical health). IV: instrumental variable; mHealth: mobile health.
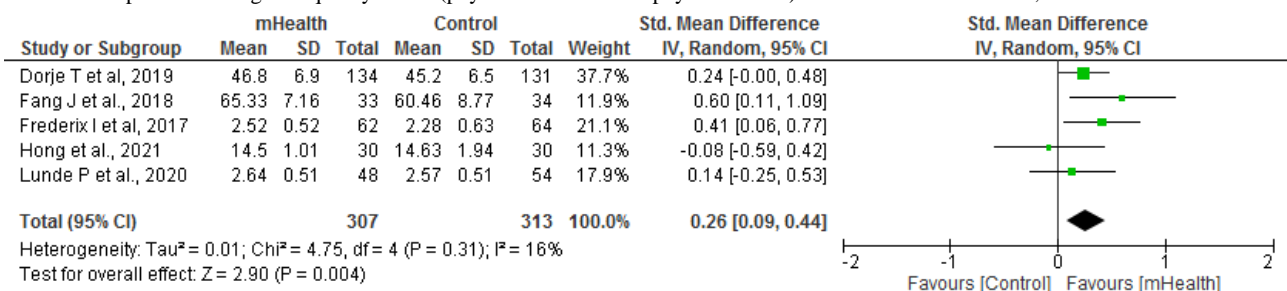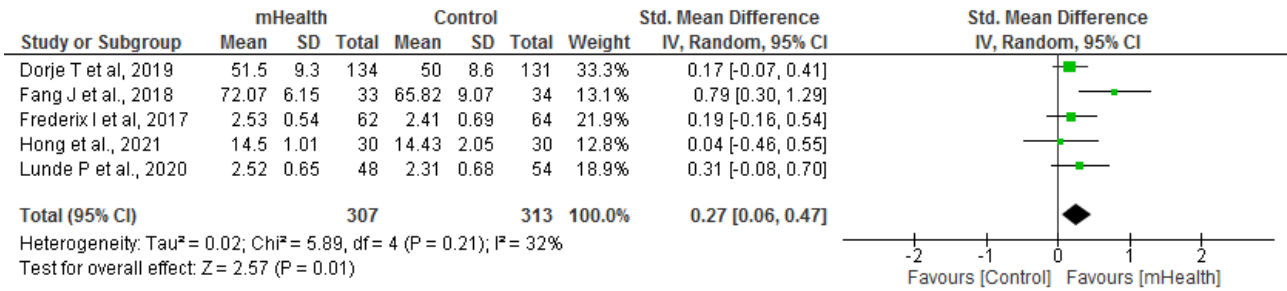
Study or Subgroup	mHealth Mean	SD	Total	Control Mean	SD	Total	Weight	Std. Mean Difference IV, Random, 95% CI
Dorje T et al, 2019	46.8	6.9	134	45.2	6.5	131	37.7%	0.24 [-0.00, 0.48]
Fang J et al., 2018	65.33	7.16	33	60.46	8.77	34	11.9%	0.60 [0.11, 1.09]
Frederix I et al, 2017	2.52	0.52	62	2.28	0.63	64	21.1%	0.41 [0.06, 0.77]
Hong et al., 2021	14.5	1.01	30	14.63	1.94	30	11.3%	-0.08 [-0.59, 0.42]
Lunde P et al., 2020	2.64	0.51	48	2.57	0.51	54	17.9%	0.14 [-0.25, 0.53]
Total (95% CI)			307			313	100.0%	0.26 [0.09, 0.44]

Heterogeneity: Tau² = 0.01; Chi² = 4.75, df = 4 (P = 0.31); I² = 16%
Test for overall effect: Z = 2.90 (P = 0.004)

Figure 7. Forest plots for changes in quality of life (mental dimension or mental health). IV: instrumental variable; mHealth: mobile health.
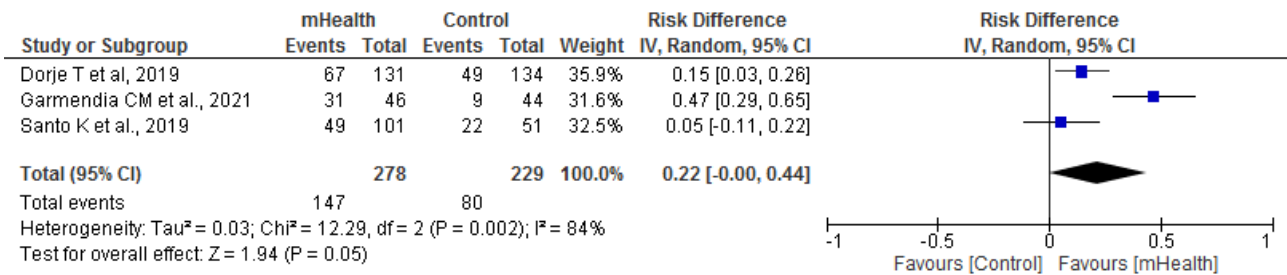
Study or Subgroup	mHealth			Control			Weight	Std. Mean Difference IV, Random, 95% CI
	Mean	SD	Total	Mean	SD	Total		
Dorje T et al, 2019	51.5	9.3	134	50	8.6	131	33.3%	0.17 [-0.07, 0.41]
Fang J et al., 2018	72.07	6.15	33	65.82	9.07	34	13.1%	0.79 [0.30, 1.29]
Frederix I et al, 2017	2.53	0.54	62	2.41	0.69	64	21.9%	0.19 [-0.16, 0.54]
Hong et al., 2021	14.5	1.01	30	14.43	2.05	30	12.8%	0.04 [-0.46, 0.55]
Lunde P et al., 2020	2.52	0.65	48	2.31	0.68	54	18.9%	0.31 [-0.08, 0.70]
Total (95% CI)			307			313	100.0%	0.27 [0.06, 0.47]

Heterogeneity: Tau² = 0.02; Chi² = 5.89, df = 4 (P = 0.21); I² = 32%
Test for overall effect: Z = 2.57 (P = 0.01)

Std. Mean Difference IV, Random, 95% CI. Favours [Control] Favours [mHealth]

Anxiety and Depression

Depression was analyzed in 22% (5/23) of trials with moderate heterogeneity (I^2=40%), and anxiety was analyzed in 17% (4/23) of homogeneous studies (I^2=0%). Fang et al [20] did not report data on depression, despite reporting data on anxiety. Anxiety was measured using the validated questionnaires, Generalized Anxiety Disorder-7 and Hospital Anxiety and Depression Scale-Anxiety. In a sample of 612 patients, no significant difference was found between the anxiety scores in both groups. Nor were there significant differences in the depression scores of a sample of 679 patients (Multimedia Appendix 9; anxiety, P=.30 and depression, P=.84). The questionnaires used were Patient Health Questionnaire-9, Hospital Anxiety and Depression Scale-Depression, and Calgary Depression Scale.

Adherence to Medication

Three authors studied adherence to medication using the 8-item Morisky Medication Adherence Scale and a self-reported questionnaire in a survey of 507 patients (I^2=84%). Adherence to medication was greater in the mHealth group (P=.05; Figure 8 [23,28,39]).

Figure 8. Forest plots for changes in adherence to medication. IV: instrumental variable; mHealth: mobile health.

Study or Subgroup	mHealth		Control		Weight	Risk Difference IV, Random, 95% CI
	Events	Total	Events	Total		
Dorje T et al, 2019	67	131	49	134	35.9%	0.15 [0.03, 0.26]
Garmendia CM et al., 2021	31	46	9	44	31.6%	0.47 [0.29, 0.65]
Santo K et al., 2019	49	101	22	51	32.5%	0.05 [-0.11, 0.22]
Total (95% CI)		278		229	100.0%	0.22 [-0.00, 0.44]
Total events	147		80			

Heterogeneity: Tau² = 0.03; Chi² = 12.29, df = 2 (P = 0.002); I² = 84%
Test for overall effect: Z = 1.94 (P = 0.05)

Risk Difference IV, Random, 95% CI. Favours [Control] Favours [mHealth]

Mortality

A total of 13% (3/23) of studies analyzed the difference in mortality between the groups. In the meta-analysis, with a sample of 2010 patients, no significant differences in all-cause mortality (P=.64) were found (Multimedia Appendix 10 [27,30,38]).

Rehospitalization

Regarding the rehospitalizations of patients during the study period in each RCT, the meta-analysis showed that rehospitalizations for both all causes (P=.04) and cardiovascular causes (P=.05) were statistically higher in the control group than in the mHealth group. These studies were homogeneous (I^2=0%; Figure 9 [19,27,30,31] and Figure 10 [19,27,29,31,33,38]).

Furthermore, a sensitivity analysis was performed by excluding each study sequentially to determine the influence of any single study on the robustness of the results, revealing no substantial difference in the overall effect for the 6-MWT, quality of life, physical activity, and rehospitalizations (Multimedia Appendix 11 [19-21,23,24,27,29-33,35,38]).

Figure 9. Forest plots for changes in rehospitalizations for all causes. IV: instrumental variable; mHealth: mobile health.
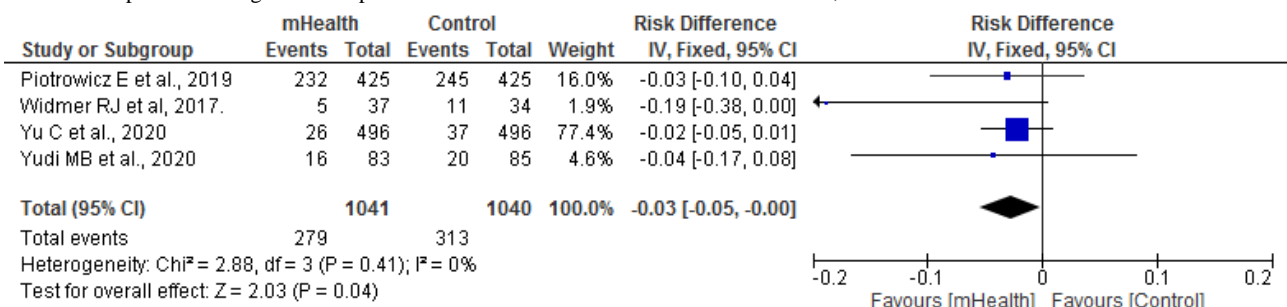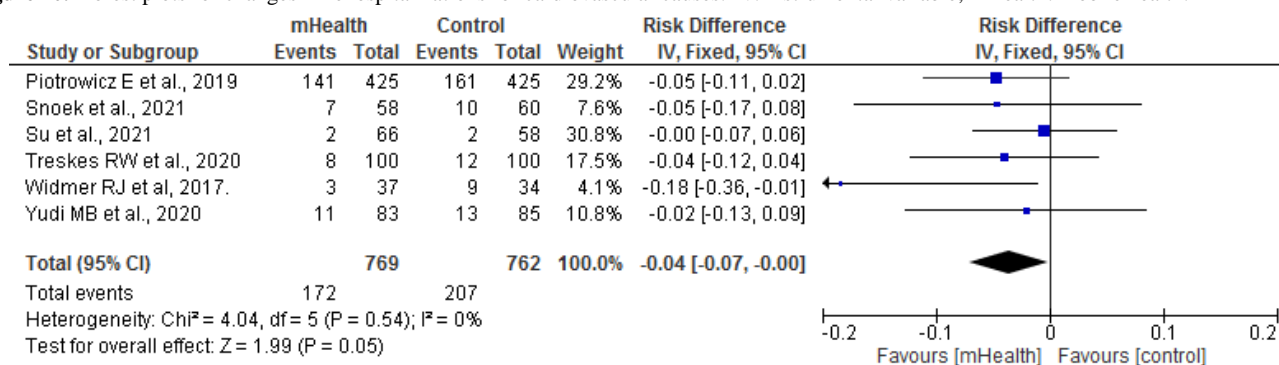
Study or Subgroup	mHealth		Control		Weight	Risk Difference IV, Fixed, 95% CI
	Events	Total	Events	Total		
Piotrowicz E et al., 2019	232	425	245	425	16.0%	-0.03 [-0.10, 0.04]
Widmer RJ et al., 2017.	5	37	11	34	1.9%	-0.19 [-0.38, 0.00]
Yu C et al., 2020	26	496	37	496	77.4%	-0.02 [-0.05, 0.01]
Yudi MB et al., 2020	16	83	20	85	4.6%	-0.04 [-0.17, 0.08]
Total (95% CI)		1041		1040	100.0%	-0.03 [-0.05, -0.00]
Total events	279		313			

Heterogeneity: Chi² = 2.88, df = 3 (P = 0.41); I² = 0%
Test for overall effect: Z = 2.03 (P = 0.04)

Risk Difference IV, Fixed, 95% CI. Favours [mHealth] Favours [Control]

Figure 10. Forest plots for changes in rehospitalizations for cardiovascular causes. IV: instrumental variable; mHealth: mobile health.

Study or Subgroup	mHealth Events	mHealth Total	Control Events	Control Total	Weight	Risk Difference IV, Fixed, 95% CI
Piotrowicz E et al., 2019	141	425	161	425	29.2%	-0.05 [-0.11, 0.02]
Snoek et al., 2021	7	58	10	60	7.6%	-0.05 [-0.17, 0.08]
Su et al., 2021	2	66	2	58	30.8%	-0.00 [-0.07, 0.06]
Treskes RW et al., 2020	8	100	12	100	17.5%	-0.04 [-0.12, 0.04]
Widmer RJ et al, 2017.	3	37	9	34	4.1%	-0.18 [-0.36, -0.01]
Yudi MB et al., 2020	11	83	13	85	10.8%	-0.02 [-0.13, 0.09]
Total (95% CI)		769		762	100.0%	-0.04 [-0.07, -0.00]
Total events	172		207			

Heterogeneity: Chi² = 4.04, df = 5 (P = 0.54); I² = 0%
Test for overall effect: Z = 1.99 (P = 0.05)

Discussion

Principal Findings

This study presents an assessment of evidence from RCTs that compared the effects of mHealth and standard interventions on lifestyle, adherence to treatment, and changes in cardiovascular risk factors after a coronary event. This meta-analysis provides evidence of the favorable effects of mHealth interventions on the variables analyzed. The fact that the studies chosen for this review were published in recent years is proof of the growing interest in mHealth interventions as a resource aimed at improving the secondary prevention of CAD.

Keeping blood lipids and blood pressure under control are very important objectives in the secondary prevention of CVDs. A meta-analysis conducted by Gencer et al [41] involving 21,492 patients aged >75 years reported that a 1 mmol/L decrease in LDL cholesterol significantly reduced the risk of vascular events by 26%. Regarding blood pressure, a meta-analysis by Ettehad et al [42] concluded that a decrease of 10 mmHg in SBP reduces the risk of important cardiovascular events by approximately 20%, CAD by 17%, and all-cause mortality by 13%. Regarding lipid variables and blood pressure, our meta-analysis did not reveal a significant advantage of smartphone technology compared with standard health care after a coronary event, possibly owing to the fact that in these cases, intensive drug treatment is prescribed that has a similar effect on patients participating in an mHealth program to those receiving standard health care. However, the results could also be a result of the high heterogeneity between the studies that measured the total and LDL cholesterol levels. Regarding SBP and DBP, our results agree with those obtained in recent meta-analyses [43-45]. However, they do not coincide with other meta-analyses that obtained improvements in DBP only [46]. They also do not coincide with the meta-analysis published by Kavradim et al [47], who observed improvements in both SBP and DBP. Concerning lipid variables, our results are in line with those published by Huang et al [44] and Al-Arkee et al [45]. In contrast, Akinosun et al [43] found improvements in LDL, HDL, and total cholesterol levels but not in triglycerides. Xu et al [46] observed significant improvements only in HDL and total cholesterol, but not in LDL cholesterol, and Kavradim et al [47] found significant improvements in total cholesterol and triglycerides, but not in LDL and HDL cholesterol. The digital technology interventions analyzed were not based on the use

of mobile phone apps, but rather on SMS text messages and web-based coaching.

The increased prevalence of obesity has become an important public health concern worldwide. Total and abdominal adiposity during adolescence is associated with atherosclerosis in adulthood and insulin resistance [48]. Abdominal obesity is the most frequently observed component of metabolic syndrome (the cluster of abdominal obesity, dyslipidemia, hyperglycemia, and hypertension). The mean prevalence of metabolic syndrome among 24,670 participants aged 35-74 years from 10 autonomous communities in Spain was found to be 31% and is associated with a 2-fold increase in the risk of CAD and a 1.5-fold increase in the risk of all-cause mortality [49]. In our meta-analysis, mHealth interventions did not lead to a significant reduction in the patients' BMI and waist circumference. In this sense, it is worth highlighting that only a few RCTs have measured waist circumference despite the positive correlation between abdominal obesity and atherosclerosis. This finding is in accordance with the results of Akinosum et al [43] and Huang et al [44] who also did not observe improvements in BMI; however, a recent meta-analysis [46] did find a reduction in BMI and waist circumference although few RCTs were included in the analysis. Moreover, each trial used a different kind of digital intervention (telephone calls, remote monitoring with smartphones, SMS text messages, medication reminder apps, conference call sessions, emails, or web apps).

A high blood glucose level is also an important risk factor leading to the onset and development of CAD. A recent meta-analysis concluded that prediabetes is associated with a greater risk of all-cause mortality and CVD in the general population and in patients with atherosclerotic CVD [50]. Our study, similar to the one performed by Akinosun et al [43], did not find a significant decrease in glycated hemoglobin or fasting blood glucose levels in the mHealth group. These results may be due to the fact that few RCTs included these variables and also because of the differences in the duration of the intervention and monitoring periods.

Regarding the number of people who had stopped smoking at the end of the intervention, the percentage was high in both groups (standard care and mHealth), but the results were not statistically significant. These findings are similar to those reported in the meta-analyses by Akinosun et al [43] and Huang et al [44], who did not report a significant difference in the prevalence of tobacco use between the groups at the end of the

study. However, another meta-analysis did conclude that telehealth inventions have a statistically significant beneficial effect, albeit a small one, on stopping smoking in patients with CAD [47] using SMS text messages, telephone calls, and telemonitoring. Akinosun et al [43] observed that mHealth interventions appeared to be more effective in improving healthy behaviors than unhealthy ones (alcohol consumption and smoking). One reason for this could be that tobacco cessation interventions use behavioral change techniques, which include social support and group discussions, and such techniques are less frequently included in mHealth interventions.

Physical inactivity is independently associated with 12.2% of the global burden of acute myocardial infarction [51]. Consequently, physical activity is considered the cornerstone on which changes in lifestyle to prevent CVD must be based, and a dose-response relationship exists between 6-MWT and the risk of future cardiovascular events. Moreover, 6-MWT is a known predictor of cardiovascular events in patients with CAD, even after adjusting for cardiovascular risk factors [31]. Therefore, the results obtained in the meta-analysis are encouraging because the use of mHealth strategies is seen to result in favorable changes in exercise capacity, which can have a positive impact on the secondary prevention of future cardiovascular events. In addition, no meta-analysis published to date was found to have studied physical capacity with 6-MWT for mHealth interventions in patients who have experienced a coronary event. These results align with existing systematic reviews of mHealth in cardiovascular patients, which demonstrate improvements in physical activity with digital technology [43,47]. However, in the systematic review by Huang et al [44], they did not observe an increase in physical activity with mHealth interventions.

Many patients do not comply with lifestyle recommendations or do not take their medication as prescribed after a cardiovascular event. Adherence to treatment by patients who are prescribed cardiovascular medication is estimated to be approximately 51% a year after a myocardial infarction [52]. Among these patients, 30% interrupt their treatment 3 months after the first infarction, whereas 50% do so after 1 year [53,54]. The results of our meta-analysis show that mHealth interventions have a positive impact on adherence to medication although there is high heterogeneity among the studies and only a few include this variable. These results are in line with those found in a recent meta-analysis [45] assessing the effects of mobile phone health care apps on adherence to medication in patients with CVD, with the apps being based on medication reminders on the mobile device. Meta-analyses by Kavradim et al [47] and Akinosun et al [43] also found increased adherence to medication with telehealth interventions in the secondary prevention of CAD and patients with CVD, respectively.

CAD is one of the main causes of disability and loss of health-related quality of life among patients with this disease [4]. Thus, improving quality of life is one of the most important objectives to be achieved with these patients. Assessing quality of life allows for the subjective evaluation of an individual's health and the determination of the impact of the disease and its treatment on their daily life. In our meta-analysis, the scores in both the physical and mental dimensions of quality of life

were statistically higher in the mHealth group, a finding that may be related to the capacity of mHealth interventions to provide remote health care to patients and answer their questions at any time. In one of the meta-analyses [44], no significant differences were observed in the quality of life between telehealth interventions and CR in patients with CAD. In general, few meta-analyses include quality of life among the study variables, which makes it difficult to make comparisons [55].

Several studies have reported that anxiety and depression are also independent risk factors for cardiovascular morbidity and mortality [56,57]. Therefore, dealing with stress, psychosocial risk factors (eg, lack of social support), and other mood disorders is an objective that takes precedence [53]. In our meta-analysis, the levels of anxiety and depression in the mHealth group were not statistically different from those in the patients receiving standard care. Our results agree with the meta-analysis by Huang et al [44]. Nevertheless, the meta-analysis by Xu et al [46] reported that mHealth strategies could alleviate depression in patients with coronary cardiopathy, but it had no effect on anxiety. These results may also be due to the fact that few RCTs include and analyze psychosocial variables.

In our meta-analysis, we did not observe differences between the intervention and usual care groups in terms of mortality, but we did find a reduction in hospitalizations for all causes and for cardiovascular causes with the digital intervention. However, these variables were not included in other meta-analyses, which makes their comparison difficult.

This review found that although the usability, viability, and acceptance of mHealth tools for modifying cardiovascular risk factors and lifestyle were included as variables in a few studies, they were highly valued by the patients. A study by Johnston et al [36] using the System Usability Scale observed that 97.5% of the patients in the intervention group said at the end of the study that they would recommend the tool to other patients in the same situation. Moreover, 68.4% of the patients reported being willing to continue using the web-based tool, and >80% found that the patient support tool provided relevant information about the disease and increased their knowledge and motivation to follow a healthier lifestyle. Al-Arkee et al [45] also reported usability results that were favorable to the intervention.

The heterogeneity of some of the variables studied was high, possibly because of the small sample sizes; different monitoring durations of the RCTs; differences in the age of the participants; and different settings in which the mHealth programs took place (hospital, home, or outpatient clinics).

In general, systematic reviews include interventions with different technologies such as mobile phones, websites, and software apps, but they do not usually compare these technologies with each other. However, the meta-analysis by Xu et al [46] conducted subgroup analyses to compare simple (telephone calls, messages, and WeChat messages) and complex (self-developed apps, wearable devices, medical platforms, and videoconferencing) mHealth interventions. The results of the subgroup analysis showed that the simple mHealth group was more conducive to controlling risk factors than the complex mHealth group. These results may be related to the age of the

patients. CVD occurs frequently in middle-age people and older adults who are from a different technological generation, and they find it difficult to use technological devices. The complicated interface design with a small font size of some complex mHealth interventions or the handling difficulties of wearable devices may reduce the engagement of patients with CVD.

Cell phones are considered efficient digital devices and have been the most widely studied because of their affordability and ease of use; however, smartphones may have advantages because of additional interaction features.

Limitations

Regarding the limitations of our study, it is worth mentioning aspects such as the fact that the participants in the included RCTs enrolled voluntarily by signing an informed consent form, which probably introduced a selection bias, as these patients might have been more motivated to adhere to secondary prevention than others who chose not to participate. Another limitation could be that to participate in the mHealth programs, the patients had to have a mobile phone or a tablet with an internet connection, which could suggest that the participants were younger. However, this limitation seems to be of little importance because nowadays, >75% of the world population has a mobile telephone with internet access and >57% of homes have an internet connection. In Europe, these figures are even higher, reaching 99% and 86%, respectively [58].

Another consideration is that the trials used nonvalidated self-reported questionnaires to analyze some objectives, resulting in the generalizability and coherence of the studies being variable. More studies are required to examine the long-term impact of smartphone-based interventions on people who have experienced a coronary event with regard to heart-related mortality and hospital admissions, as these are important measures of the success of secondary prevention strategies.

Strengths

A strength of our meta-analysis is that RCTs with very similar interventions were selected, involving the use of an app or web portal and programs based on SMS text messages or reminders and telephone calls were excluded. As a result, the interventions analyzed used the newest and most up-to-date technology. To the best of our knowledge, this is the first meta-analysis to group these interventions based on mobile apps for secondary prevention exclusively in patients with CAD after a coronary event, not with risk of CVD. Another strength is the inclusion of many kinds of behavioral, metabolic, and psychosocial variables, providing a broad view of the results being obtained with mHealth technology. All the studies included in this review and meta-analysis were RCTs that are the key to scientific evidence in clinical research. In addition, these clinical trials were conducted in a wide variety of countries in Europe, America, Asia, and Oceania.

Future trials should include larger sample sizes, less-studied variables such as quality of life or readmissions; long-term follow-up; comprehensive explanation of the intervention (frequency, length, and intensity); cost-effectiveness analysis; usability; application of emerging technologies; apps adapted to the age and clinical situation of patients (comorbidity and immobility); and software and hardware improvements such as larger interface fonts or accessible and understandable programs. All these aspects will improve the quality of the trials and help identify the characteristics of the most effective mHealth interventions.

Conclusions

mHealth technology has a positive effect on patients who have undergone a coronary event in terms of their exercise capacity, performance of physical exercise, adherence to medication, physical and mental quality of life, and hospital readmissions for all causes and cardiovascular causes. More research is required with long-term follow-ups and cost analyses to determine the clinical importance of these findings and to promote their generalization, implementation, and feasibility. A promising future for mHealth technology will be based on the development of apps that are user-friendly and personalized and include motivation and feedback strategies.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Complete search strategy.
[PDF File (Adobe PDF File), 462 KB - mhealth_v10i12e39593_app1.pdf]

Multimedia Appendix 2

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Grading of Recommendations, Assessment, Development and Evaluations summary of findings: mobile health versus standard care.

[PDF File (Adobe PDF File), 613 KB - mhealth_v10i12e39593_app2.pdf]

Multimedia Appendix 3

Funnel plots for outcome variables.

[PDF File (Adobe PDF File), 506 KB - mhealth_v10i12e39593_app3.pdf]

Multimedia Appendix 4

Characteristics of included studies.

[PDF File (Adobe PDF File), 235 KB - mhealth_v10i12e39593_app4.pdf]

Multimedia Appendix 5

Forest plots for changes in blood lipids.

[PDF File (Adobe PDF File), 426 KB - mhealth_v10i12e39593_app5.pdf]

Multimedia Appendix 6

Forest plots for changes in systolic blood pressure, diastolic blood pressure, BMI, and waist circumference.

[PDF File (Adobe PDF File), 433 KB - mhealth_v10i12e39593_app6.pdf]

Multimedia Appendix 7

Forest plots for changes in glycated hemoglobin, glucose, heart rate, and smoking cessation.

[PDF File (Adobe PDF File), 412 KB - mhealth_v10i12e39593_app7.pdf]

Multimedia Appendix 8

Forest plots for changes in oxygen consumption peak.

[PDF File (Adobe PDF File), 388 KB - mhealth_v10i12e39593_app8.pdf]

Multimedia Appendix 9

Forest plots for changes in anxiety, depression, and quality of life.

[PDF File (Adobe PDF File), 410 KB - mhealth_v10i12e39593_app9.pdf]

Multimedia Appendix 10

Forest plot for changes in mortality.

[PDF File (Adobe PDF File), 380 KB - mhealth_v10i12e39593_app10.pdf]

Multimedia Appendix 11

Sensitivity analysis.

[PDF File (Adobe PDF File), 429 KB - mhealth_v10i12e39593_app11.pdf]

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Abbreviations

6-MWT: 6-minute walk test
CAD: coronary artery disease
CR: cardiac rehabilitation
CVD: cardiovascular disease
DBP: diastolic blood pressure
HDL: high-density lipoprotein
LDL: low-density lipoprotein
mHealth: mobile health
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PROSPERO: International Prospective Register of Systematic Reviews
RCT: randomized controlled trial
SBP: systolic blood pressure

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<u>Original Paper</u>

Mobile Health Apps for Patient-Centered Care: Review of United States Rheumatoid Arthritis Apps for Engagement and Activation

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Abstract

Background: Rheumatoid arthritis (RA) is a highly dynamic and individualized disease in terms of its patterns of symptomatic flare-ups and periods of remission. Patient-centered care (PCC) aligns patients' lifestyle goals with their preferences for managing symptoms and side effects through the selection of therapies appropriate for disease management. Mobile health (mHealth) apps have the potential to engage and activate patients in PCC. mHealth apps can provide features that increase disease knowledge, collect patient-generated health indicators and behavioral metrics, and highlight goals for disease management. However, little evidence-based guidance exists as to which apps contain functionality essential for supporting the delivery of PCC.

Objective: The objective of this study was to evaluate the patient-centeredness of United States–based rheumatoid arthritis mobile apps in terms of patient engagement and activation.

Methods: A search of mobile apps on 2 major United States app stores (Apple App Store and Google Play) was conducted from June 2020 to July 2021 to identify apps designed for use by patients with RA by adapting the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analyses) guidelines for mobile health app screening based on the literature. Reviewers conducted a content analysis of mobile app features to evaluate their functionality for patient engagement and activation. Engagement and activation were assessed using the Mobile Application Rating Scale (MARS) and social cognitive theory, respectively. Apps were ranked by their ability to facilitate PCC care along 2 dimensions: engagement and activation.

Results: A total of 202 mobile apps were initially identified, and 20 remained after screening. Two apps emerged with the greatest ability to facilitate PCC. Both apps were scored as having acceptable or good patient engagement according to the MARS. These 2 apps also had high patient activation according to social cognitive theory, with many features within those apps representing theoretical constructs such as knowledge, perceived self-efficacy, and expectations about outcomes that support behavioral management of RA.

Conclusions: We found very few mobile apps available within the United States that have functionality that both engages and activates the patient to facilitate PCC. As the prevalence of mobile apps expands, the design of mobile apps needs to integrate patients to ensure that their functionality promotes engagement and activation. More research is needed to understand how mobile app use impacts patient engagement and activation, and ultimately, treatment decisions and disease trajectory.

KEYWORDS

rheumatoid arthritis; rheumatism; arthritis; mobile app; mobile applications; mHealth; patient engagement; patient activation; patient-centered care; patient centred; person centered; Mobile Application Rating Scale; social cognitive theory; mobile health; review; systematic search; app feature; content analysis; functionality; user rating; patient rating

Introduction

Mobile health (mHealth) apps are emerging as an important approach to support the delivery of patient-centered care (PCC) for chronic conditions such as rheumatoid arthritis (RA). PCC seeks to integrate patient values into clinical decisions by encouraging active collaboration and shared therapeutic decisions between the patient and rheumatological provider [1]. This collaboration is imperative to managing the symptoms of RA more effectively, including chronic pain, fatigue, and joint inflammation, which affect 2.1 million people in the United States [2-4]. One-third of patients with RA experience alternating periods of disease control and relapse, and women are 2 to 3 more times likely to be afflicted than men [5,6].

To assist patients, numerous mHealth apps have been developed to increase knowledge of the disease, track problematic symptoms and side effects, and support social interactions [7,8]. Emerging evidence suggests that patients with RA are willing to adopt these apps [8]. Yet, despite their promise, there remains a lack of evidence guiding patients and health professionals as to which apps to adopt and use [9]. Several recent systematic reviews of RA apps in different countries focused on their ease of use and ability to support self-management of the disease [7,10-13]. The reviews uniformly reported a lack of high-quality apps that promote patient use and recommended more research to understand their efficacy [7,10-13]. Uncertainty also exists as to whether mHealth apps can improve patient-centered outcomes, including patient experience and satisfaction with care [9]. One challenge to assessing patient-centeredness is a lack of shared understanding about what constitutes relevant outcomes and how to evaluate them within the digital space [9,14,15].

mHealth apps that have the potential to advance PCC must demonstrate functionality to engage and activate the patient [9,14,16]. Engaged and activated patients collaborate with their rheumatologist, receive and internalize information related to their care, are involved in decision-making, and take the behavioral actions necessary to follow through on treatment plans [1,9]. These actions lead to improved patient experiences and satisfaction [17-19]. When applied to mobile app evaluation, the literature provides definitions of patient engagement and activation [9]. Patient engagement is the extent to which patients can use the app features (ie, amount, frequency, duration, and depth of usage) in addition to the user's overall experience with the app [9]. Patient activation refers to the willingness and ability of patients to take behavioral actions to manage their RA and overall health [9]. In assessing mHealth apps, patients must perceive that the app has the features they desire to support them in taking behavioral actions to collaborate with providers and manage their RA between clinical visits [9]. With an increasing number of mHealth apps for RA available within the United States, patients and health care professionals need evidence-based guidance on which apps contain the functionality essential for improving the delivery of PCC. Therefore, the objective of this study was to evaluate the patient-centeredness of United States–based RA mHealth apps in terms of patient engagement and activation.

Methods

mHealth App Identification

To identify mobile apps that facilitate PCC, we conducted a systematic search of Apple (iOS) and Google Play (Android) stores in the United States by adopting the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analyses) guidelines for a health app–focused review [20-23]. From June 1, 2020 to July 1, 2020, 2 independent reviewers (authors MC and HT) conducted searches of both stores using the terms "rheumatoid arthritis" OR "RA apps" OR "RA tracking" OR "RA management" OR "pain management" OR "pain tracking" OR "symptom tracking" OR "arthritis." The app inclusion criteria were (1) smartphone apps that could run on iOS or Android software systems, (2) apps available for download in Apple and Google Play app stores within the United States, and (3) those specific to arthritis or RA and potentially relevant for use by a patient to manage their disease. After additional review, apps were excluded if they were (1) not intended for the target age group 18 years and up, (2) not in the English language, (3) a clinic tool intended for use only by providers, (4) provided only educational material from scientific journals and other resources, and (5) solely telehealth apps. Duplicates were examined based on the app logo and description. If the logo and description were identical, then 1 was removed. The 2 independent reviewers met to review the list of apps and discuss and reconcile any differences based on the inclusion and exclusion criteria. Reviewers came to a consensus on the final list of apps to download.

In July 2020, apps were downloaded in either the Android or iOS version depending on the device available to the reviewer. Android-only apps were downloaded and viewed using a Tracphone Alcatel TCL LX A502 smartphone. IOS apps were downloaded using iPhones (10 and 11) running software version iOS. Downloaded apps were further excluded after each of 2 independent reviewers verified that the app (1) was not recently updated and could not be opened and function, (2) had a feature or 2 that resulted in the app malfunctioning, (3) was removed from the Google Play and/or Apple stores during the study period, or (4) participation required a specific invitation from a research group. For the final set of apps, each reviewer completed the tutorial and navigated through the key features. The reviewers gathered operating characteristics for each app that included (1) app name, (2) logo, (3) operating system, (4) developer, (5) platform (ie, Apple or Android), (6) most recent version available or the date that the app was created, (7) price, (8) total number of features within the app, and (9) approximate

number of downloads. Each independent reviewer reviewed the other's work for consistency.

Data Extraction

For the final set of apps, our team developed a data extraction process from August to December 2020 that evaluated patient engagement and activation of mHealth apps based on definitions and practices used within the mHealth literature [9,24]. Patient engagement is defined as the desire and capability to actively choose to participate in care in a way that is consistent with the individual's values and preferences in cooperation with a health care provider or institution for the purposes of improving clinical outcomes or experiences with care [1,25]. When applied to mHealth apps, the literature has defined patient engagement to have an objective component assessing the amount, frequency, duration, and depth of usage in addition to a subjective component characterizing the user's overall experience with the technology [9]. Based on these definitions, our team created a data extraction tool utilizing the Mobile Application Rating Scale (MARS), which was developed by the Queensland University of Technology [24-26]. We selected MARS to assess patient engagement because it evaluates the quality of mHealth app's useability based on 22 items within 5 information technology parameters of (1) engagement, (2) functionality, (3) aesthetics, (4) information, and (5) subjective quality [24]. These 5 parameters align with the objective and subjective components of how patient engagement is defined within the mHealth technology literature [9,24]. MARS has a specific patient engagement parameter assessed through 5 items: (1) entertainment, (2) interest, (3) customizability, (4) interactivity, and (5) relevance to its target group. When creating the patient engagement section of the data extraction tool, our team determined all 5 MARS parameters were necessary to capture both objective and subjective components of patient engagement as applied to mHealth apps [9]. Following the patient engagement parameter within the MARS is functionality, which is evaluated through 3 items: (1) technical performance, (2) ease of use, navigation, and (3) general design [24]. Aesthetics has 3 items that assess the app's (1) layout, (2) graphics, and (3) visual appeal [24]. Information is assessed through 6 items that include examining the accuracy, quality, and quantity of credible knowledge in the app [24]. Subjective quality has 4 items assessing whether users would recommend the app to other people, and the users' overall rating of the app [23]. Each parameter of the 5 parameters within MARS is rated on a scale of 1-5 (1: inadequate, 2: poor, 3: acceptable, 4: good, and 5: excellent). The data extraction tool contained all 5 parameters with the rating scale included [24].

Patient activation is the patient's willingness and ability to take behavioral actions to manage their health [9]. When assessing mHealth apps, patients must perceive that the app has the features they desire to support them in taking behavioral actions to collaborate with providers and manage their RA between clinical visits [9]. To date, there are measures for evaluating patient activation resulting from interventions (ie, Patient Activation Measure and Patient Health Engagement Scale.) Yet, to our knowledge, no methodology exists to apply a priori to evaluate app functionality to promote such activation prior to app adoption. Thus, when creating our data extraction process

for activation, we applied social cognitive theory (SCT), which describes how individuals internalize their experiences along with the actions of others and influences from the environment to adopt new health behaviors [27,28]. When applied to RA, the theory specifies that a person's knowledge of their disease and self-efficacy beliefs operate together with goals for living to form expectations about treatment that, in turn, foster collaboration with providers and treatment adherence. During our data extraction process, our team developed the patient activation portion of the data extraction based on SCT [27,28]. Patients with RA were included on the research team because they provide the patient perspective in study design, data analysis, and interpretation of the findings [9,29-31]. Our team worked iteratively with patients, meeting biweekly to gain feedback to develop the patient activation portion of the data extraction tool.

The patient activation portion of the data extraction tool contained the 6 categories of SCT [27,28]: (1) knowledge, (2) perceived self-efficacy, (3) outcome expectations, (4) goal formation, (5) sociostructural factors, and (6) self-regulation [24]. These categories have constructs within them that are directly related to important components necessary to foster behavioral change [27,28]. Knowledge contains 1 construct: inclusion of educational resources to provide information about the disease and treatment. Perceived self-efficacy contains 4 constructs that examine the translation of personal experiences and social persuasion into beliefs about treatment and disease control. Outcome expectations has 3 constructs related to assisting patients form expectations about their disease control. Goal formation has 2 constructs related to helping patients identify goals relevant to treatment decisions. Sociostructural factors has 2 constructs related to social and environmental factors that exist outside of the individual's control. Self-regulation has 4 constructs related to medication adherence and following through on other relevant behaviors for disease management. The data extraction tool for patient activation contained the 6 categories of SCT and the subconstructs with their definitions.

Data Analysis

From December 2020 to May 2021, 2 independent raters (authors MC and HT) evaluated the final set of app features for patient engagement and activation using content analysis and applying the data extraction tool. They completed the patient engagement portion of the data extraction tool by scoring each of the 5 MARS parameters according to the scale described in the Data Extraction section. When comparing the independent ratings of the parameters, they noted only 5 differences among the parameter ratings. These were discussed, and a total MARS score was calculated following the literature [24]. Our team met to collectively discuss the results from the reviewers' assessments.

The 2 reviewers also independently applied the patient activation portion of the data extraction tool to the final set of apps. The tool allowed them to conduct a content analysis of each feature determining whether the definitions of SCT categories and constructs were present [32-36]. After the independent analysis, the reviewers met to discuss any discrepancies and achieve

consensus about which features related to which construct/category to ensure high interrater reliability [31]. Consensus was achieved through iterative discussions about what a particular construct/category meant and how a feature within an app represented it. After achieving consensus among the reviewers, the rest of our research team met with the reviewers and 2 patients with RA for a further discussion about features to finalize the determination of how features aligned with constructs/categories [32-35]. Constructs coded as "present," based on app features, were summed to determine the total number of SCT constructs within each of the 6 categories for each app [27,28].

To determine the quality of the app for patient activation, our team used the results from the content analysis to develop an SCT ratio. The ratio was calculated by dividing the number of constructs identified within the app by the total number of app features. An app with a social cognitive ratio of 1 meant that it displayed an equal number of constructs as compared to app features, which suggests a good app for patient activation because approximately every feature within the app relates to a construct. Apps with an SCT ratio higher than 1 represented a high-quality app for patient activation because many features within the app relate to more than 1 theoretical construct. This ratio was important to patients with RA who worked with our team. They felt the ratio helped identify good and high-quality apps that contained features facilitating patient activation aligned with SCT. Further, the ratio helped identify apps that were more streamlined and did not contain other functionalities that distracted from focus on the adoption of health behaviors

supporting PCC. Apps were ranked based on the calculated SCT ratio.

The results of the engagement and activation analyses were plotted on a perceptual map to determine each app's ability to facilitate PCC. Perceptual mapping is a useful technique to evaluate how products compare relative to consumer perceptions and product attributes [36]. The perceptual map plots engagement on the horizontal axis using the MARS score and activation on the vertical axis using the SCT ratio. Apps with a higher MARS score and higher SCT-to-total feature ratio demonstrate a greater ability to facilitate PCC in the clinical management of RA.

Results

Identification

The initial search of key words yielded an original sample of 202 mobile apps from Google Play and Apple App stores (Figure 1). After 38 duplicate apps were removed, 164 remained. Of those, 119 apps met the exclusion criteria and were removed from the sample prior to downloading from the Google Play or Apple App stores. The 45 remaining apps were downloaded and assessed for further eligibility in the study. Of the downloaded apps, 25 met further exclusion criteria, and 20 remained for analysis. The operating characteristics of the remaining apps show that all apps were developed (Figure 2). Among the apps, 12 were available on both Android and iOS operating systems. In addition, 16 were updated in the last 3 years, and 19 were freely available to patients with no monetary cost for the app needed upon download (Figure 2).

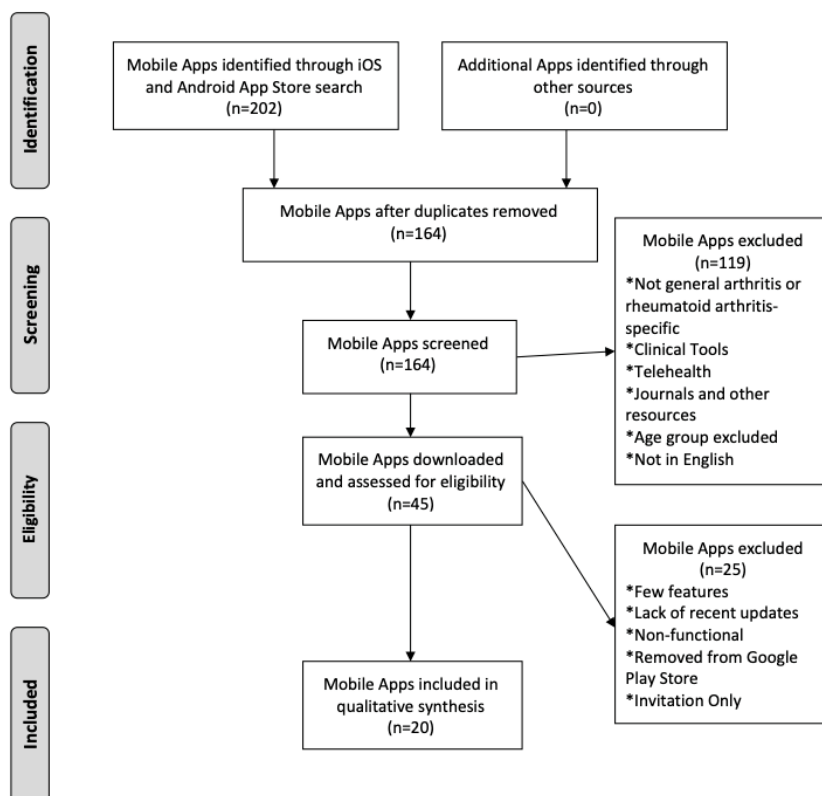**Figure 1.** Identification process of mobile applications for rheumatoid arthritis in the United States.

Figure 2. Operating characteristics of US rheumatoid arthritis mobile apps. N/A: not applicable; RA: rheumatoid arthritis.

| App Name	Logo	Operating System	Developer	iOS version	Android version	Updated Year	Price, US $	Total Features	Number of installs
Arthritis Advice		Android	moreFlow	–	1.1.3	2019	Free	2	500+
Arthritis Power		iOS, Android	Global Healthy Living Foundation	2.7.0	2.7.0	2020	Free	15	5,000+
Arthritis Treatment Free App - Cure Arthritis		Android	Beatrix	–	1.0.0	2020	Free	2	500+
ArthritisID		iOS	Arthritis Consumer Experts	1.0.5	–	2014	Free	6	N/A
cliexa-RA		iOS, Android	CN4CE, Inc.	2.19	2.19	2019	Free	13	500+
LiveWith Arthritis		iOS	eTreat Medical Diagnostics Inc.	1.1.17	–	2020	Free*	13	100+
My Arthritis		iOS, Android	Ampersand Health Limited	2.306	2.33.128	2020	Free	18	1,000+
My Vectra		iOS, Android	Crescendo Bioscience, Inc.	2.0.0	2.0.1	2019	Free	10	5,000+
Paddison Program for Rheumatoid Arthritis		iOS, Android	Clint Paddison	2.1	1.2	2020	Free	4	1,000+
Qigong for Arthritis Relief		iOS, Android	YMAA Publication Center, Inc.	1.0.3	1.0.4	2019	Free*	2	1,000+
RA Healthline		iOS, Android	Healthline Media, Inc.	1.0.4	6.9.0	2020	Free	2	5,000+
RA Manager		iOS	Point of Care	10.6.0	–	2020	Free	13	N/A
RA Monitor		iOS, Android	RPM Healthcare, LLC	1.3.1	1.0.43	2020	Free	16	5,000+
RAISE		iOS, Android	Publicis Development	1.0.3	2.0.0	2019	Free	8	500+
RAPA - RA Patient Application		iOS	jacsonmedia Ltd.	1.0	–	2015	Free	7	N/A
Rheumatoid Arthritis Diary		iOS, Android	cellHigh	1.7.98	1.6.8	2020	4.99	10	100+
Rheumatoid Arthritis Support		iOS, Android	MyHealthTeams	12.0.8	12.0.8	2020	Free	3	10,000+
Therapies for Arthritis		Android	IMAPPZ	–	1.3	2020	Free	3	100+
TRACK + REACT		iOS, Android	Arthritis Foundation	2.0.1	1.4	2018	Free	13	10,000+
Your Exercise Solution		iOS, Android	Arthritis Foundation	1.0.5	1.0.4	2017	Free	4	1,000+

Patient Engagement

For the patient engagement analysis, each app's score for the 5 parameters (engagement, functionality, aesthetics, information, and subjective), along with the overall MARS score is shown (Figure 3). The percentage of apps rated as good (ie, score greater than 4 and less than 5) varied with the parameter, with 15% (n=3) so rated for engagement, 45% (n=9) for functionality,

20% (n=4) for aesthetics, and 10% (n=2) for containing information helpful to patients. In terms of the subjectivity parameter, only 10% (n=2) had scores indicating acceptability (ie, score greater than 3 and less than 4), with the user indicating they would recommend the app to other people. For the overall MARS score, only 1 app scored greater than a 4, indicating at least a good rating across all 5 parameters.

Figure 3. Patient engagement evaluations of rheumatoid arthritis mobile apps using the Mobile Application Rating Scale (MARS). Apps appear based on their overall MARS score from highest to lowest. MARS: Mobile Application Rating Scale; RA: rheumatoid arthritis.

App name	Logo	MARS Categories					Overall MARS
		Engagement (5 items)	Functionality (4 items)	Aesthetics (3 items)	Information (6 items)	Subjective (4 items)	
RA Healthline		4.4	4.63	4.67	3.86	3.5	4.16
My Arthritis		3.8	3.75	4.33	4.18	3.75	3.98
TRACK and REACT		3.9	3.63	3.67	4.19	3.13	3.71
RAISE: Rheumatoid Arthritis		3.3	4.63	4.83	3.57	2.75	3.68
RA Manager		4	4.25	3.83	3.56	2.63	3.57
Arthritis Power		3.6	4.25	3.83	3.85	2.63	3.54
RA Monitor		3.8	3.88	3	3.49	3.38	3.5
My Vectra		3.6	4.38	4.17	3.3	2.5	3.46
Rheumatoid Arthritis Support		4.1	4.13	3.33	3.15	2.63	3.37
ArthritisID		3.1	4.25	3.17	3.32	1.88	3.03
Paddison Program for Rheumatoid Arthritis		3.3	4.25	3.5	2.8	1.75	2.95
Your Exercise Solution		3.1	3.38	3	3.4	1.75	2.89
Cliexa-RA		3.2	3.75	2.83	2.88	1.88	2.84
Rheumatoid Arthritis Diary		3.7	3.75	2.17	2.5	2.13	2.78
Qigong for Arthritis		3.1	4.25	2.33	2.68	1.25	2.58
LiveWith Arthritis		3.1	2.75	3.5	2.44	1.38	2.58
Arthritis Advice		2.5	3.5	2.33	3.02	1.25	2.38
RAPA - RA Patient Application		2.5	3.5	1.83	2.65	1.25	2.17
Arthritis Treatment Free App - Cure Arthritis		2.3	3.5	1.83	1.92	1	1.99
Therapies for Arthritis		2.2	3.5	1.67	2.24	1	1.97

Patient Activation

The results of the patient activation analysis based on SCT are displayed (Figure 4). Among the apps, 85% (n=17) improved patient knowledge of the disease through the inclusion of educational resources, and 45% (n=9) promoted self-efficacy toward treatment by having at least 1 of 4 constructs focusing on the translation of experiences and social persuasion into beliefs about disease control. Over half of the apps (n=11, 55%) included features that helped patients form expectations about their disease control. Only 1 app (5%) included a goal formation feature. Moreover, 30% (n=6) of the apps addressed sociostructural factors that exist outside of the individual's control. Slightly over half (n=12, 60%) of the apps included features for improving self-regulation through monitoring of

the disease or symptoms. While many apps contained a few features that align with SCT, only 25% (n=5) contained 5 or more of the 16 constructs, and no app had features within all 6 categories. In terms of the quality of the app for patient activation, 2 apps (10%) had a social cognitive ratio equal to 1, meaning the app displayed an equal number of constructs as compared to total app functions. This suggests a good app for patient activation because each function within the app relates to a construct. Five (25%) apps had an SCT ratio higher than 1, representing high-quality apps for patient activation because the app had features within it relating to more than one 1 construct. Of those 5 apps, 2 (10%) had a ratio of 2 or higher, meaning many features within the app represented multiple SCT constructs (Figure 4).

Figure 4. Patient activation evaluation of rheumatoid arthritis mobile apps using social cognitive theory. RA: rheumatoid arthritis; SCT: social cognitive theory.

App name	Logo	SCT Categories						Total SCT Constructs	SCT Constructs/App Feature Ratio
		Knowledge (1 Construct)	Perceived Self-Efficacy (4 Constructs)	Outcome Expectations (3 Constructs)	Goal Formation (2 Constructs)	Sociostructural Factors (2 Constructs)	Self Regulation (4 Constructs)		
RA Healthline		1	2	2	0	0	0	5	2.50
Rheumatoid Arthritis Support		1	2	1	0	2	0	6	2.00
Paddison Program for Rheumatoid Arthritis		1	2	3	0	0	1	7	1.75
Arthritis Advice		1	1	0	0	1	0	3	1.50
Qigong for Arthritis		1	1	1	0	0	0	3	1.50
Arthritis Treatment Free App - Cure Arthritis		1	0	1	0	0	0	2	1.00
RAISE: Rheumatoid Arthritis		1	2	2	0	1	2	8	1.00
Your Exercise Solution		1	0	1	0	1	0	3	0.75
TRACK and REACT		1	0	1	2	1	4	9	0.69
ArthritisID		1	0	0	0	0	1	2	0.67
Therapies for Arthritis		1	1	0	0	0	0	2	0.66
RAPA - RA Patient Application		1	0	0	0	0	2	3	0.43
RA Manager		1	0	1	0	1	1	4	0.30
RA Monitor		1	0	1	0	0	2	4	0.25
My Arthritis		1	1	1	0	0	1	4	0.22
Arthritis Power		1	1	0	0	0	1	3	0.20
My Vectra		1	0	0	0	0	1	2	0.20
Cliexa-RA		0	0	0	0	0	2	2	0.15
Rheumatoid Arthritis Diary		0	0	0	0	0	1	1	0.10
LiveWith Arthritis		0	0	0	0	0	1	1	0.08

Patient-Centered Care

The perceptual map demonstrates each app's ability to facilitate PCC through patient engagement (ie, MARS score) and patient activation measured by the SCT feature to overall feature ratio (Figure 5). Apps in the upper right quadrant demonstrate the greatest patient-centeredness per these 2 dimensions. RA Healthline had both a good ability to foster patient engagement (MARS score 4.16) and the highest patient activation assessment (SCT feature to total feature ratio of 2.5). Additionally, Rheumatoid Arthritis Support was located in the upper right quadrant. It had a MARS score of 3.17, indicating acceptable patient engagement and an SCT to overall app feature ratio of 2. These 2 apps stood out among the rest because they were able to score highly in terms of useability needed for patient engagement via the MARS. They also had features that satisfied multiple categories and SCT constructs. Patients on our team noted that this also allowed them to be efficient in their design with respect to patient activation since they had higher SCT-to-total feature ratios. As shown in Figure 1, a number of other apps scored highly in patient engagement (ie, MARS) but scored lower in terms of patient activation, as measured by the number of features demonstrating SCT content to overall feature ratio (lower right quadrant).

Figure 5. Perceptual map of US mobile apps' ability to facilitate patient-centered care. MARS: Mobile Application Rating Scale; SCT: social cognitive theory.

Discussion

Principal Findings

To our knowledge, this is the first evaluation of mHealth apps for RA to assess their ability to facilitate PCC. In PCC, there is a role for both the patient and the provider with shared decision-making at the point of care. As an initial step, such apps must foster patient engagement and activation to enhance shared decision-making. Our findings demonstrate there are few mobile apps available within the United States that contain the necessary features to adequately support patients as active partners in their care. Specifically, only 2 apps emerged as having an acceptable or good ability to foster patient engagement and having quality content to promote patient activation, which are 2 necessary components to supporting the patient's role in PCC. However, both these apps lacked a goal-setting feature that is important to integrate patient values into clinical decisions that guide PCC.

Comparison With Prior Work

These findings are consistent with previous reviews of RA apps that are largely focused on useability and self-management. Those reports also found the quality and content of the available mHealth apps to be highly variable. For example, studies found a lack of high-quality mobile apps that provide a comprehensive user experience or longitudinal disease tracking that aligned with clinical guidelines [10,13]. Additionally, few use validated questionnaires or even have the ability to support important aspects of clinical management such as physical activity [11,12]. Moreover, even with the more limited focus on self-management, the efficacy of the available apps is largely uncertain [7]. Overall, the general findings of these reviews are that most apps are of low-to-moderate quality and need more emphasis on working with patients and providers in their development [37].

Our study extends this previous work by evaluating features in their ability to engage the patient and support their activation to facilitate PCC of RA. Specifically, our assessment was guided by SCT, which contains constructs that enable patient activation [27,28]. Both engagement and activation are necessary for patients to effectively collaborate with their rheumatologist to reach shared therapeutic decisions. As patients continue to adopt mHealth apps, we recommend (as others have) that patients, as the end users of the app, be involved in the selection of desired functions and the app design to ensure both dimensions of patient engagement and activation are adequately met [10-13,37]. Additionally, if PCC for RA is to be achieved, app functionality in the areas of goal formation and preferences for symptom and side effect management is critical. Goal formation and identification of treatment preferences are central to how patients approach the treatment selection process. Features that support patients in these areas, along with disease tracking and recording of problematic symptoms and side effects, may enable more efficient and effective discussions surrounding treatment selection, leading to improved outcomes. A pragmatic approach to development is needed to balance the necessary features needed for patient engagement and activation against development costs. Development cost considerations are important to ensure that mobile apps for RA remain free for patients to use. App features need to be created that can promote multiple parameters of patient engagement via the MARS and multiple constructs of SCT to facilitate efficient app use. Future research should focus on establishing the efficacy of mobile apps for RA in terms of the sustainability of use that is necessary to provide clinically relevant information. Additionally, focus should be placed on the activation mechanism to determine if and how apps impact decision-making, outcomes, and the clinical workflow to ensure its translation into clinical practice.

Strengths and Limitations

There were several strengths of this review. First, we analyzed each mobile app's ability to promote PCC through the necessary

components of patient engagement and activation. Following other studies, we used the MARS to assess patient engagement. SCT from the health promotion and education literature was used to evaluate the quality of the content of the apps for patient activation. A novel decision extraction tool was developed by which to evaluate the extent to which mHealth apps for RA utilize SCT. Additionally, our team relied on patients who had RA to design the study, code, review, and interpret the findings. One limitation of our study is that the review only encompassed mobile apps available in US mobile app stores. Further, this review focused only on mobile apps for RA and arthritis, but patients may use apps designed for other diseases, pain, or alternative medical approaches to managing this disease. This review also focuses on reviewing app contents for the ability to potentially foster patient engagement and activation. There are also limitations in the MARS, in that it focuses on app quality and useability; however, it is applicable to evaluating patient engagement of mHealth technology [9,24]. As noted, future research is needed to evaluate the efficacy of apps in terms of patient engagement and activation as outcomes of an intervention using these apps.

Conclusions

Patient-centered care of RA aligns patients' goals for living with their preferences for symptom and side effect management to enable the selection of a therapy that promotes greater adherence and more effective disease control. We found that there are only 2 mobile apps available within the United States that rate as acceptable or good in terms of patient engagement and activation, which are 2 dimensions necessary for facilitating PCC. As the prevalence of mobile apps expands, the design of these mobile apps needs to include patients to ensure their engagement and activation. Physicians also are critical to ensure that clinically relevant information is being collected and used in decision-making. Areas for further investigation of mHealth apps include their impacts on patient engagement, activation, treatment decisions, and disease trajectory.

Authors' Contributions

MJC, ABK, JS, MC, and HT were involved in the study design and planning. MC and HT were involved in app identification and content analysis with oversight from MJC, ABK, and JS. PRF was involved in initial manuscript drafting, including the formation of tables and figures with oversight from MJC. LCL and RDH provided numerous helpful comments when preparing the manuscript for publication. All authors provided a critical review of the manuscript for publication.

Conflicts of Interest

MJC is the owner of Optimal Choice, a consulting business that develops digital health apps and health economics textbooks. RDH provides consulting services to Optimal Choice, LLC. RDF also is collaborating with M Cozad on the development of a mobile application for metastatic breast cancer and for rheumatoid arthritis. HT is now an associate with Peter Millar but has no conflicts of interest.

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Abbreviations

MARS: Mobile Application Rating Scale
mHealth: mobile Health
PCC: patient-centered care
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-analyses
RA: rheumatoid arthritis
SCT: social cognitive theory

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<u>Original Paper</u>

Individual and Parental Factors of Adolescents' mHealth App Use: Nationally Representative Cross-sectional Study

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Abstract

Background: Knowledge of the characteristics of adolescents who use mobile health (mHealth) apps to monitor health and how these characteristics differ from those of app nonusers is limited.

Objective: We aimed to determine mHealth app use based on adolescent and parental factors, including sociodemographics, digital skills, and health indicators, in a nationally representative sample of Czech adolescents (N=2500).

Methods: Adolescents aged 11 to 16 years and one of their parents participated in an online survey in 2021. A professional research agency recruited the participants. Quotas were used to ensure the sample's representativeness. The sociodemographic factors were the adolescents' age, gender, and parental perceived financial security. The adolescents also provided information about their screen time, eHealth literacy, BMI, health anxiety, physical activity, and sleep quality. Parents reported their digital skills, mobile phone attitudes, and the mediation of their children's online health information–seeking behaviors. We evaluated the differences between the users and nonusers of mHealth apps and identified the significant predictors of mHealth app use. Next, we separately examined how these factors were associated with the use of mHealth apps that track calorie intake or expenditure, number of steps, weight, or sports activity (eg, exercise, running, and working out), as well as other mHealth apps (eg, those that track sleep and heart rate).

Results: More than half of the adolescents (1429/2455, 58.21%) reported using mHealth apps. App users were relatively older and, more often, girls. Apps that counted the number of steps were used most frequently, and adolescents whose parents reported higher perceived financial security used them more regularly. Overall, being older and physically active and having higher eHealth literacy skills were associated with using mHealth apps. Adolescents with higher BMI, health anxiety, and lower sleep quality more frequently used mHealth apps to track calorie intake or expenditure, weight, and health indicators. mHealth apps to track physical activity were used more regularly by girls. There was a positive association between parental mediation of online health information–seeking behaviors and adolescents' mHealth app use.

Conclusions: These findings demonstrated that older age, physical activity, and eHealth literacy skills were the common underlying factors of adolescents' mHealth app use. We initially showed parents as significant role models for their children's adoption of, and engagement with, mHealth apps when they actively mediate their online health information–seeking behaviors. Improving the eHealth literacy skills of adolescents through parental guidance might enhance health technology use in this population. Tracking eating behaviors, weight, and health were more prevalent for adolescents who reported higher BMI, health anxiety, and lower sleep quality. Future research studies should examine the determinants and health outcomes of adolescents' mHealth app use longitudinally.

KEYWORDS

Introduction

Background

Adolescents use smartphones frequently, and the internet has become an integral part of their lives over the past decades [1,2]. Adolescents use their smartphones for, among other things, health-related purposes such as seeking online health information and using mobile apps to track their health [3,4]. Most studies on adolescents' use of mobile health (mHealth) apps have evaluated the apps' efficacy for disease management [5] and for improving health outcomes [6] such as physical activity [7,8], dietary behaviors [7], weight management [9], and sexual and reproductive health [10]. These mHealth apps were developed by researchers independently or in collaboration with app developers to guide the apps' design and content. Otherwise, they were chosen from among the already available mHealth apps.

mHealth apps are mainly designed to enable users to pursue a healthy lifestyle, and they are primarily clustered around monitoring and managing features related to health, nutrition, and physical activity [11,12]. They allow users to track health-related features such as number of steps, heart rate, and sleep quality, and they support the monitoring and management of eating (eg, calorie intake or expenditure and weight management) and exercise (eg, fitness and sports activity) behaviors. Although studies on the efficacy of mHealth apps in improving health outcomes in adolescents are reported frequently, studies on representative samples that investigate the characteristics of adolescents who use mobile apps to monitor health and how these characteristics differ from those of app nonusers have scarcely been conducted. Determining the prevalence and correlates of adolescents' use of mHealth apps can provide valuable information about their technology use to support a healthy lifestyle and wellness.

In a nationally representative sample of American adolescents, 70% of those aged between 14 and 22 years reported using mHealth apps in 2020 [4], and this percentage was slightly higher than that reported in a previous nationally representative sample of American adolescents (64%) in 2018 [3]. The most frequently used apps were related to fitness, sleep, menstruation, nutrition, and meditation [4]. Another study investigated the use of physical activity apps in a nationally representative sample of Finnish adolescents in 2017 [13]. The results showed that approximately half of the adolescents (52.8%) aged between 11 and 15 years owned these apps to track their physical activity; however, only 16.2% of these adolescents used the apps actively to track their physical activity. By contrast, almost half (47.4%) reported not owning these apps, and an additional 36.5% did not use the apps actively. A low proportion of mHealth app use (18.8%) was reported among Vietnamese youth aged 15 to 25 years in a cross-sectional study conducted in 2015 [14].

Studies that examined the sociodemographic correlates of mHealth app use among adolescents showed that older age and female sex were associated with using mobile apps for health [3,4,13]. Adolescents with a higher socioeconomic status were more likely to use physical activity trackers [13]. In addition, studies reported connections among mHealth app use, BMI,

and physical activity. A higher BMI was related to the frequency of use of fitness and nutrition apps in a study with adolescents [15] and to the intention to use physical activity apps in another study with college students [16]. Adolescents who exercised at least once per week were more likely to use mHealth apps to track physical activity than those who never exercised or exercised rarely [13]. Although these findings provided preliminary evidence, only a few adolescent factors were investigated, limiting our understanding of mHealth app use in this population.

mHealth app use is mainly concerned with seeking health information and monitoring relevant health indicators to promote health and wellness [17]. Thus, the factors that promote online health information–seeking and health-monitoring behaviors might be potentially associated with the use of mobile apps for healthy lifestyle purposes. Therefore, in addition to sociodemographic characteristics, BMI, and physical activity, which were related to using mHealth apps in previous studies [4,13,15], we examined the roles of adolescents' eHealth literacy, screen time, health anxiety, and sleep quality in this study. eHealth literacy refers to the knowledge and skills related to obtaining, understanding, and evaluating online health information and pursuing it to promote health and prevent illnesses [18,19]. Previous research identified an association between higher eHealth literacy and health-promoting behaviors in adolescents [20] and between higher health literacy and using mHealth apps in adults [21]. Therefore, we examined the role of eHealth literacy in the mHealth app use of adolescents. We also examined the role of adolescents' screen time because the time spent online is associated with, in general, searching for online information [22]. In addition, we examined the roles of health anxiety and sleep quality because their physical manifestations can be tracked by mobile apps that monitor health indicators such as heart rate and sleep.

Thus far, most studies have focused on adolescent-related factors to determine the use of mHealth apps and neglected to examine the social determinants of such behaviors; for instance, there is currently a lack of evidence for the role of parents in their adolescent children's adoption of mHealth apps. Nevertheless, parents model their children's online behaviors [23,24], and parental factors connected with adolescents' adoption of new technologies deserve further research. Parental mediation refers to the behaviors and strategies applied by parents to regulate their children's media use [25]. Previous studies showed that parental mediation was associated with adolescents' online health behaviors and eHealth literacy skills [26,27]. In this study, we focused on the parental mediation of online health information–seeking behaviors, which refers to parents' involvement in enhancing adolescents' eHealth literacy skills for assessing the quality and trustworthiness of online health information. eHealth literacy is closely connected to health-promoting behaviors [20]. Therefore, we expect adolescents who receive parental mediation to improve their eHealth literacy skills to be more likely to adopt digital technologies that promote health, including mHealth apps. We also examined the role of parental digital skills in adolescents' adoption of mHealth apps. Recent studies highlight the significance of parental factors in adolescents' technology use

[28]. In addition, we know from previous research that parental digital skills are associated with increased opportunities for adolescents [25]. Therefore, we expect adolescents with higher parental digital skills to be more likely to explore health-promoting technologies such as mHealth apps. Finally, we examined parents' attitudes toward their children's use of mobile phones because parental mobile phone attitudes might influence the amount of time that adolescents spend online and the variety of online activities they engage in with their mobile phones [29].

There are various mHealth apps available in the market to monitor and manage a healthy lifestyle (eg, health-related features, nutrition, and physical activity). Nevertheless, the frequency with which adolescents use these different mHealth apps and whether the use patterns differ depending on adolescent and parental factors are relatively unknown. Previous research demonstrated an association between higher BMI and fitness and nutrition apps [15,16] and between higher levels of physical activity and fitness-related apps [13]. Nevertheless, further research is required to understand app use in this population; for instance, factors such as health anxiety and lower-quality sleep may be more closely related to using mHealth apps to track health-related features. By contrast, factors such as adolescents' eHealth literacy, screen time, and parental mediation of their online health information–seeking behaviors might not differentiate among the user groups. Thus, they might explain adolescents' general adoption and use patterns of new technologies for health management purposes. Therefore, we evaluated the roles of adolescent and parental factors separately in adolescents' use of different types of mHealth apps in this study.

Objectives

This study examined the prevalence of mHealth app use in a nationally representative sample of Czech adolescents. The mobile internet penetration rate in the Czech Republic (91%) is similar to the European Union average (92%) [30], and 82% of the Czech children aged 9 to 16 years use their smartphones to access the internet at least daily [2]. This study provides the initial evidence from a nationally representative sample concerning adolescents' mHealth app use in Europe.

We evaluated the differences between users and nonusers of mHealth apps and identified the significant predictors of mHealth app use based on sociodemographic and selected adolescent and parental factors. Next, we separately examined how these factors were associated with use of mHealth apps that track (1) calorie intake or expenditure, (2) number of steps, (3) weight, or (4) sports activity (eg, exercise, running, and working out), as well as (5) other mHealth apps (eg, those that track sleep and heart rate). No previous study has explored the role of parents in the mHealth app use of adolescents. In addition, to the best of our knowledge, this study is the first to examine sociodemographic, adolescent, and parental factors together in the mHealth app use of adolescents and how these factors might be associated with the use of different types of apps.

Methods

Recruitment

This study recruited a nationally representative sample of 2500 Czech adolescents (1250/2500, 50% girls) aged 11 to 16 (mean 13.43, SD 1.70) years and 2492 caregivers, of whom 1589 (63.76%) were women aged 18 to 74 (mean 42.75, SD 7) years. The data constitute the first wave of a longitudinal study that examined the impact of information and communication technologies on the well-being of adolescents. A professional agency recruited the participants and conducted the online data collection in June 2021 as part of the Future project (Modeling the Future: Understanding the Impact of Technology on Adolescents' Well-being). The target group for eligibility was Czech households, with 1 parent or caregiver and 1 adolescent (aged 11-16 years) who would fill out the questionnaire online. The agency selected eligible participants for the final sample from a combined pool of 3 Czech online panels (approximately 165,000 panelists) and 980 newly recruited households. Quota sampling was used with equal distributions for the adolescents' gender and age. The sampling procedure considered household income, administrative region according to the Nomenclature of Territorial Units for Statistics, and municipality size to ensure a proportional representation of Czech households with children. Before the data collection, cognitive testing in the form of semistructured interviews was conducted to test the comprehension of the questionnaires by respondents from different age groups. In addition, pilot testing was conducted on 195 adolescents and one of their parents to check the data distributions in all variables and to determine the dimensions and internal reliabilities of the scales. Adolescents and parents filled out an online questionnaire at their homes. Only 1 adolescent and 1 parent were recruited from each household. The computer-assisted web interviewing method was used. The agency obtained written informed consent from the adolescents and their parents before participation. Before they filled in the questionnaires, the participants were briefed about the survey's aim, anonymity, and the possibility of refusing to participate. They were also informed about the possibility of answering any question with *I don't know* or *I prefer not to say* options. The agency checked the completion times for the questionnaires and monitored the consistency of the entries between the parent and the child. The agency also applied quality checks on the collected data and removed respondents with poor data quality from the final data set.

Ethics Approval

The research ethics committee of Masaryk University approved this study (EKV-2018-068).

Measures

Sociodemographic Characteristics

Both adolescents and parents reported their gender, and they responded to an open-response question to indicate their age. The parents provided information about their perceived financial security. The question was as follows: *How does your household manage its total monthly income?* The response scale included (1) *with great difficulty*, (2) *with difficulty*, (3) *with minor*

difficulty, (4) *somewhat easily*, (5) *easily*, and (6) *very easily*. Parental perceived financial security was used as an indicator of familial affluence.

Screen Time

Adolescents reported the time they spent using computers (laptop or desktop) and mobile phones or tablet devices, as well as watching television, including DVDs and Netflix, during usual weekdays. The screen time, calculated in hours, was obtained by adding the time spent using each device.

eHealth Literacy

eHealth literacy was measured using the eHealth Literacy Scale [31]. Adolescents reported on their knowledge of online health information sources (ie, *I know what health resources are available on the internet*), how to navigate the internet to obtain answers to health-related questions (ie, *I know where to find helpful health resources on the internet*), and their perceived skills to evaluate the quality of online health information (ie, *I can tell high-quality health resources from low-quality health resources on the internet*). The response scale ranged from 1 (strongly disagree) to 5 (strongly agree). Higher scores indicated better eHealth literacy skills. The internal consistency was adequate (Cronbach α=.89).

BMI Calculation

The BMI was calculated from the adolescents' self-reported answers to open-ended questions about their height (in centimeters) and weight (in kilograms).

Health Anxiety

Health anxiety was measured with a modified version of the Multidimensional Inventory of Hypochondriacal Traits [32], which measures self-reported health anxiety in cognitive, behavioral, perceptual, and affective domains. In this study, 4 items from the affective domain to assess hypochondriacal worry were used. Adolescents reported how much the following statements applied to them: *I worry a lot about my health*; *When I experience pain, I fear I may be ill*; *Reading articles about disease makes me worry about my health*; and *I am concerned with the possibility of being diagnosed with a serious disease*. The response options included (1) *very untrue*, (2) *somewhat untrue*, (3) *neutral*, (4) *somewhat true*, and (5) *very true*. Higher scores indicated increased health anxiety. The internal consistency was adequate (Cronbach α=.85).

Physical Activity

Adolescents responded to the following question: *How many of your free-time hours each week do you usually exercise to the extent that you sweat and feel shortness of breath (excluding the compulsory physical education at school)?* The response options included (1) *less than half an hour per week*, (2) *about half an hour per week*, (3) *about 1 hour per week*, (4) *about 2-3 hours per week*, (5) *about 4-6 hours per week*, and (6) *about 7 hours or more per week*.

Sleep Quality

Sleep quality was addressed with the following question: *In the last month, how would you rate your overall sleep quality?* The response options were (1) *very bad*, (2) *fairly bad*, (3) *fairly*

good, and (4) *very good*. Lower scores were indicative of a worse quality of sleep.

Parental Mediation of Online Health Information–Seeking Behaviors

Parental mediation of adolescents' online health information–seeking behaviors was measured with 4 items adapted from the eHealth Literacy Scale [31]. The parents reported the frequency of their involvement in discussing the trustworthiness and quality of online health information with their adolescent children in the preceding few months. The items consisted of how often parents discussed with their children the following topics: *Whether we can trust health-related information on the internet*, *How we can tell that health-related information on the internet is true or false*, *How we can tell that the author of health-related information on the internet is trustworthy*, and *How we can evaluate the quality of health-related information on the internet*. The response options included (1) *never*, (2) *a few times at most*, (3) *several times a month*, (4) *several times a week*, (5) *every day*, and (6) *several times a day*. The internal consistency was adequate (Cronbach α=.94).

Parental Digital Skills

Parents evaluated how advanced they were in terms of using (1) computers, (2) the internet, and (3) smartphones. The response options ranged from 1=*beginner* to 8=*expert*. Parental digital skills were determined by the average score of the items.

Parental Mobile Phone Attitudes

Parental mobile phone attitudes were measured by adapting the 5 items from a previous study [33] that evaluated parental attitudes toward their children's internet use. We changed the word "internet" to "mobile phones" in this study. The items consisted of the following statements: *Mobile phones should be used by the whole family*, *Mobile phones harm children in learning*, *Mobile phones will enhance the overall development of a child*, *Mobile phones harm children in developing thinking skills*, and *Children need to learn to use mobile phones now to be successful in the future*. The parents indicated their attitudes toward their children's mobile phone use on a scale that ranged from 1=*strongly disagree* to 5=*strongly agree*. The reverse items were recoded so that higher numbers represented more positive attitudes. The internal consistency was adequate (Cronbach α=.67).

Use of mHealth App by Adolescents

Adolescents' app use was determined by their response to the following question: *You can use various applications on your phone, tablet, and other devices. Do you use applications to monitor health and exercise (e.g., counting steps, tracking calories, weight, sports activities, eating/drinking, stress, sleep)?* The response options were (1) *No* and (2) *Yes*. Those adolescents who indicated that they were using mHealth apps responded to an additional question about the frequency of using different apps: *Such applications can be used to monitor or record data in various areas of health. How often have you used them in the last six months in the following areas?* The use frequency was assessed for (1) calorie intake or expenditure, (2) number of steps, (3) weight, (4) sports activity (eg, exercise, running,

and working out), and (5) other health apps (eg, those that track sleep and heart rate). The response options included (1) *never*, (2) *once*, (3) *no more than a few times*, (4) *several times a month*, (5) *several times a week*, (6), *daily*, and (7) *several times a day*.

Statistical Analysis

Descriptive statistics were run for the sociodemographic, adolescent, and parental factors, including means, SDs, and frequencies for the whole sample, app users, and nonusers. The differences in the studied variables between app users and nonusers were analyzed using independent sample t tests and chi-square difference tests. A 2-tailed α=.05 was applied to statistical testing. The effect sizes were calculated using the Hedges g correction for independent sample t tests and the ϕ coefficient for chi-square difference tests. Hierarchical logistic regression analysis examined the significant predictors of mHealth app use. We entered the sociodemographic factors in the first step, followed by entering adolescent factors in the second step and parental factors in the third step. We presented the adolescents' use frequency of different apps and conducted separate hierarchical regression analyses to identify the significant factors related to the adolescents' use of each app type. The analyses were run using SPSS software (version 28.0; IBM Corp) [34]. Mahalanobis distances were computed to check

multiple outliers, and the data obtained from 1.24% (31/2500) of the participants with significant Mahalanobis distance values at $P<.001$ were deleted.

Results

Prevalence of mHealth App Use and Sample Characteristics

The total sample size consisted of 2469 adolescents and one of their parents. More than half of the adolescents (1429/2455, 58.21%) reported using mHealth apps on their devices. We examined the sociodemographic, adolescent, and parental factors of the whole sample and the differences between app users and nonusers (Table 1). Girls accounted for 49.9% (1232/2469) of the sample, and the mean age of the participants was 13.42 (SD 1.70) years. The caregivers (n=2333) were aged between 18 and 74 (mean 42.74, SD 7.01) years, and most of the caregivers who responded to the questionnaires were women (1567/2461, 63.67%). More than half of the households (1369/2449, 55.9%) reported managing their monthly income somewhat easily or easily. At the same time, 24.66% (604/2449) reported managing their household income with minor difficulty, 6.45% (158/2449) with difficulty, and 2.9% (71/2449) with great difficulty, whereas 10.09% (247/2449) of the participants reported managing their household income very easily.

Table 1. Sociodemographic, adolescent, and parental factors of the sample.

Variables	Total sample (N=2469)	App users[a] (n=1429)	App nonusers (n=1026)	P value	Effect size
Sociodemographic factors					
Age (years), mean (SD)	13.42 (1.70)	13.61 (1.65)	13.16 (1.72)	<.001[b]	0.267
Gender, girl, n (%)	1232 (49.9)	759 (53.11)	466 (45.42)	<.001[b]	0.076
Parental perceived financial security, mean (SD)	3.95 (1.17)	4 (1.16)	3.87 (1.18)	.01[b]	0.106
Adolescent factors, mean (SD)					
Screen time in hours	7.25 (4.05)	7.4 (4)	7.03 (4.1)	.03[b]	0.092
eHealth literacy	3.34 (0.87)	3.46 (0.83)	3.17 (0.9)	<.001[b]	0.329
BMI	20.43 (3.84)	20.48 (3.56)	20.38 (4.19)	.55	0.026
Health anxiety	2.47 (0.97)	2.54 (0.98)	2.35 (0.94)	<.001[b]	0.195
Physical activity	4.35 (2.15)	4.66 (2.11)	3.91 (2.14)	<.001[b]	0.356
Sleep quality	3.24 (0.64)	3.21 (0.66)	3.28 (0.62)	.01[b]	0.106
Parental factors, mean (SD)					
Parental OHIS[c] mediation	2.34 (1.03)	2.46 (1.06)	2.16 (0.96)	<.001[b]	0.289
Parental digital skills	5.59 (1.35)	5.63 (1.34)	5.53 (1.37)	.08	0.073
Parental mobile phone attitudes	3.26 (0.67)	3.28 (0.65)	3.24 (0.7)	.08	0.072

[a]App use was determined by "Yes" or "No" responses to the item assessing the use of mobile health apps by adolescents. The number of app users and nonusers is less than the total sample size because of missing values on this variable.

[b]Significant P value.

[c]OHIS: online health information seeking.

Adolescents' screen time on weekdays was, on average, 7 hours and 15 minutes (SD 4 hours 3 minutes). The mean BMI was in

the normal range. The adolescents evaluated their eHealth literacy skills rather positively, had a medium level of health

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anxiety, and their sleep quality ranged between *fairly good* and *very good*. They were physically active between *2 to 3 hours per week* and *4 to 6 hours per week*. The mean parental mediation of online health information–seeking behaviors was between *several times a month* and *several times a week*. Parents evaluated their digital skills highly and had somewhat positive attitudes toward their adolescent children's use of mobile phones.

Comparison Between App Users and Nonusers

There were statistically significant differences between app users and nonusers regarding age, gender, and parental perceived financial security (Table 1). App users were relatively older ($t_{2453}=-6.47$; $P<.001$) and, more often, girls ($\chi^2_1=14.1$; $P<.001$), and their parents reported higher perceived financial security ($t_{2433}=-2.58$; $P<.001$). All adolescent factors were significantly different between app users and nonusers, except for BMI ($t_{2189}=-0.59$; $P<.55$). App users reported significantly longer screen time ($t_{2440}=-2.24$; $P=.02$) and better eHealth literacy skills ($t_{2445}=-8.04$; $P<.001$). They were more likely to report higher health anxiety ($t_{2453}=-4.76$; $P<.001$) and lower sleep quality ($t_{2444}=2.58$; $P<.001$). In addition, they were physically more active than app nonusers ($t_{2407}=-8.6$; $P<.001$). As for the parental factors, only the parental online health information–seeking mediation differed between the groups. The parents of app users reported a higher frequency of mediating their adolescent children's online health information–seeking behaviors than the parents of app nonusers ($t_{2422}=-7.02$; $P<.001$). Although significant differences were observed between app users and nonusers, the effect sizes for the observed differences were small for age, eHealth literacy, and parental online health information–seeking mediation, and they were negligible for gender, parental perceived financial security, screen time, health anxiety, and sleep quality.

The hierarchical logistic regression analysis examined the correlates of mHealth app use by the adolescents (Table 2). The results demonstrated that female sex and older age were significantly associated with mHealth app use, but parental perceived financial security was not. After controlling for sociodemographic factors, the adolescent factors that explained mHealth app use were physical activity, eHealth literacy, health anxiety, and sleep quality. Adolescents who were physically more active and had higher eHealth literacy skills were more likely to use mHealth apps. Using mHealth apps was associated with higher health anxiety and lower sleep quality. There were no significant relationships between mHealth app use and the adolescents' BMI and screen time. In the final step, the roles of parental factors were examined, controlling for sociodemographic and adolescent factors. The results demonstrated that adolescents whose parents were more likely to mediate their children's online health information–seeking behaviors were more likely to use mHealth apps. Factors related to parental digital skills and mobile phone attitudes were not significantly associated with mHealth app use of the adolescents.

Factors of mHealth App Use by Type of App

The remaining analyses focused on the subsample of adolescents who reported using mHealth apps (n=1429). First, we examined the frequency of mHealth app use for each mHealth app type (Table 3). The apps that counted the number of steps were the most frequently used mHealth apps for adolescents: 48.7% (693/1423) reported using them daily or several times a day. These were followed by mHealth apps that tracked health indicators such as heart rate and sleep quality: 21.67% (308/1421) used them daily or several times a day. Sports-related mHealth apps that track exercise, fitness, and physical activity were used daily or several times a day by 17.36% (247/1423) of the adolescents. The least frequently used mHealth apps were those that tracked calorie intake or expenditure and weight. mHealth apps related to calorie intake or expenditure were used by 12.22% (173/1416) of the adolescents daily or several times a day, whereas 6.86% (97/1415) of the adolescents used mHealth apps to track weight daily or several times a day.

Table 2. Sociodemographic, adolescent, and parental factors related to adolescents' mobile health app use.

Variable	B	SE	P value	Exp (B) (95% CI)
Block 1 (sociodemographic factors)[a]				
Age (years)	0.13	0.03	<.001[b]	1.14 (1.08-1.21)
Gender	–0.35	0.09	<.001[b]	0.71 (0.59-0.85)
Parental perceived financial security	0.08	0.04	.07	1.08 (0.99-1.17)
Block 2 (adolescent factors)[c]				
Screen time in hours	–0.00	0.01	.76	1.0 (0.97-1.02)
eHealth literacy	0.23	0.06	<.001[b]	1.26 (1.13-1.41)
BMI	0.01	0.01	.52	1.01 (0.98-1.03)
Health anxiety	0.15	0.05	.003[b]	1.16 (1.05-1.28)
Physical activity	0.17	0.02	<.001[b]	1.18 (1.13-1.24)
Sleep quality	–0.16	0.08	.03[b]	0.85 (0.73-0.99)
Block 3 (parental factors)[d]				
Parental OHIS[e] mediation	0.19	0.05	<.001[b]	1.21 (1.10-1.34)
Parental digital skills	0.02	0.04	.57	1.02 (0.95-1.09)
Parental mobile phone attitudes	0.02	0.07	.80	1.02 (0.89-1.17)

[a]Nagelkerke R^2=0.03.

[b]Significant P value.

[c]Nagelkerke R^2=0.10.

[d]Nagelkerke R^2=0.11.

[e]OHIS: online health information seeking.

Table 3. Adolescents' use of different types of mobile health (mHealth) apps (N=1429).

Type of mHealth app	Never, n (%)	Once, n (%)	A few times at most, n (%)	Several times a month, n (%)	Several times a week, n (%)	Daily, n (%)	Several times a day, n (%)
Calorie intake or expenditure (n=1416)	465 (32.84)	131 (9.25)	324 (22.88)	167 (11.79)	156 (11.02)	136 (9.61)	37 (2.61)
Number of steps (n=1423)	61 (4.29)	40 (2.81)	143 (10.05)	232 (16.3)	254 (17.85)	515 (36.19)	178 (12.51)
Weight (n=1415)	498 (35.19)	139 (9.82)	304 (21.48)	231 (16.33)	146 (10.32)	74 (5.23)	23 (1.63)
Sports activity (n=1423)	212 (14.9)	87 (6.11)	273 (19.19)	298 (20.94)	306 (21.5)	178 (12.51)	69 (4.85)
Health (n=1421)	329 (23.15)	98 (6.9)	243 (17.1)	211 (14.85)	232 (16.33)	249 (17.52)	59 (4.15)

To identify the sociodemographic, adolescent, and parental factors related to mHealth app use, we conducted separate hierarchical linear regression analyses by each app type (Table 4). The results demonstrated that, regardless of the kind of app, older age was associated with a higher frequency of mHealth app use. Gender was significantly associated with the use of mHealth apps for physical activity (ie, number of steps and sports activity). Girls used these mHealth apps more frequently. Higher perceived financial security by parents was associated with the frequency of using mHealth apps that tracked the number of steps. After controlling for sociodemographic characteristics, the adolescent factors associated with using all mHealth app types were the adolescents' eHealth literacy skills and their level of physical activity. mHealth apps were used

more frequently by adolescents who had higher eHealth literacy skills and who were physically more active. Higher BMI was associated with the use of mHealth apps to manage calorie intake or expenditure and weight. Adolescents with lower sleep quality and higher health anxiety used mHealth apps to track weight and health indicators more frequently (eg, heart rate and sleep quality). The adolescents' screen time was not significantly associated with the use of mHealth apps. After controlling for sociodemographic and adolescent factors, the only parental factor related to the adolescents' mHealth app use was parental online health information–seeking mediation. Adolescents whose parents reported a higher frequency of mediating their children's online health information–seeking behaviors used mHealth apps to track calorie intake or expenditure, weight,

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physical activity, and health more frequently. Parental digital skills and mobile phone attitudes were not significantly associated with the use of mHealth apps.

Table 4. Sociodemographic, adolescent, and parental factors related to adolescents' frequency of mobile health app use by type of app (N=1429).

	Calorie intake or expenditure (n=1416)		Number of steps (n=1423)		Weight (n=1415)		Sports activity (n=1423)		Health (n=1421)	
	β	P value	β	P value	β	P value	β	P value	β	P value
Block 1 (sociodemographic factors)[a]										
Age (years)	.09	.003[b]	.07	.03[b]	.07	.02[b]	.12	<.001[b]	.08	.005[b]
Gender	−.05	.08	−.07	.02[b]	−.05	.08	−.06	.03[b]	−.00	.94
Parental perceived financial security	.00	.99	.07	.01[b]	−.05	.08	−.01	.62	.02	.50
Block 2 (adolescent factors)[c]										
Screen time	.03	.27	−.03	.40	.04	.19	−.03	.28	−.02	.41
eHealth literacy	.10	<.001[b]	.06	.04[b]	.09	.003[b]	.11	<.001[b]	.08	.008[b]
BMI	.10	<.001[b]	.03	.32	.09	.001[b]	.05	.01	−.00	.87
Health anxiety	.05	.07	−.00	.89	.11	<.001[b]	−.01	.65	.08	.004[b]
Physical activity	.14	<.001[b]	.19	<.001[b]	.12	<.001[b]	.31	<.001[b]	.20	<.001[b]
Sleep quality	−.04	.17	−.04	.18	−.06	.02[b]	−.04	.12	−.06	.03[b]
Block 3 (parental factors)[d]										
Parental OHIS[e] mediation	.17	<.001[b]	.00	.99	.24	<.001[b]	.14	<.001[b]	.16	<.001[b]
Parental digital skills	−.02	.50	.05	.07	.02	.56	.02	.59	.02	.51
Parental mobile phone attitudes	.02	.59	−.03	.27	.01	.73	−.00	.95	.02	.56

[a]Calorie intake or expenditure: R^2=0.02, number of steps: R^2=0.02, weight: R^2=0.02, sports activity: R^2=0.02, and health: R^2=0.01.

[b]Significant P value.

[c]Calorie intake or expenditure: R^2=0.08, number of steps: R^2=0.06, weight: R^2=0.09, sports activity: R^2=0.13, and health: R^2=0.08.

[d]Calorie intake or expenditure: R^2=0.10, number of steps: R^2=0.06, weight: R^2=0.15, sports activity: R^2=0.15, and health: R^2=0.11.

[e]OHIS: online health information seeking.

Discussion

Principal Findings

Overview

This study focused on mHealth app use by adolescents. It examined the sociodemographic, adolescent, and parental factors for mHealth app use and how they were related to the frequency of using different types of mHealth apps in a nationally representative sample of Czech adolescents. Previous research identified an association between mHealth app use and adolescents' age, gender, socioeconomic status, BMI, and physical activity [3,4,13,16]. In addition to these variables, we investigated whether adolescents' eHealth literacy, screen time, health anxiety, and sleep quality were associated with their mHealth app use. Furthermore, we initially examined parental factors, including the parents' digital skills and mobile phone attitudes as well as their mediation of their children's online health information–seeking behaviors. To the best of our knowledge, this is the first study to explore the role of parents in their adolescent children's use of mHealth apps. It provides a more complex and comprehensive understanding of mHealth app use by adolescents.

Prevalence of mHealth App Use

More than half of the adolescents (1429/2455, 58.21%) reported using mHealth apps on their devices. The mHealth app use rate was higher than that in a previous study that examined the ownership of physical activity apps (52.8%) in a nationally representative sample of Finnish adolescents in 2017 [13], but it was lower than the use rates in nationally representative samples of American adolescents, who reported use rates of 69% in 2020 and 64% in 2018 [3,4]. Similar to the studies conducted on the American samples, we asked adolescents to report whether they used any mHealth apps on their devices. The difference in the reported rates, albeit lower (by approximately 10%), might be related to the sample characteristics; for instance, the American samples included

participants aged between 14 and 22 years, whereas the age range in the Czech sample was between 11 and 16 years. Having emerging adults who are frequent users of mHealth apps [35] as participants might have contributed to the increased use rates in the American samples. Nevertheless, future research might consider the country-level differences and how they might be associated with adopting new technologies for health promotion purposes among adolescents.

Comparison Between App Users and Nonusers

The findings demonstrated that adolescents' age and gender differed between the groups of app users and nonusers. App users were more often adolescent girls and older. These findings were in line with previous research that indicated sociodemographic differences for age and gender between mHealth app users and nonusers in representative adolescent samples [3,4,13]. The increased use of health technologies in older adolescents and girls could be associated with the higher frequency of online health information–seeking behaviors reported for this segment of adolescents [27]. To interpret our findings further, it should be noted that the between-group comparisons revealed a small effect size for age, whereas the effect size for gender was negligible (Table 1). Nevertheless, both variables significantly predicted adolescents' mHealth app use when controlling for adolescent and parental factors in the logistic regression analysis (Table 2). Therefore, their roles should be considered in understanding the mHealth app use of adolescents.

A previous study that used an objective measure to determine socioeconomic status reported higher family affluence for adolescents who used physical activity apps than for those who did not use such apps [13]. We assessed the perceived financial security of parents as an indicator of familial affluence in this study. The results revealed that the parents of app users perceived higher financial security than the parents of nonusers (Table 1). However, the effect size for the observed difference was too small to be considered significant. Furthermore, it did not significantly predict mHealth app use in the logistic regression analysis when adolescent and parental variables were also included in the model (Table 2). Thus, contrary to our expectation, family affluence did not play a significant role in explaining the mHealth app uptake of the adolescents. Further research can examine whether similar findings would be observed when objective criteria are used to determine socioeconomic status.

In this study, mHealth app users were physically more active than nonusers. A previous study demonstrated higher use of physical activity apps with increasing physical activity among adolescents [13]. The adolescents in our study were asked to report whether they used any mHealth apps on their devices. Thus, our findings indicate that higher levels of physical activity (such as taking part in sports activities) are related to adolescents' adoption of mHealth apps. Health consciousness could be a possible explanation for the connection between physical activity and mHealth app use. Health-conscious individuals are more aware of their health conditions, are more motivated to stay healthy, and perceive higher personal responsibility for their health [36]. Higher health consciousness

is related to healthier lifestyle behaviors such as regular physical activity [37,38].

We found initial evidence for the significant role of higher eHealth literacy skills in differentiating between mHealth app users and nonusers. Previous studies in representative adult samples showed that those with higher health literacy skills were more likely to use mHealth apps [17,21]. This study found a similar pattern and showed that adolescents who used mHealth apps were more skillful in understanding and using online health information for health purposes than adolescents who did not use mHealth apps. These findings suggest that the digital disparities in health literacy skills, which limited the use of technology for health purposes in adult samples, were similarly related to the limited use of mHealth apps among adolescents. Therefore, enhancing eHealth literacy skills could be a significant route to the reduction of digital disparities concerning mHealth app use.

This study newly showed that mHealth app users were more likely to score worse on health anxiety and sleep quality than nonusers. It seems that some adolescents could use mobile apps to improve their health status. However, it should be noted that the effect sizes were negligible when comparing app users with nonusers (Table 1), and the odds ratios were closer to 1 when predicting the probability of mHealth app use in the logistic regression analysis (Table 2). Therefore, our findings should be replicated before they can be generalized. Further research can examine the specific types of apps used by these users and how app use is related to their health outcomes; for instance, using an app to diagnose bodily symptoms was associated with increased health anxiety in a previous study [39]. There were no significant differences in BMI between the groups. A previous study with adolescents reported a higher use frequency for nutrition and physical activity apps with increasing BMI [15]. The BMI of app users and nonusers was in the normal range in this study. Future research could investigate whether app users and nonusers would differ in underweight, normal weight, overweight, and obese BMI categories.

App users reported longer screen time than nonusers (Table 1), meaning that app users used digital devices more than nonusers. Nevertheless, the effect size was negligible, and mere duration of digital activity did not significantly predict mHealth app use after controlling for sociodemographic factors (Table 2). Future studies could determine whether certain online activities are related to mHealth app use.

This study is the first to consider parents' behaviors, skills, and attitudes in adolescents' mHealth app use. The only parental variable that differed between the groups was the parental mediation of online health information–seeking behaviors. The parents of app users were more actively involved in mediating their children's online health information–seeking behaviors than the parents of nonusers. In other words, adolescents whose parents discussed the reliability and trustworthiness of online health information more frequently with their children were more likely to use mHealth apps. This finding supports previous research that demonstrated the significant role of parental mediation of internet use in adolescents' online health behaviors and eHealth literacy skills [26,27]. Parental involvement in

enhancing the eHealth literacy skills of adolescents could be a significant social determinant for their health-promoting behaviors in the digital space. Therefore, improving the eHealth literacy skills of parents and encouraging their involvement in guiding their children's critical appraisal skills to evaluate online health information could promote adolescents' use of online health information and technologies.

Factors of mHealth App Use by Type of App

This study contributes to the literature by revealing the factors of adolescents' app use by type of app. We separately examined the roles of sociodemographic, adolescent, and parental factors in the frequency of using mHealth apps for tracking (1) calorie intake or expenditure, (2) number of steps, (3) weight, (4) sports activity (eg, exercise, running, and working out), and (5) other health apps (eg, those that track sleep and heart rate).

The adolescents most frequently reported using mHealth apps to count the number of steps, followed by apps that track health and physical activity. mHealth apps that track the number of steps are often built-in apps delivered in major mobile phone companies' latest smartphones. Therefore, one of the possible explanations for the frequent use of these mHealth apps might be related to their ready availability. Previous studies of American adolescents reported fitness apps to be the most commonly used [3,4]. However, in their analyses, they did not examine the apps that tracked the number of steps separately, and they did not report on the factors related to their use.

Higher levels of physical activity and older age were associated with adolescents' use of physical activity apps in a previous study [13]. Our findings expanded on this and showed that higher levels of physical activity and older age were associated with using apps to track calorie intake or expenditure, weight, exercise, health, and the number of steps. Furthermore, we initially showed that adolescents with higher eHealth literacy skills used mHealth apps more frequently. Persistence is essential for achieving the long-term benefits of using mHealth apps [40]. Therefore, these findings are novel because they indicated that persistence in using different types of apps could be associated with the same underlying factors. Future research could investigate whether the general factors identified in this study explain the use of other types of mHealth apps such as those related to meditation or menstruation.

mHealth apps that track calorie intake or expenditure and weight were more frequently used by adolescents who had a higher BMI. A previous study demonstrated an association between higher BMI and adolescents' use of fitness and nutrition apps [15]. Our findings supported the link between BMI and tracking eating behaviors and weight. However, we could not show a connection between adolescents' BMI and fitness app use. Instead, using fitness-related mHealth apps was significantly associated with the female sex. Adolescent girls tracked the number of steps and sports activities more regularly than boys. Body dissatisfaction is more prevalent in adolescent girls than boys [41]. Thus, the extent to which the use of physical activity apps by adolescent girls is connected to an effort to control their bodies or improve their health needs to be investigated.

Adolescents with higher health anxiety and lower sleep quality tracked their weight, heart rate, and sleep quality more frequently with mHealth apps. Studies indicate an association among excess BMI, health anxiety, and somatic complaints [42]. Similarly, the sleep-wake cycle and heart rate variability are related [43]. There is also an association between excess BMI and the quality and duration of sleep [44]. Therefore, it is reasonable to find an association among adolescents' health anxiety, poor sleep quality, and mHealth app use to track BMI, heart rate, and sleep quality. We also found that adolescents with higher BMI used mHealth apps to track eating behaviors and weight more frequently. Altogether, these findings suggest an association between poorer well-being as related to BMI, health anxiety, and sleep quality and the monitoring of indicators such as eating behaviors, weight, heart rate, and sleep quality with mHealth apps. Whether the frequent use of mHealth apps is related to better well-being or worsened outcomes because of the increasing risk for certain conditions (eg, eating disorders and somatic complaints) in these adolescents should be investigated.

After controlling for sociodemographic and adolescent factors, the only parental variable associated with app use was the parental mediation of online health information–seeking behaviors. Adolescents who received parental mediation of their online health information–seeking behaviors more frequently used mHealth apps to track calorie intake or expenditure, weight, exercise, and health. However, parental mediation did not significantly predict the frequency of using apps that track the number of steps. Instead, parental perceived financial security was a significant predictor of using these apps. As mentioned earlier, apps that count the number of steps are mostly built-in apps in the latest smartphones. Regardless of parental involvement, adolescents whose parents perceive higher financial security could be more likely to have, and already use, these apps on their mobile phones. Therefore, the role of parental online health information–seeking mediation might have been attenuated for these types of apps. Nevertheless, overall, our findings highlight parents as significant role models for their children's adoption of, and engagement with, mHealth apps when they actively mediate their online health information–seeking behaviors.

Limitations and Future Research

The limitations of this study should be considered when interpreting its findings. The cross-sectional design of the study limits the interpretability of the results; for instance, although physical activity was associated with mHealth app use, we cannot determine whether it is a consequence of using mHealth apps or a precursor for engagement and use patterns. The assessments were based on self-reports. Thus, we could not control the response characteristics of the participants. The data were collected when lockdown regulations regarding the COVID-19 epidemic were in force in the Czech Republic. It is possible that the frequency of using mHealth apps might have been influenced by these regulations. The majority of the parents who completed the questionnaires were mothers. Therefore, the results should not be generalized to parental dyads. On the basis of t test statistics, we identified significant differences between users and nonusers of mHealth apps. However, effect sizes for

the observed differences were either negligible or in the small range, limiting the generalizability of the findings. Therefore, determining the factors that differentiate the groups with larger effect sizes are required. In addition to group-based differences, we conducted logistic regression analysis to predict adolescents' mHealth app use, controlling for the roles of sociodemographic, adolescent, and parental factors hierarchically. We also examined the predictors of mHealth app use by type of app. Overall, this study provides a comprehensive overview of how adolescent and parental factors, including sociodemographics, digital skills, and health indicators, were associated with mHealth app use in a representative sample of adolescents in Europe.

Future research could determine how adolescents' use of mHealth apps might be related to their health outcomes and behaviors longitudinally. In addition, a previous study identified individual factors that may cause harm because of the potentially maladaptive use of mHealth apps in an adult sample [45]. Another study raised concerns about the long-term impact of the use of nutrition and fitness apps on young adults at risk of maladaptive eating and excessive exercise [46]. Therefore, future research could also investigate those factors that are related to potentially harmful psychological and health outcomes of adolescents' mHealth app use.

Conclusions

This study examined mHealth app use of adolescents in a representative sample. It showed that older age, higher eHealth literacy skills, and physical activity were related to adolescents' use of mHealth apps. Girls were more likely to adopt mHealth app technologies, and they tracked their physical activity with apps more regularly than boys. In addition, adolescents who reported higher BMI, health anxiety, and lower sleep quality used health apps more frequently to manage weight, eating behaviors, and health. Finally, we showed initial evidence for the significant role played by parental mediation of online health information–seeking behaviors in adolescents' adoption and use of mHealth apps. These findings facilitate a more comprehensive understanding of health technology use by adolescents.

Conflicts of Interest

None declared.

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Abbreviations

mHealth: mobile health

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