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Review

Advancements in Wearable Sensor Technologies for Health Monitoring in Terms of Clinical Applications, Rehabilitation, and Disease Risk Assessment: Systematic Review

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Abstract

Background: Wearable sensor technologies such as inertial measurement units, smartwatches, and multisensor systems have emerged as valuable tools in clinical and real-world health monitoring. These devices enable continuous, noninvasive tracking of gait, mobility, and functional health across diverse populations. However, challenges remain in sensor placement standardization, data processing consistency, and real-world validation.

Objective: This systematic review aimed to evaluate recent literature on the clinical and research applications of wearable sensors. Specifically, it investigated how these technologies are used to assess mobility, predict disease risk, and support rehabilitation. It also identified limitations and proposed future research directions.

Methods: This review was conducted according to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. We searched the PubMed, Scopus, and Web of Science databases up to March 9, 2025. Inclusion criteria focused on studies using wearable sensors in clinical or real-world environments. A total of 30 eligible studies were identified for qualitative synthesis. Data extracted included study design, population characteristics, sensor type and placement, machine learning algorithms, and clinical outcomes.

Results: Of the included studies, 43% (13/30) were observational, 27% (8/30) were experimental, and 10% (3/30) were randomized controlled trials. Inertial measurement unit–based sensors were used in 67% (20/30) of the studies, with wrist-worn devices being the most common (13/20, 65%). Machine learning techniques were frequently applied, with random forest (6/30, 20%) and deep learning (5/30, 17%) models predominating. Clinical applications spanned Parkinson disease, stroke, multiple sclerosis, and frailty, with several studies (4/30, 13%) reporting high predictive accuracy for fall risk and mobility decline (area under the receiver operating characteristic curve up to 0.97).

Conclusions: Wearable sensors show strong potential for mobility monitoring, disease risk assessment, and rehabilitation tracking in clinical and real-world settings. However, challenges remain in standardizing sensor protocols and data analysis. Future research should focus on large-scale, longitudinal studies; harmonized machine learning pipelines; and integration with cloud-based health systems to improve scalability and clinical translation.

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KEYWORDS

wearable sensors; health monitoring; systematic review; gait analysis; rehabilitation; mobile health; mHealth

Introduction

Throughout this paper, we use standardized terminology to ensure clarity and consistency. The term "wearable sensor" refers to any body-worn device capable of measuring physiological or biomechanical parameters, including inertial measurement unit (IMU)–based sensors, smartwatches, smart insoles, and multisensor systems. "IMU" refers specifically to devices incorporating accelerometers, gyroscopes, and magnetometers for motion tracking. When referring to specific device types (eg, smartwatches and smart insoles), we use the precise terminology to distinguish their unique features and applications.

Wearable sensors have gained significant attention in clinical research and health care for their ability to provide continuous, real-world assessments of mobility and physiological health. These devices, including IMU-based sensors, smartwatches, and multisensor systems, have transformed traditional gait and activity monitoring by enabling remote, noninvasive tracking of movement patterns and health status [1]. The integration of advanced analytics, particularly machine learning (ML), has further enhanced their diagnostic and predictive capabilities, positioning wearable sensors as key tools in digital health and precision medicine [2].

Gait analysis and mobility tracking have been central to wearable sensor applications, particularly in neurological, musculoskeletal, and age-related conditions. In Parkinson disease (PD), wearable sensors have been used to detect subtle changes in gait speed, stance and swing phase durations, and postural instability, aiding in early disease detection and progression monitoring. In stroke rehabilitation, these sensors enable remote motor recovery assessment and provide continuous mobility data outside traditional clinical settings [3]. Wearable sensors also demonstrate high efficacy in frailty assessment and fall risk prediction, offering objective, real-time alternatives to conventional tools such as the Performance-Oriented Mobility Assessment (POMA) and Timed Up and Go (TUG) tests.

Despite their growing clinical adoption, several challenges hinder the widespread implementation of wearable sensor technology. Variability in sensor placement, study methodologies, and data processing techniques limits cross-study comparability and reproducibility [3]. Additionally, while controlled laboratory studies have validated their accuracy, real-world validation remains insufficient, necessitating further large-scale, longitudinal studies to assess their usability and reliability across diverse populations [4]. Furthermore, standardization of ML frameworks and data interpretation methodologies is essential to ensure consistent clinical application [5].

This systematic review aimed to provide a comprehensive evaluation of wearable sensor research, analyzing their clinical applications, technological advancements, and methodological challenges. By synthesizing evidence from recent studies, we highlight key trends in wearable sensor use, discuss their implications for health care, and propose future directions to enhance their impact in mobility monitoring and rehabilitation.

Methods

Study Design

The protocol of this review was not registered in PROSPERO due to its exploratory nature and inclusion of emerging sensor studies. However, the review process followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 guidance to ensure methodological transparency. The study selection process followed PRISMA 2020 guidelines, including identification, screening, eligibility assessment, and final inclusion. This review focused on studies published in the last 10 years that investigated the applications and effectiveness of wearable sensors, including smartwatches, in remote health monitoring, rehabilitation, and disease assessment. Full-text articles were included to ensure a comprehensive analysis. We aimed to synthesize evidence on clinical and research applications of wearable sensors, particularly for gait analysis, fall risk assessment, and disease monitoring. Given study heterogeneity, we categorized and synthesized the findings narratively, emphasizing disease-specific insights and sensor use trends.

Search Strategy

A comprehensive database search was conducted across PubMed, Scopus, and Web of Science.

The search strategy combined terms related to wearable technologies, inertial sensors, digital biomarkers, and rehabilitation. Representative Boolean operators were used as follows:

> *("smartwatch" OR "smart watch" OR "wearable sensor" OR "wearable sensor") AND ("accelerometer" OR "acceleration sensor" OR "inertial sensor" OR "IMU") AND ("remote monitoring" OR "digital biomarkers" OR "telemedicine" OR "wearable health tracking") AND (aging OR older adults OR elderly OR Parkinson OR stroke OR "gait disorders" OR "neurological disorders" OR "movement disorders" OR "fall risk" OR rehabilitation OR "functional mobility" OR sarcopenia OR osteoarthritis OR dementia) NOT review.*

The initial search yielded 4226 records. Of these 4226 records, after removing duplicates and studies unrelated to clinical applications (n=3664, 86.7%), 562 (13.3%) remained for screening. Of these 562 studies, those focusing solely on technical performance comparisons (n=501, 89.1%) were excluded, leaving 61 (10.9%) for eligibility assessment. Of these 61 studies, an additional 31 (51%) were excluded due to limited relevance to disease-related applications, resulting in 30 (49%) studies included in the final review. The search was finalized on March 9, 2025. In total, 30 studies met the inclusion criteria and were included in the final synthesis. Additional references cited throughout the manuscript (n=43) were used for background, context, and methodological justification.

Study Selection Process

A single researcher conducted study selection and data extraction following a predefined protocol to minimize bias. The eligibility criteria were clearly defined and consistently applied. Studies published from March 9, 2015, to March 9, 2025, were considered, reflecting a 10-year search window. Eligible study designs included randomized controlled trials (RCTs), observational studies, and experimental validation studies conducted in either clinical or real-world settings. Both research-grade and commercial wearable sensors were included provided that they reported measurable health or functional outcomes. Only English-language, peer-reviewed articles were included, and conference abstracts, reviews, and purely technical feasibility reports without human participants were excluded. Quality appraisal using the Newcastle-Ottawa Scale (NOS), Joanna Briggs Institute (JBI) appraisal tools, or version 2 of the Cochrane risk-of-bias tool for randomized trials (RoB 2) was conducted to describe study rigor but did not influence inclusion decisions.

Any uncertainties during the selection process were resolved by re-evaluating studies against the predefined inclusion criteria. Data extraction was conducted manually using a standardized form. No independent reviewers cross-checked the extracted data, which is acknowledged as a limitation. Missing or unclear data were clarified when possible, by contacting the corresponding authors. No automation tools were used for data collection.

Participant Selection in the Included Studies

The included studies targeted diverse populations, including healthy adults; older individuals; and patients diagnosed with neurological disorders (eg, stroke and PD), musculoskeletal disorders (eg, sarcopenia and osteoarthritis), or metabolic conditions (eg, diabetes). Participants could walk independently and provided informed consent. We excluded studies lacking clear participant definitions or standard gait analysis metrics to maintain consistency. Pediatric studies were excluded except for those including toddler cohorts (aged <3 years) and specifically designed for developmental gait analysis. To ensure data quality, studies were required to report a minimum wear time of 30 minutes of valid sensor data per session.

Wearable Sensor Technology

The wearable sensors reviewed featured advanced components such as high-precision accelerometers, gyroscopes, and pressure sensors. These sensors accurately captured key gait and mobility parameters: step length, stance and swing phase durations, plantar pressure distribution, and center of pressure. Smartwatches were primarily used for activity tracking and remote monitoring, whereas wearable sensors and foot-mounted sensors specialized in gait and postural assessments. The wearable sensors integrated seamlessly into daily life, ensuring high usability and real-world applicability.

Data Acquisition and Analysis

Data were collected using a variety of wearable sensor systems, including IMUs, smart insoles, smartwatches, and pressure-sensing devices. Sensor placement varied by study objective and included the wrist, waist, ankle, thigh, lumbar spine, and foot. The IMU sensors incorporated accelerometers, gyroscopes, and magnetometers with sampling rates ranging from 10 to 1149 Hz depending on the device and measurement context. Pressure-sensitive insoles provided additional biomechanical insights through plantar pressure distribution and force-time characteristics.

Wireless data transmission via Bluetooth or cloud platforms enabled real-time monitoring and digital biomarker extraction. Embedded preprocessing algorithms were applied to reduce noise, improve signal quality, and enhance feature extraction accuracy. Studies used various ML techniques, including random forest (6/30, 20%), deep learning (5/30, 17%), elastic net regression (4/30, 13%), and principal component analysis (PCA; 2/30, 7%), for pattern recognition, mobility classification, and disease risk prediction. All reported quantitative values (eg, area under the receiver operating characteristic curve [AUROC], accuracy, and improvement rate) were extracted from individual studies and are presented descriptively, not as pooled estimates.

The methodological quality of the included studies was systematically evaluated using appropriate assessment tools based on the study design. The NOS was applied to prospective cohort studies, whereas the JBI critical appraisal checklist was used for observational, cross-sectional, and experimental studies. For RCTs, the RoB 2 tool was used to ensure a robust evaluation of study quality. The results of the quality assessment guided the interpretation of the reliability and clinical applicability of the findings. Studies were categorized as low (JBI or NOS score of ≥8), moderate (JBI or NOS score of 6-7), or high (JBI or NOS score of ≤5) risk of bias according to established thresholds.

Ethical Considerations

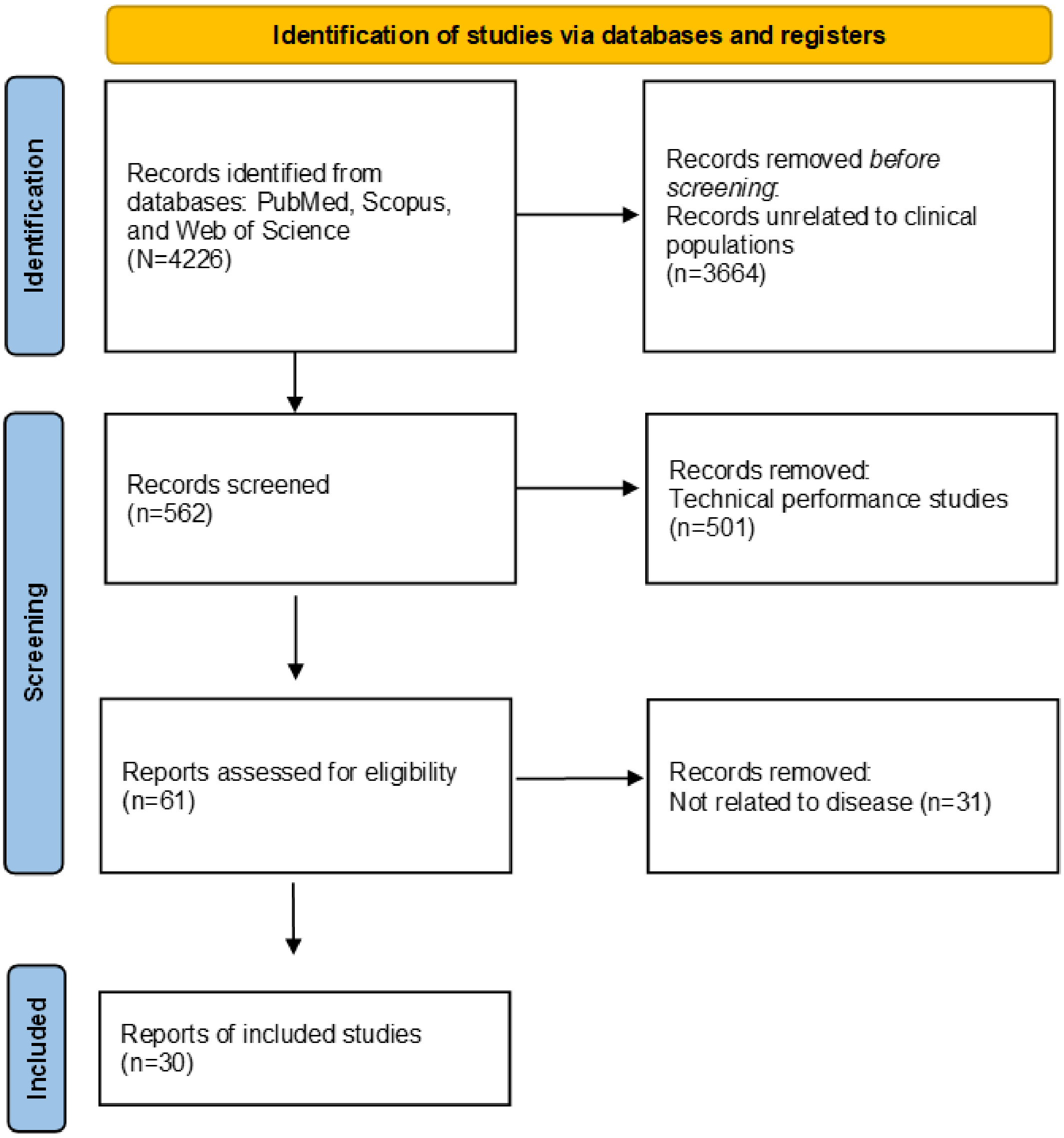
All studies included adhered to ethical standards for human research, following the Declaration of Helsinki. As this study is a systematic review of published literature and did not involve human participants, interventions, or identifiable private data, ethics approval was not required. Data privacy and participant well-being were prioritized across the studies.

Results

Study Design and Population Characteristics

A total of 4226 records were identified through database searching. After removing duplicates and screening titles and abstracts, 562 articles remained for full-text assessment. Of these, 30 studies met the inclusion criteria and were included in the final review. The full screening process is summarized in Figure 1 (PRISMA 2020 flow diagram). Among the analyzed studies, the most frequently used research design was prospective observational studies, accounting for 43% (13/30) of the total. Experimental studies comprised 27% (8/30), whereas RCTs were limited to 10% (3/30). Cross-sectional studies and cohort studies accounted for 13% (4/30) and 7% (2/30), respectively. Observational studies were most common due to their feasibility, whereas experimental studies validated sensor-based assessments. RCTs were scarce, indicating limited rigorous intervention-based evaluations. Cohort studies were included in long-term monitoring applications.

Figure 1. PRISMA flow diagram illustrating the screening process of papers for study selection.



The studies focused on various populations, with healthy adults being the most common participant group, as summarized in Table 1. Studies involving neurodegenerative diseases such as PD, stroke, Huntington disease, and multiple sclerosis (MS) were also prevalent. Healthy adults were often included for sensor validation and reliability assessment, whereas studies on neurodegenerative diseases primarily aimed at mobility and functional monitoring. Research on frailty in older adults (4/30, 13%) focused on mobility assessment, balance, and fall risk analysis. The reviewed studies covered a wide range of age groups and health conditions. Studies involving healthy adults typically included participants from early adulthood to middle age, with some extending to adolescent and pediatric populations. Research on neurodegenerative diseases such as PD and Huntington disease focused primarily on older adults, whereas cardiovascular disease– and frailty-related studies involved older participants as well. Certain studies (12/30, 40%) targeted specific conditions such as osteoarthritis, rheumatoid arthritis, MS, cystic fibrosis, stroke, and spinal cord injury, highlighting the diverse application of wearable sensors, particularly smartwatches, in different clinical populations. The distribution of male and female participants varied across studies, with some (1/30, 3%) focusing specifically on age-based differences in sensor performance and health monitoring.

Table 1. Summary of study populations in the reviewed studies.

Study	Participant age (y)	Number of male/female participants	Health condition
Bolam et al [6], 2021	Mean 66.8 (SD 7.0)	6/8	Knee osteoarthritis
Angelucci and Aliverti [7], 2023	Mean 26.8 (SD NR[a]; range 23-54)	9/11	Healthy adults
Greene et al [8], 2021	PD[b] 1 (clinical cohort): mean 67.3 (SD 7.1); PD 2 (exercise cohort): mean 64.9 (SD 7.3)	27/17	PD
Gordon et al [9], 2019	Mean 51 (SD 12)	9/8	HD[c]
Presley et al [10], 2023	Range 13-24	6/12	Healthy adults and adolescents
De Cannière et al [11], 2020	Mean 63 (SD 1)	65/24	CVD[d] and heart failure
Nunes et al [12], 2024	HD: mean 51.9 (SD 11); pre-HD stage: mean 36.5 (SD 13.1); control: mean 58.9 (SD 12.2)	8/8 (HD group)	HD, pre-HD stage, and controls
Mahadevan et al [13], 2020	Control: mean 43.9 (SD 10); PD: mean 68.1 (SD 8.1)	Control: 27/33; PD: 23/12	PD
Seo et al [14], 2024	Mean 61 (SD 12)	12/7	Stroke (upper-limb hemiparesis)
Odhiambo et al [15], 2023	Mean 27.25 (SD NR; range 20-56)	16/12	Healthy adults
Hwang and Effenberg [16], 2021	Mean 29.8 (SD 6.8)	6/6	Healthy adults
Wu et al [17], 2021	Mean 48 (range 26-66)	2/2	Healthy adults
John and Soangra [18], 2022	Control: mean 74 (SD 8.7); Stroke: mean 69 (SD 8.4)	Control: 6/8; Stroke: 8/6	Stroke vs healthy older adults
Meyer et al [19], 2022	Mean 51 (SD 7)	5/16	Multiple sclerosis
Toumieux et al [20], 2015	Not specified	Not specified	Stroke
Elstub et al [21], 2022	Not specified	6/3	Healthy runners
Perraudin et al [22], 2018	RA[e]: mean 50.7 (SD 11.4); PA[f]: mean 47.5 (SD 15.5); OA[g]: mean 60.7 (SD 4.5); healthy: mean 48 (SD 13.6)	RA: 18 female; PA: 2 female; OA: 10 female; healthy: 15 female	RA, PA, and OA
Giggins et al [23], 2025	Mean 77.5 (SD 8.4)	12/39	Frailty levels
Savi et al [24], 2020	Mean 37.5 (SD 11.5)	6/18	Cystic fibrosis
Haghi et al [25], 2023	Mean 26.7 (SD NR)	22/8	Healthy adults
DasMahapatra et al [26], 2018	Mean 52 (SD 10.6)	28/86	Multiple sclerosis
Sun et al [27], 2019	OA: mean 78.2 (SD 6.1); YA[h]: mean 24.4 (SD 3.9)	OA: 4/6; YA: 6/6	Healthy adults
Ramezani et al [28], 2019	Community: mean 82.16 (SD 9.55); hospital: mean 84.22 (SD 13.87)	Community: 41/104; hospital: 5/4	Older adults with multiple chronic conditions
Liew et al [29], 2024	Mean 20.8 (SD 1.6)	9/9	Healthy adults
Kwon et al [30], 2019	13-35 months (1-year-olds: 11; 2-year-olds: 11)	10/12	Healthy toddlers
Martin et al [31], 2015	Mean 58 (SD 8; range 18-69)	26/22	CVD prevention and obesity
Hup et al [32], 2024	Various	Not specified	OHCA[i] and SCA[j]
Browne et al [33], 2020	Mean 13.3 (SD 2.3)	9/11	Pediatric obesity
Burns et al [34], 2020	≥18	Not specified	Rotator cuff and shoulder pain
Bailey et al [35], 2024	Mean 51 (SD 9; range 28-63)	11/4	Spinal cord injury and wheelchair users

[a]NR: not reported.

[b]PD: Parkinson disease.

[c]HD: Huntington disease.

[d]CVD: cardiovascular disease.

[e]RA: rheumatoid arthritis.

[f]PA: psoriatic arthritis.

[g]OA: old adult.

[h]YA: young adult.

[i]OHCA: out-of-hospital cardiac arrest.

[j]SCA: sudden cardiac arrest.

Sensor Use and Data Analysis in Wearable Research

Studies relied heavily on IMU sensors (20/30, 67%) and smartwatches (8/30, 27%). Shoe-mounted sensors and multisensor systems incorporating electrocardiograms were less frequently used. Wrist-worn sensors (13/30, 43%) were the most common due to ease of wear and practical data collection. Smartwatches, as a subset of wrist-worn devices, were frequently used for continuous activity tracking and health monitoring. Additionally, ankle and thigh placements (7/30, 23%) were primarily used for gait analysis, whereas foot and insole sensors (2/30, 7%) were implemented for more specialized balance and gait assessments.

The predominant activity type studied was gait analysis, which appeared in 60% (18/30) of the studies, followed by activities of daily living (12/30, 40%), balance assessments (8/30, 27%), energy expenditure evaluations (6/30, 20%), and rehabilitation exercises (6/30, 20%). Gait analysis was especially relevant in research focused on neurodegenerative diseases and mobility impairments, where smartwatches were often used for free-living gait monitoring. Studies on activities of daily living leveraged smartwatches for continuous data collection in real-world settings. Balance assessments were primarily conducted for frailty and fall risk evaluations, with some smartwatch-based apps integrating accelerometry for postural control analysis.

Data processing in wearable sensor research used a range of ML techniques. Random forest was the most commonly applied method (6/30, 20%), followed by deep learning models (5/30, 17%), elastic net regression and support vector machines (SVMs; 4/30, 13%), and PCA (2/30, 7%). Random forest was frequently used in gait analysis and activity recognition, whereas deep learning models were applied for long-term movement pattern analysis, particularly in smartwatch-based apps. Elastic net and SVM were commonly used for classification tasks, and PCA was used for dimensionality reduction, optimizing the performance of wearable sensor data processing.

Clinical Applications of Wearable Sensors

Overview

The diverse clinical applications of wearable sensors, categorized into 5 main areas—healthy individuals, age-related conditions, neurological conditions, musculoskeletal disorders, and metabolic conditions—are summarized in Table 2.

Table 2. Summary of clinical results for wearable sensors across populations.

Category and condition	Key findings	Clinical significance and utility
Rehabilitation assessment and functional recovery		
Knee arthroplasty (TKA[a] and UKA[b])	Bone stimulus: +52%; impact load: +371%; OKS[c]: +52%; EQ-5D: +32%	IMU[d]-based wearables support accurate postoperative monitoring and personalized recovery for knee arthroplasty.
CR[e]	6MWD[f] prediction error: 42.8 m; R^2=0.661	CR progress can be reliably tracked remotely, improving long-term care.
Stroke—upper-limb rehabilitation	Movement quality classification accuracy: 92%; F_1-score: 0.95	IMUs enable remote monitoring of home-based rehabilitation, enhancing adherence and personalization.
Rotator cuff injury rehabilitation	Exercise classification accuracy: 99.99%	Smartwatches improve rehabilitation compliance and exercise tracking at home.
Lumbar mobility assessment	Significant ROM[g] differences between wrist and lumbar sensors (up to 8, *P*=.003)	Wrist-worn sensors allow for remote lumbar mobility assessment for rehabilitation use.
Disease state prediction and risk assessment		
PD[h]—tremor and fall risk	Tremor detection accuracy: 83%; sensitivity: 86%; specificity: 86%; fall risk prediction RMSE[i]: 0.42	Wearables objectively monitor PD symptoms and fall risk for early intervention.
HD[j]	Sensitivity: 85%; specificity: 72%; accuracy: 81%; AUROC[k]: 0.82	HD motor decline can be tracked remotely for personalized care.
Frailty assessment in older adults	QTUG[l] accuracy: 75.8%; ScanWatch-enhanced model: 79.3%	Wearables detect frailty early, enabling preventive intervention in older adults.
OHCA[m] detection	Optimized balance between sensitivity and specificity	OHCA can be detected in real time via wearables for rapid emergency response.
Activity and behavior tracking		
Arthritis—pain and function monitoring	5-STS[n] performance significantly correlated with morning pain scores (*P*<.05)	IMUs enable noninvasive, remote tracking of arthritis pain and function.
CF[o]—activity monitoring	Fitbit and iOS smartphone showed strong agreement with SWA[p]	Consumer wearables offer scalable, affordable physical activity monitoring.
Consumer vs research-grade wearables (activity monitoring)	Z-Track sedentary behavior detection: AUC[q]=0.95; MVPA[r] detection: AUC=0.93	Fitbit-level devices reliably track sedentary behavior and activity levels.
Medication adherence monitoring	Medication intake detection accuracy: 93.6%; sensitivity: 92%	Wearables automate medication tracking, improving adherence in chronic care.
Gait analysis and balance assessment		
Gait symmetry analysis (head-worn sensor)	Gait event detection accuracy: 99.35%	Head-worn sensors support gait symmetry analysis for neurological rehabilitation.
Balance assessment (smartwatch based)	Strong correlation between smartwatch and research-grade sensors (*r*=0.861-0.970)	Smartwatches enable balance monitoring at home to prevent falls.
MS[s]—balance and mobility	AUROC=0.97	Wearables track long-term mobility and balance in MS, supporting personalized rehabilitation.

[a]TKA: total knee arthroplasty.
[b]UKA: unicompartmental knee arthroplasty.
[c]OKS: Oxford knee score.
[d]IMU: inertial measurement unit.
[e]CR: cardiac rehabilitation.
[f]6MWD: 6-minute walk distance.
[g]ROM: range of motion.
[h]PD: Parkinson disease.
[i]RMSE: root mean square error.
[j]HD: Huntington disease.
[k]AUROC: area under the receiver operating characteristic curve.
[l]QTUG: quantitative timed up and go.

[m]OHCA: out-of-hospital cardiac arrest.
[n]5-STS: 5-time sit-to-stand assessment.
[o]CF: cystic fibrosis.
[p]SWA: sensewear armband.
[q]AUC: area under the curve.
[r]MVPA: moderate to vigorous physical activity.
[s]MS: multiple sclerosis.

Rehabilitation Assessment and Functional Recovery

Wearable sensors were used to analyze gait metrics in both young and older adults. Studies on young adults focused on plantar pressure distribution, step length, swing time, and ground reaction force, achieving high accuracy in real-time gait analysis, such as 95% using the FreeWalker system with a 1000-Hz sampling frequency. Advanced ML techniques further enhanced center of pressure prediction accuracy by over 30%. Among older adults, wearable sensors were effective in assessing fall risk and mobility. Improvements were observed in swing time (+6.45%) and slip and trip classification accuracy, which exceeded 98% (P<.05).

Disease State Prediction and Risk Assessment

Studies addressed frailty and fall history using wearable sensors to measure load distribution, gait phases, and stance and swing time. Load distribution assessments demonstrated high reliability, with intraclass correlation coefficient values reaching 0.91 and strong correlations for the left (r=0.7171) and right (r=0.7502) foot. Fall risk indexes provided significant predictive accuracy, with AUROC values of 0.919 (P<.05), making them comparable to traditional tools such as the POMA and TUG tests. These findings emphasize the potential of wearable sensors for early identification of frailty and fall risk in older adults.

Activity and Behavior Tracking

Wearable sensors were used to evaluate gait characteristics in individuals with stroke, MS, and PD. Among stroke survivors, significant reductions in gait speed and step length were observed compared to controls, with strong correlations between Fugl-Meyer Assessment lower-limb scores and stance time differences (R^2=0.71). In MS, high agreement was reported between the FeetMe and GAITRite systems (intraclass correlation coefficient>0.8), validating the utility of wearable sensors for mobility monitoring. For individuals with PD, significant differences were detected in gait speed, stride length, and swing and stance time compared to healthy controls (P<.05), demonstrating the role of wearable sensors in tracking disease progression.

Gait Analysis and Balance Assessment

Wearable sensors were effective in managing diabetes and other metabolic disorders. For diabetes, total contact casts reduced forefoot contact area by 5% and peak pressure by 8% (P<.05), effectively offloading pressure and reducing the risk of complications. These devices provide actionable data that support better management of metabolic health and reduce disease-related complications.

Quality Assessment Results

The quality assessment results are summarized in Table 3, with the studies rated using the JBI critical appraisal tools scoring between 5 and 8 out of 10, NOS-rated cohort studies scoring between 6 and 7 out of 9, and RoB 2–rated RCTs scoring 8 out of 10. Of the 30 included studies, 6 (20%) were rated as low risk, and 24 (80%) were rated as having a moderate risk of bias. Studies investigating wearable sensor–based mobility assessments, gait analysis, and rehabilitation applications showed high feasibility and reliability, particularly those incorporating real-time monitoring and signal processing techniques. However, several studies (26/30, 87%) exhibited limitations such as small sample sizes, lack of validation in real-world settings, and limited applicability to diverse patient populations. Additionally, some studies (12/30, 40%) faced technical challenges, including sensor displacement errors, signal-to-noise ratio issues, and data synchronization difficulties.

Table 3. Quality assessment summary of the reviewed studies.

Study	Study design	Quality score	Risk-of-bias category
Bolam et al [6], 2021	Prospective cohort study	7/9 (NOS[a])	Moderate
Angelucci and Aliverti [7], 2023	Experimental study	6/10 (JBI[b] tool)	Moderate
Greene et al [8], 2021	Experimental study	7/10 (JBI tool)	Moderate
Gordon et al [9], 2019	Observational study	6/10 (JBI tool)	Moderate
Presley et al [10], 2023	Experimental study	8/10 (JBI tool)	Low
De Cannière et al [11], 2020	Prospective cohort study	7/9 (NOS)	Moderate
Nunes et al [12], 2024	Observational study	6/10 (JBI tool)	Moderate
Mahadevan et al [13], 2020	Observational study	8/10 (JBI tool)	Low
Seo et al [14], 2024	Observational study	7/10 (JBI tool)	Moderate
Odhiambo et al [15], 2023	Experimental study	8/10 (JBI tool)	Low
Hwang and Effenberg [16], 2021	Observational study	7/10 (JBI tool)	Moderate
Wu et al [17], 2021	Observational study	7/10 (JBI tool)	Moderate
John and Soangra [18], 2022	Observational study	6/10 (JBI tool)	Moderate
Meyer et al [19], 2022	Observational study	7/10 (JBI tool)	Moderate
Toumieux et al [20], 2015	Experimental study	5/10 (JBI tool)	Moderate
Elstub et al [21], 2022	Experimental study	7/10 (JBI tool)	Moderate
Perraudin et al [22], 2018	Observational study	7/10 (JBI tool)	Low
Giggins et al [23], 2025	Cross-sectional study	6/10 (JBI tool)	Moderate
Savi et al [24], 2020	Cross-sectional study	7/10 (JBI tool)	Moderate
Haghi et al [25], 2023	Experimental study	8/10 (JBI tool)	Moderate
DasMahapatra et al [26], 2018	Observational study	6/10 (JBI tool)	Low
Sun et al [27], 2019	Experimental study	7/10 (JBI tool)	Moderate
Ramezani et al [28], 2019	Pilot study	6/10 (JBI tool)	Moderate
Liew et al [29], 2024	Cross-sectional study	6/10 (JBI tool)	Moderate
Kwon et al [30], 2019	Observational study	7/10 (JBI tool)	Moderate
Martin et al [31], 2015	RCT[c]	8/10 (RoB 2[d])	Low
Hup et al [32], 2024	Clinical study	7/10 (JBI tool)	Moderate
Browne et al [33], 2020	RCT	8/10 (RoB 2)	Moderate
Burns et al [34], 2020	Prospective cohort study	7/9 (NOS)	Moderate
Bailey et al [35], 2024	Cross-sectional study	7/10 (JBI tool)	Moderate

[a]NOS: Newcastle-Ottawa Scale.

[b]JBI: Joanna Briggs Institute.

[c]RCT: randomized controlled trial.

[d]RoB 2: version 2 of the Cochrane risk-of-bias tool for randomized trials.

Discussion

Expanding the Role of Wearable Sensors in Health Monitoring

Wearable sensor technology, including IMU-based smartwatches, smart insoles, and multisensor systems, has significantly transformed health monitoring, rehabilitation tracking, and disease risk assessment [36]. These devices enable continuous, real-world tracking of mobility and functional health, addressing key limitations of traditional clinical assessments [37]. The reviewed studies highlight these devices' diverse applications in neurological, musculoskeletal, cardiovascular, and metabolic conditions, supporting early disease detection, remote therapy adherence, and precision rehabilitation [38].

Observational studies accounted for 43% (13/30) of the reviewed studies, reflecting the feasibility of longitudinal monitoring, whereas experimental studies made up 27% (8/30), playing a crucial role in validating sensor-based assessments. However, the limited number of RCTs, representing only 10% (3/10) of the studies, underscores the need for rigorous intervention-based research to establish causal relationships between wearable sensor use and patient outcomes. The study populations were diverse, with healthy individuals comprising 33.3% of the participants, often included for sensor validation and reliability testing. Clinical populations, including individuals with PD, stroke, frailty, and cardiovascular conditions, were the primary focus of applied research, demonstrating the potential for wearable sensors to support patient management in real-world health care settings.

Evolution of Wearable Sensor Applications

In our review, 30% (9/30) of the included studies conducted validation in healthy adults, indicating that early wearable-sensor research primarily focused on device feasibility and performance testing before expanding into clinical populations. These devices have revolutionized mobility monitoring, particularly in neurodegenerative conditions such as PD, MS, and stroke, where continuous tracking of gait parameters enables early detection of motor impairments and disease progression. They also play a significant role in frailty assessment (4/30, 13%) and fall risk prediction. Smart insoles demonstrate high predictive accuracy (AUROC=0.919; P<.05) as noninvasive, real-world mobility assessment tools.

Technological Integration and Advances in Data Processing

The studies primarily used IMU-based systems (20/30, 67%) and smartwatches (8/30, 27%). Wrist-worn sensors were the most common, representing 43% (13/30) of the devices used, as they offer practicality, ease of wear, and convenience for everyday use. Ankle- and thigh-mounted sensors accounted for 23% (7/30) of applications and were primarily used for gait and posture assessments, whereas multisensor systems integrating electrocardiograms and pressure sensors provided additional biomechanical and cardiovascular insights, although they were less frequently studied.

Advances in ML have significantly enhanced data interpretation and predictive capabilities in wearable sensor applications [2]. Random forest models, applied in 20% (6/30) of the studies, were widely used for gait classification and activity recognition, whereas deep learning techniques were applied in 17% (5/30) of the studies and demonstrated high accuracy in long-term movement analysis. Elastic net regression and SVMs were used in 13% (4/30) of cases for classification tasks, whereas PCA was used in 7% (2/30) of the studies to reduce dimensionality and optimize data processing. However, variability in feature extraction methods remains a challenge. Standardized approaches are needed to improve reproducibility and clinical translation.

Clinical Applications of Wearable Sensors

Wearable sensors demonstrated strong feasibility across multiple health care applications, including rehabilitation monitoring, disease risk assessment, activity tracking, and gait analysis. For rehabilitation assessment, wearable sensors improved postsurgical monitoring in patients who underwent knee arthroplasty, showing 52% better bone stimulus and 371% better impact load tracking. Wearable sensors for cardiac rehabilitation demonstrated reliable 6-minute walk distance prediction, with an error of 42.8 m and an R^2 value of 0.661, facilitating remote patient monitoring. In stroke rehabilitation, IMU-based movement quality assessments achieved 92% accuracy (F_1-score=0.95), supporting their use for personalized therapy and remote monitoring.

Recent studies have also extended the application of IMU-based wearable sensors to shoulder rehabilitation. Tranquilli et al [39] demonstrated that a single IMU could simultaneously capture joint mobility and muscle strength dynamics during postinjury recovery. Ajčević et al [40] applied IMU sensors to quantify shoulder kinematics and evaluate therapeutic response in adhesive capsulitis, whereas Parel et al [41] introduced a kinematic biofeedback program integrating inertial sensors for patients after rotator cuff repair. These studies highlight the versatility of IMU technology for upper-limb functional assessment and real-time feedback during rehabilitation.

Wearable sensors also played a key role in disease prediction and risk assessment. In PD monitoring, wearable technology achieved an accuracy of 83% in tremor detection and both a sensitivity and specificity of 86% in fall risk prediction, supporting the feasibility of early intervention strategies. Fall risk assessments using wearable sensors reached an AUROC value of 0.919, demonstrating their ability to provide noninvasive, real-world alternatives to clinical assessments such as the TUG and POMA tests.

Activity and behavior tracking applications showed high accuracy, particularly in arthritis-related pain and function monitoring, where significant correlations were observed between morning pain scores and 5-time sit-to-stand performance, with P values of less than .05. Consumer wearables such as Fitbit and iOS-integrated smartwatches achieved a strong agreement with research-grade sensors, with an AUROC of 0.93, demonstrating their feasibility for large-scale, real-world activity tracking. In medication adherence monitoring, smartwatch-based tracking achieved an accuracy of 93.6%, highlighting its potential for improving adherence in chronic disease management.

Gait and balance assessments using wearable sensors provided highly accurate insights into functional mobility. Head-worn IMU–based gait symmetry analysis reached an accuracy of 99.35%, indicating its effectiveness in neuromuscular rehabilitation and postural correction. Wearable sensor–based assessments of balance and mobility for patients with MS achieved an AUROC of 0.97, reinforcing their potential to support personalized rehabilitation planning and disease progression monitoring.

The included studies encompassed diverse populations, including healthy adults, neurological patients (eg, PD), individuals with musculoskeletal disorders, and pediatric or rehabilitation cohorts. This diversity introduces biomechanical and physiological variability in gait patterns, movement strategies, and sensor placement feasibility. Differences in muscle coordination, assistive device use, and experimental environments further contribute to heterogeneity. Given these variations, direct quantitative comparisons between studies were avoided. Instead, a narrative synthesis was used to identify overarching technological and methodological trends across populations. This approach emphasizes generalizable insights—such as the importance of standardized placement, calibration, and cross-population validation—while acknowledging disease-specific distinctions in biomechanics and sensor performance.

Many of the included studies (19/30, 63%) used ML algorithms such as random forest, deep learning, elastic net regression, and PCA for signal interpretation and disease classification. However, reporting transparency and methodological rigor varied substantially. Several studies (26/30, 87%) were limited by small sample sizes and internal validation only, increasing the risk of model overfitting. In addition, few studies (4/30, 13%) provided sufficient details regarding cross-validation protocols, feature selection strategies, or hyperparameter optimization.

Adherence to standardized ML reporting frameworks—such as the Transparent Reporting of a Multivariable Model for Individual Prognosis or Diagnosis–Artificial Intelligence and Prediction of Model Risk of Bias Assessment Tool–Artificial Intelligence—was rarely observed, which may affect reproducibility and generalizability.

Future research should emphasize external validation, open-source code sharing, and adherence to established ML reporting standards to ensure reliability and transparency in sensor-based clinical modeling.

Challenges in Wearable Sensor Research

Despite the promising applications of wearable sensors, several challenges remain that must be addressed to ensure widespread clinical adoption and real-world impact.

First, small sample sizes (26/30, 87% of the studies) and limited real-world validation (12/30, 40% of the studies) reduced finding generalizability. Short study durations (8/30, 27%) also hindered long-term effectiveness assessment. Beyond these methodological limitations, the scope of this review was restricted to English-language, peer-reviewed publications, excluding gray literature such as conference abstracts and theses. This language restriction and publication bias may have favored studies reporting positive or statistically significant outcomes, potentially overestimating the clinical impact of wearable sensor technologies. Furthermore, although some studies (3/30, 10%) discussed the potential cost-effectiveness of sensor-based systems, no direct economic evaluations were identified, limiting the ability to substantiate financial feasibility claims.

Technical challenges also persist. Variability in signal-to-noise ratios, sensor displacement errors, and inconsistencies in data collection protocols underscore the need for improved hardware design and standardized preprocessing algorithms. Differences in feature extraction and model architectures limit cross-study comparisons and reproducibility.

Finally, the field urgently requires greater standardization. Variability in sensor placement, protocols, and data interpretation hinders reproducibility and large-scale comparison. Establishing consensus-driven guidelines for wearable sensor research—including standardized task protocols, data reporting frameworks, and model transparency criteria—will be essential to enable scalability, reproducibility, and eventual clinical translation.

Future Directions

To fully realize the potential of wearable sensors in health care, future research should focus on several key areas. Expanding RCTs is essential to establish causal relationships between wearable sensor use and health outcomes beyond feasibility studies. Standardized data analysis frameworks will improve comparability and reproducibility, enabling integration into multicenter trials and large-scale studies. Long-term, multicenter studies will enhance real-world validation and assess sensor accuracy, usability, and adoption across health care settings.

Integration with cloud-based platforms and telemedicine will enhance scalability and enable real-time remote monitoring across diverse populations [42]. Cost-effectiveness analyses will determine financial feasibility and accessibility, supporting broader health care adoption and effective use in resource-limited settings [43].

Conclusions

This systematic review highlights the growing clinical relevance of wearable sensors for rehabilitation monitoring, disease risk assessment, and personalized health care. IMU-based smartwatches, multisensor systems, and gait-monitoring devices demonstrate high accuracy in mobility assessment, fall risk prediction, and chronic disease management for digital health and precision medicine.

Despite their utility, the following challenges remain: small sample sizes, real-world validation gaps, and inconsistent ML methodologies. Future research should standardize protocols, expand clinical trials, and integrate sensors into telemedicine and cloud-based analytics platforms.

Overcoming these challenges will enable wearable sensors to revolutionize health care through real-time, noninvasive monitoring that bridges traditional clinical assessments and continuous real-world health tracking.

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Data Availability

This systematic review paper does not include original data or materials as it primarily synthesizes and analyzes existing studies. Therefore, there are no specific datasets or materials available for sharing.

Authors' Contributions

BG contributed to the conception and design of the study, data analysis, interpretation of the results, and drafting of the manuscript. Yoo JI supervised the study and served as the corresponding author. All other authors critically reviewed the manuscript and approved the final version for submission.

Conflicts of Interest

None declared.

Multimedia Appendix 1
PRISMA 2020 checklist.
[PDF File (Adobe PDF File), 103 KB - mhealth_v14i1e76084_app1.pdf]

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Abbreviations

AUROC: area under the receiver operating characteristic curve
IMU: inertial measurement unit
JBI: Joanna Briggs Institute
ML: machine learning
MS: multiple sclerosis
NOS: Newcastle-Ottawa Scale
PCA: principal component analysis
PD: Parkinson disease
POMA: Performance-Oriented Mobility Assessment
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RCT: randomized controlled trial
RoB 2: version 2 of the Cochrane risk-of-bias tool for randomized trials
SVM: support vector machine
TUG: Timed Up and Go

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Original Paper

Analysis of Training Behavior in Users of a Fitness App: Cross-Sectional Study

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Abstract

Background: Mobile health (mHealth) apps are increasingly being used to promote physical activity (PA) and can support exercise uptake and maintenance. Despite their potential, these tools face high dropout rates and inconsistent adherence, posing a significant challenge. Understanding how users engage with fitness apps is essential for improving user experience and health outcomes.

Objective: This study aims to analyze user behavior patterns in the Mammoth Hunters (MH) fitness app (Mammoth Hunters SL), focusing on retention (days from registration to user's last recorded training session), average weekly training frequency, and adherence (alignment between planned and actual training). We examined how these outcomes are influenced by sociodemographic, motivational, and other variables.

Methods: This cross-sectional study involved 2771 Mammoth Hunters app users. In a subsample (n=289), training data were complemented by motivational data acquired through online surveying via an ad-hoc scale (internal consistency >0.83) based on the self-determination theory (SDT). Descriptive statistics and nonparametric tests (Kruskal-Wallis, Dunn post-hoc, and Spearman correlation) were used to assess correlation between sociodemographic, motivation, and training behavior variables.

Results: Mean retention (days) was significantly higher among males than females (135 vs 109, respectively; $P<.01$), users in the subscription vs free plan (154 vs 81; $P<.001$), active or very active individuals vs inactive, midbuilt vs thin body types (132 vs 120; $P=.001$), and those with slightly lower BMI. Users pursuing antiaging or muscle gain goals showed longer retention than those aiming to lose weight (gain: 132, antiaging: 128, lose weight: 116; $P<.001$). Average weekly frequency (sessions per week) of training was statistically significantly different by sex (male: 1.9 vs female: 1.8; $P=.04$), body type (thin: 1.96 vs mid: 1.77; $P=.04$), activity level (very active: 2.05 vs inactive: 1.83; $P=.04$), and motivation type (extrinsic introjected motivation correlated positively: $r=0.17$; $P<.05$), but did not correlate with perceived difficulty or fitness goals. Adherence, defined as actual vs targeted training frequency, was only significantly different among body types, with thin users showing higher adherence than the midbuilt group (57% vs 52.1%; *P*=.02). Intrinsic motivation showed a positive correlation with retention (*r*=0.19; *P*=.002), as did identified motivation (*r*=0.12; *P*<.05).

Conclusions: This study shows that retention is influenced by demographic factors, with males, subscribers, previously active, midbuilds, those aiming to gain muscle, and individuals with autonomous types (ie, intrinsic and identified) of motivation displaying greater long-term participation. These findings provide valuable preliminary insight into the complexities of exercise training behavior in apps. They suggest that training frequency, retention, and adherence do not respond to the same factors. App developers, researchers, and trainers should assess these variables separately and develop strategies accordingly.

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KEYWORDS

fitness app; physical activity; exercise adherence; retention; motivation; mHealth

Introduction

Adherence to Physical Activity and Exercise

Physical activity (PA) and exercise are fundamental components of a healthy lifestyle, with well-established benefits for physical and mental well-being. PA, as defined by the World Health Organization (WHO), encompasses any bodily movement that results in energy expenditure, while exercise is considered a structured subset of PA, performed with the intent of improving or maintaining physical fitness [1]. Regular engagement in PA is crucial for reducing the risk of chronic diseases, yet adherence to recommended activity levels remains a global challenge [2]. Despite the widespread awareness of PA benefits, sustaining an active lifestyle is often hindered by behavioral, environmental, and psychological barriers [3]. Understanding factors that influence adherence is therefore critical for improving PA participation and ensuring long-term engagement.

Influence of mobile health on PA Behaviors

In recent years, mobile health (mHealth) apps have emerged as a potential solution to bridge the gap between PA recommendations and actual adherence. Fitness apps, a subset of mHealth, offer structured training programs, progress tracking, and personalized feedback, aiming to enhance motivation and user engagement. The widespread availability of smartphones has contributed to a surge in fitness app usage, with millions of users accessing digital exercise programs globally [4]. These apps incorporate behavior change techniques such as goal setting, social support, and gamification to facilitate sustained exercise habits [5]. However, despite their potential, high attrition rates and inconsistent long-term adherence pose significant challenges to their effectiveness [6]. Recent evidence reinforces that these barriers still persist across different populations and intervention designs. For example, several authors reported significant dropout rates even in gamified or socially incentivized fitness apps [7,8]. Similarly, previous studies highlighted continued adherence challenges in young individuals or older adults despite tailored mHealth interventions [6,7,9].

Adherence to exercise, particularly in digital interventions, remains a complex issue, often inconsistently defined across studies. Traditional adherence models typically assess exercise frequency, duration, and intensity, yet these criteria may not fully capture engagement in app-based fitness programs [3]. Furthermore, users may abandon apps due to technical difficulties, loss of motivation, or unrealistic expectations [10]. Consequently, understanding the determinants of fitness app adherence requires a multidimensional approach, integrating psychological, technological, and behavioral perspectives [11].

The challenges surrounding fitness app adherence are compounded by factors such as user characteristics, app usability, and the broader social and environmental contexts in which users engage with digital interventions. Studies have highlighted that individual attributes such as age, sex, health consciousness, and baseline PA levels may influence the likelihood of sustained engagement with fitness apps [12]. Additionally, app design elements, including intuitive navigation, feedback mechanisms, and interactive features, play a crucial role in user retention [13]. Social and motivational factors, such as competition, social support, and reinforcement strategies, have also been shown to impact adherence levels in digital exercise interventions [5]. Recent evidence highlights the importance of incorporating behavioral theories and enhancing usability and perceived value in reducing attrition and promoting sustained engagement with mHealth tools. For instance, recent findings emphasize the relevance of behavioral theories in crafting more effective mHealth interventions, showing how tailored features can reduce dropout and improve user retention [14]. Similarly, perceived value and usability have been identified as key drivers of long-term engagement with digital health tools [15]. Other studies suggest that personalization, motivational strategies, and social features are critical to increasing user commitment [12,16], overall highlighting the multifactorial nature of adherence and reinforcing the need for user-centered app design approaches.

Given the rising reliance on digital solutions for health and fitness, it is imperative to explore how different aspects of fitness apps contribute to sustained PA engagement. Previous research presents mixed findings on the long-term efficacy of fitness apps in promoting adherence, with some studies reporting positive behavior changes and others limited long-term impact [8,17].

Understanding real users' training behavior, beyond theoretical frameworks or self-reported intentions, is essential to identify how engagement translates into real-world usage. Analyzing app usage data provides evidence of behavior patterns, allowing researchers to identify which user profiles are more likely to sustain app use. This study establishes a theoretical and practical differentiation between adherence and retention, and how they relate to user motivation to exercise. This is a critical matter, since sustained usage is key to ensuring the long-term impact of digital health interventions [18].

Study Goal

This study aims to explore the factors influencing the training behavior of users of a fitness app, focusing specifically on exercise adherence, retention, and motivation, and to explore how these outcomes are influenced by sociodemographic, motivational, and training-related factors. We hypothesize that sociodemographic characteristics, motivation types, and training behaviors significantly influence users' retention, adherence, and frequency of training. Understanding these factors is essential for optimizing fitness app design, improving intervention strategies, and ultimately promoting long-term participation in exercise.

Methods

Data Collection and Processing

Data were collected in collaboration with Mammoth Hunters (MH; Mammoth Hunters SL), a fitness app that focused on high-intensity interval exercises to improve strength, endurance, and mobility. MH delivered structured programs rooted in functional movement, making it an ideal platform for investigating digital fitness adherence, motivation, and retention. MH was launched in 2014 by a team of fitness experts and scientists from Barcelona, Spain. A free version with limited access to certain workouts and features was available upon registration, while the Pro version (per subscription) provided full access to personalized plans, a greater variety of workouts, and advanced tracking tools. MH ceased operations in September 2021, being one of the most widely used high-intensity training apps worldwide, having accumulated a total of 719,421 users. The company's shutdown, as well as its noninvolvement in any of the stages of study, ensured no conflict of interest.

The study used a cross-sectional design. Data in the MH app database included user registries ranging from November 21, 2020, to May 27, 2022. Motivation data were collected via online surveying on March 20, 2022. Data cleaning and descriptive analyses were conducted using the R programming language (version 4.3.1; R Core Team) in the R Studio environment software (version 2023.9.1.494; Posit, PBC).

The initial MH dataset contained 5858 entries, which corresponded to users who had granted informed consent to share their deidentified data for analysis. To ensure the accuracy and relevance of the data, several cleaning steps were executed, including a convenience selection of the most relevant variables and exclusion of registries with insufficient or missing data (see Table S1 in Multimedia Appendix 1 for more detail of the MH app's original variables).

Outliers were identified through data visualization and consultation of descriptive statistics. A decision was made to remove all outliers to avoid distortion in the analysis, based on two main reasons: (1) certain tests run by MH staff members had intentionally introduced outlier scores to facilitate their identification and removal, and (2) some outliers resulted from the arbitrary temporal cutoff applied to the dataset, specifically, some participants had only just begun training with the app shortly before the data extraction date, leading to unrealistic extreme values in some outcome variables (eg, extremely low retention or extremely high adherence). Therefore, all values exceeding Q3+1.5×IQR or falling below Q1–1.5×IQR were removed.

The motivation-related outcome variables were determined using the means of the composite scores from the observable items corresponding to each factor in the scale, allowing us to define the latent variables. Outcome variables retention, frequency, and adherence were derived from existing variables on the mobile app (eg, number of sessions executed, last training date, and user sign-up date) to enhance analytical depth. User retention was calculated as the number of days between a user's initial registration date within the fitness app and their last recorded training session. Weekly training frequency was calculated by dividing the total number of training sessions completed by a user by the total number of weeks from their first to their last executed session. Adherence was quantified as the percentage to which a user's actual average weekly training frequency aligned with their initial plan (self-declared upon registration). Additionally, data types were adjusted as required to ensure compatibility and accuracy.

Following the described data cleaning steps, the final dataset comprised 2771 user entries. See Table 1 for more details on study variables.

Table 1. Description of explanatory and outcome variables.

Explanatory variables	Type	Description
Sex	Categorical; sociodemographic	User biological sex, with 2 categories: female and male.
Body type	Categorical; sociodemographic	Self-reported body type selected by the user at registration, out of 3 available categories: thin, mid, and strong.
Activity level	Categorical; sociodemographic	User activity level at the time of registration in the fitness app, with 3 categories: inactive, active, and very active.
Fitness goal	Categorical; sociodemographic	The goal the user aims to achieve through app use (selected from 3 available categories: lose weight, gain muscle, and antiaging).
Pro version	Categorical; training	Indicative of app user being subscribed to a payment ("Pro") program or not. Two categories: yes and no.
Training schedule	Categorical; training	Time of day in which the user executes most (>50%) of their training sessions. Processed into 3 categories: morning (5:30-12:30 hours), afternoon (12:31-20 hours), and night (20-5:29 hours).
Age	Numerical; sociodemographic	User's reported age at registration.
BMI	Numerical; sociodemographic	User BMI calculated from their declared height and weight.
Subjective body fat	Numerical; sociodemographic	Users' self-reported body fat.
Difficulty	Numerical; training	Average perceived exertion reported at the end of the training session. 0 (lowest)-10 (highest).
Enjoyment	Numerical; training	Average user-reported enjoyment after each training session. 0 (lowest)-5 (highest).
SDT[a]-based variables		
Intrinsic motivation	Numerical; motivation	Average score of the intrinsic motivation items on the scale: a decimal number between 1 (lowest) and 5 (highest).
Identified extrinsic motivation	Numerical; motivation	Average score of the identified extrinsic motivation items on the scale: a decimal number between 1 (lowest) and 5 (highest).
Introjected extrinsic motivation	Numerical; motivation	Average score of the introjected extrinsic motivation items on the scale: a decimal number between 1 (lowest) and 5 (highest).
Outcome variables		
Retention	Numerical; training	Measured as the total number of days from the user registration date in the app to their last recorded training session.
Frequency, weekly average	Numerical; training	Calculated by dividing the total number of user sessions by the total number of weeks between their first and last recorded sessions.
Adherence	Percentage; training	Defined as the percentage alignment between the user's actual weekly training frequency and their predefined weekly training goal.

[a]SDT: self-determination theory.

Motivational data, which had been previously collected (March 20, 2022) by means of an ad-hoc scale (Table S2 in Multimedia Appendix 1), provided insight as to the motivational regulation of a subsample (n=753) of MH users. The scale was based on the self-determination theory (SDT) [19,20]. It showed good fit indices and a 3-factor structure as confirmed per exploratory and confirmatory factor analyses, with internal consistency indices >0.830 for the 3 subscales (intrinsic, identified extrinsic, and introjected extrinsic motivations). Data obtained through surveying (n=753) and data obtained from the MH fitness app (n=2771) were then merged, and a sample consisting of n=328, for which both training and motivational data were available, was obtained. Thirty-nine registries had to be disregarded due to missing data for the calculation of adherence and weekly training frequency outcome variables. A resulting total of 289 was complete for all explanatory and outcome study variables.

Descriptive Analysis for Sociodemographic, Training, and Motivation Variables

Following data cleaning, descriptive statistics were computed to summarize and describe the dataset's characteristics. Frequencies and percentages were calculated for categorical variables to provide an overview of their distribution and proportions within the sample. For numerical variables, measures of central tendency (mean and median) and measures of dispersion (minimum, maximum, and quartiles) were obtained to characterize data distribution and its variability.

Inferential Analysis of Explanatory Variables

Normality was assessed using the D'Agostino-Pearson test, along with skewness and kurtosis coefficients to quantify distributional properties. Additionally, histograms and quantile-quantile plots were inspected to visually evaluate deviations from normality. The results indicated significant departures from normality, and nonparametric tests were used for subsequent analyses. The Kruskal-Wallis test was conducted to evaluate differences among groups, followed by post-hoc analysis using the Bonferroni correction to adjust for multiple comparisons. The effect size was assessed using Dunn, which quantifies the magnitude of observed differences. To examine relationships between numeric variables, Spearman correlation tests were performed. The Holm correction was applied to control for multiple comparisons and to adjust the significance levels accordingly. For training behavior analysis, the categorical variables evaluated were sex, Pro version, self-declared level of previous PA, body type, fitness goal, and training schedule. Additionally, explanatory numerical variables included age, BMI, subjective body fat, perceived difficulty, and enjoyment. Intrinsic, identified extrinsic, and introjected extrinsic motivations were also considered (Table 1). The relationship of all these variables was analyzed with three outcome variables: adherence, frequency, and retention.

Inferential Analysis of Outcome Variables

Adherence was calculated as the percentage match between the target weekly frequency, as selected by the user upon sign-up, and the actual, executed weekly training frequency. The latter was averaged by dividing the total number of executed sessions by the total number of weeks from the sign-up date to the last executed session for the given user. Finally, retention was measured as the total number of days from the user sign-up date to the user's last recorded training session (Table 1). Outcome variables were analyzed through the same procedures as explanatory variables.

Ethical Considerations

Ethical approval for this study was obtained from the Research Ethics Committee of Universitat Ramon Llull in March 2020 (reference code 1920003P). All included users provided informed consent to use their data for research purposes, either through the app at registration or through the motivational survey. All data were anonymized before analysis, ensuring the privacy and confidentiality of participants in compliance with data protection regulations. No compensation was provided to participants, as the data were collected retrospectively and only for research purposes.

Results

Descriptive Results for Sociodemographic, Training, and Motivation Variables

Our sample consisted of 2771 MH users. Of them, a 64.8% majority identified as male, and 35.2% as female. Their age range spanned from 21 to 64 years, with a median age of 43 years and a mean age of 42.45 years. Users' fitness goals varied, with the largest segment (46.6%) aiming to "gain muscle" mass, followed by those wanting to "lose weight" at 32%. A smaller portion, 21.4%, pursued "antiaging" benefits. Table 2 provides full details on sample description and other results.

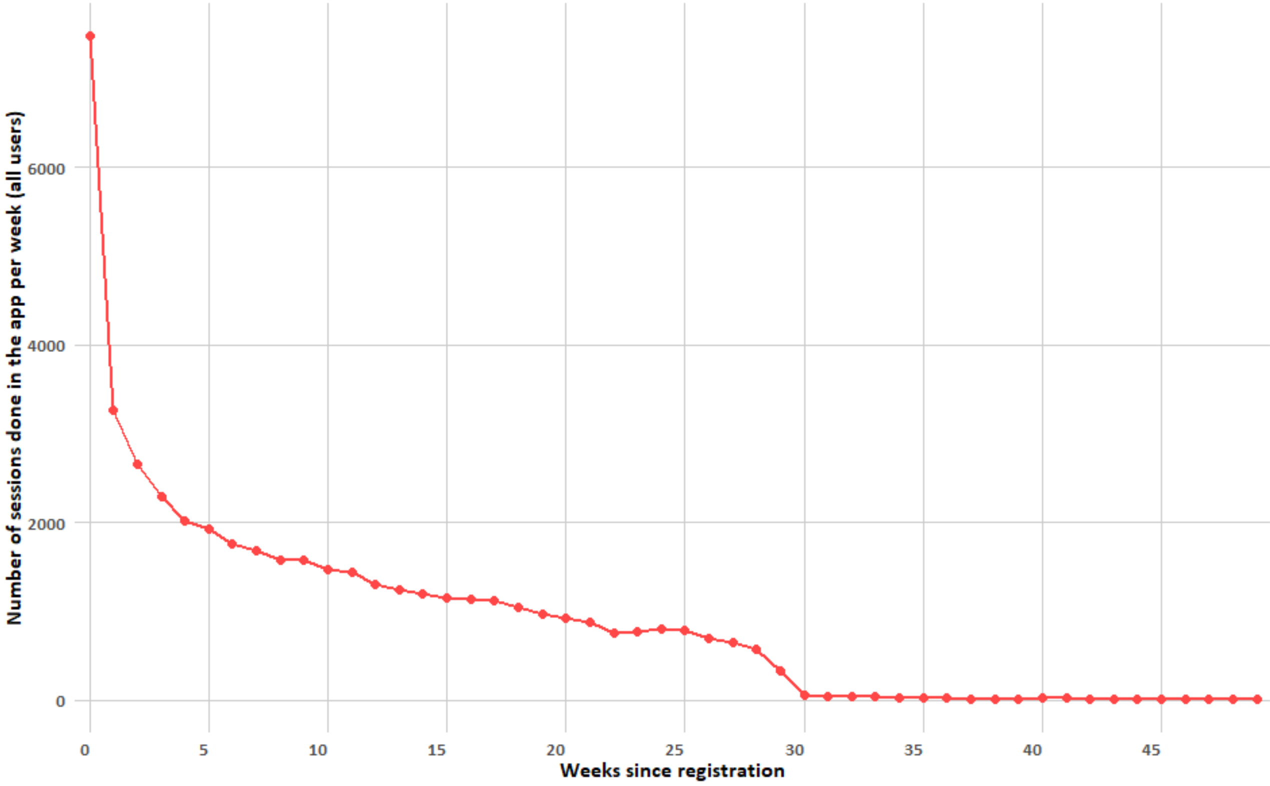
Table 2. Descriptive characteristics of the Mammoth Hunters user sample (N=2771).

Variable	Values
Sex, n (%)	
Male	1796 (64.8)
Female	975 (35.2)
Age (years)	
Mean (SD)	42.45 (9.8)
Median (IQR)	43 (21)
Range (minimum-maximum)	21-64
Body type, n (%)	
Thin	1269 (45.8)
Midbuild	1419 (51.2)
Strong	191 (6.9)
Body fat	
Mean (SD)	22.2 (6.4)
Median (IQR)	20 (14)
Range (minimum-maximum)	6-40
BMI	
Mean (SD)	23.46 (2.9)
Median (IQR)	23.44 (3.8)
Subscription type, n (%)	
Pro (paid) users	1726 (62.3)
Standard (free) users	768 (27.7)
Physical activity level, n (%)	
Active	1640 (59.2)
Very active	454 (16.4)
Inactive	675 (24.4)
Actual training schedule, n (%)	
Morning	928 (33.5)
Afternoon	1372 (49.5)
Night	471 (17)
Training difficulty (1-10)	
Mean (SD)	5.56 (1.78)
Median (IQR)	5.40 (2.10)
Range (minimum-maximum)	1-9.5
Enjoyment (1-5)	
Mean (SD)	3.58 (0.82)
Median (IQR)	3.50 (1.20)
Motivation (1-5)	
Intrinsic	
Mean (SD)	4.01 (0.74)
Median (IQR)	4 (0.90)
Range (minimum-maximum)	1.5-5
Identified extrinsic	

Variable	Values
Mean (SD)	4.42 (0.50)
Median (IQR)	4.67 (0.67)
Range (minimum-maximum)	3-5
Introjected extrinsic	
Mean (SD)	4.22 (0.61)
Median (IQR)	4.33 (1)
Range (minimum-maximum)	1-5
Retention (days)	
Mean (SD)	125.99 (92.60)
Median (IQR)	132.72 (144.36)
Range (minimum-maximum)	3.49-410.82
Training frequency (sessions per week)	
Mean (SD)	1.87 (1.52)
Median (IQR)	1.62 (1.84)
Range (minimum-maximum)	0.07-6.59
Adherence (%)	
Mean (SD)	54.24 (32.81)
Median (IQR)	47.31 (52.81)
Range (minimum-maximum)	1.18-166.67

Figure 1 illustrates the number of training sessions completed each week, by the total number of users, over a 49-week span. At the beginning, there was a sharp peak in the number of training sessions, with 7469 sessions recorded in the first week after user registration, for a total of 2771 users. Following this peak, the number of sessions decreased rapidly over the next several weeks. It declined to 2295 by the end of the first month (a reduction of 69.3%), to 1678 by the end of the second month, and to 1448 (a reduction of 80.6%) by the end of the third. By around week 10, the decline began to stabilize, though a gradual downward trend persisted. By the 30th week, the number of sessions plateaued at a much lower level, approximately below 100 sessions in a week.

Figure 1. Total number of sessions in time (per training week) for all users (N=2771).



The time from user registration to their first training session ranged from 0 to 319.84 days, with a median delay of 7.98 days and a mean of 30 days. Most users initiated training within the first few days after registering, and the frequency declined steeply after 10 days. Delays beyond 50 days were rare, and only a very small proportion of users waited more than 100 days. A small subgroup of 31 users showed exceptionally long delays between 200 and 350 days.

Differences Between Training Outcome Variables

Retention Results

All categorical variables except for training schedule showed statistically significant differences to retention (Table 3). For the sex variable, retention values were statistically significantly (P<.001) higher in the "male" group when compared to the "female" group, though the effect size was small (Dunn r=0.14). For the Pro version variable, indicative of whether the user was or was not subscribed for service at the time of data download, retention values were statistically significant (P<.001) with a moderate-to-large effect size (Dunn r=0.41), higher in the "yes" group than in the "no" group." In regard to activity level, retention values were statistically significant (P<.001, Dunn r=0.11; and P<.001, Dunn r=0.07, respectively) and were higher for the "active" and "very active" groups than for the "inactive" group. No statistically significant (P>.05, Dunn r=0.03) differences were found in retention values between the "active" and "very active" groups. Refer to Figure 2 for further details on the Kruskal-Wallis results for the outcome variables.

Figure 2. Summary of Kruskal-Wallis findings for each outcome variable.

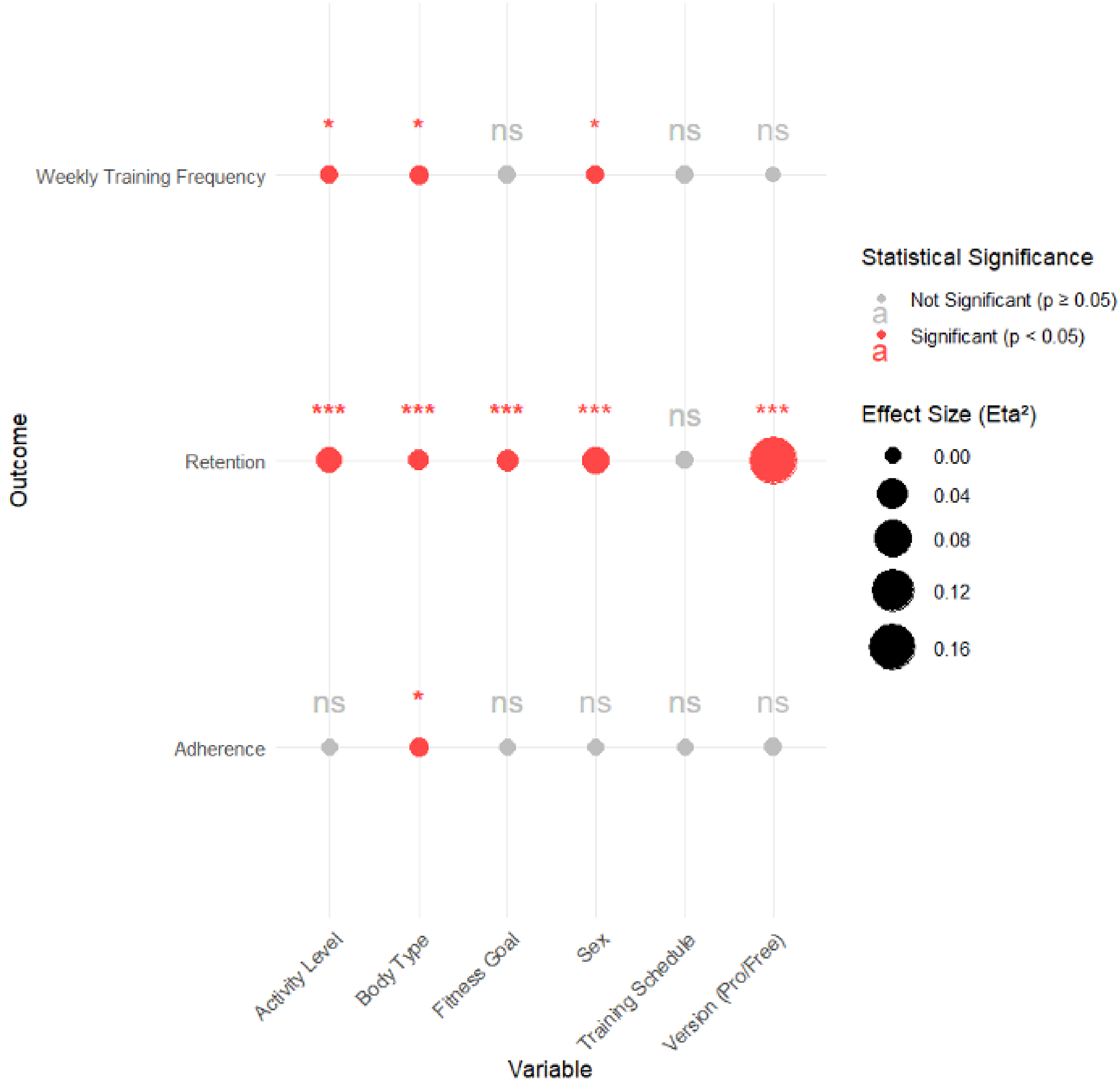


Table 3. Retention (in days), relative to categorical variables levels according to the multivariate analysis of variance (n = 2771).

Variable and group	Mean (SD)	H[a]	η^2 [b]	*P* [c]
Sex		56.151	0.019	<.001[d]
Female	109.43 (75.51)			
Male	134.99 (73.86)			
Pro version		459.965	0.163	<.001[d]
No	80.73 (70.11)			
Yes	153.53 (64.47)			
Activity level		47.414	0.016	<.001[d]
Inactive	109.74 (74.84)			
Active	130.69 (75.65)			
Very active	139.72 (69.57)			
Body type		14.303	0.004	.001[e]
Mid	132.37 (74.16)			
Thin	120.16 (76.27)			
Strong	117.44 (75.63)			
Fitness goal		21.982	0.007	<.001[d]
Antiaging	128.45 (70.23)			
Gain	132.15 (76.62)			
Lose	115.8 (75.18)			
Training schedule		3.613	0.000	.16
Afternoon	125.51 (74.23)			
Morning	128.49 (76.54)			
Night	119.07 (77.71)			

[a]H: Kruskal-Wallis H value.

[b]η2: eta squared.

[c]*P:* Kruskal-Wallis significance.

[d]*P*<.001.

[e]*P*<.01.

For the body type variable, the "mid" group retention values were statistically significantly higher (*P*<.002; Dunn *r* 0.07) than those in the "thin" group. No statistically significant differences were found in retention values between the "mid" and "strong" groups, nor between the "strong" and "thin" groups (*P*>.05; Dunn *r*=0.04 and *P*>.05; Dunn *r*=0.00, respectively). In the fitness goal variable, retention values were significantly lower for the "lose weight" group compared to the "antiaging" and "gain muscle" groups (*P*<.02; Dunn *r*=0.05 and *P*<.001; Dunn *r*=0.09, respectively) (Table 4).

Table 4. Post-hoc comparison of retention by categorical variable levels.

Variable	Comparison	U[a]	*P* value
Sex	• Female-male	• –7.493	• <.001b
Pro version	• No-yes	• –21.447	• <.001b
Activity level	• Active-inactive • Active-very active • Inactive-very active	• 6.067 • –1.796 • –5.641	• <.001b • .22 • <001b
Body type	• Mid-strong • Mid-thin • Strong-thin	• 2.034 • 3.579 • –0.234	• .13 • <.001c • >.99
Fitness goal	• Antiaging-gain • Antiaging-lose • Gain-lose	• –0.607 • 2.858 • 4.597	• >.99 • .01d • <.001b
Training schedule	• Afternoon-morning • Afternoon-night • Morning-night	• –1.062 • 1.266 • 1.850	• .87 • .62 • .19

[a]*U:* Standardized test statistic.

[b]***P*<.001**.

[c]*P*<.01.

[d]*P*<.05.

Regarding explanatory numerical variables, all of them showed statistically significant correlations with retention. Age had a moderate positive correlation (r=0.21; P<.001) with retention, while subjective body fat and BMI showed a low negative correlation (r=–0.13; P<.001; r=–0.06; P<.01, respectively). Training difficulty had a moderate, positive correlation (r=0.24; P<.001), and enjoyment had a low, positive correlation (r=0.11; P<.001).

Of all motivation dimensions, intrinsic motivation had the highest positive correlation (r=0.19; P<.01) with retention. Identified extrinsic motivation had a small, statistically significant, positive correlation (r=0.12; P<.05). Introjected extrinsic motivation had a much lower, positive, and nonstatistically significant correlation (r=0.07; P>.05; Table 5).

Table 5. Results of the correlation tests for motivation variables (N=289).

Variable	r [a]	P value
Retention		
INTRINS[b]	0.19	.01[c]
IDENT, extr.[d]	0.12	<.05[c]
INTROJ, extr.[e]	0.07	.22
Frequency, weekly		
INTRINS	0.001	>.99
IDENT, extr.	0.008	>.99
INTROJ, extr.	0.168	.01[c]
Adherence		
INTRINS	–0.002	>.99
IDENT, ext.	0.021	>.99
INTROJ, ext.	0.138	.06

[a]*r:* Spearman correlation coefficient.

[b]INTRINS: Intrinsic motivation.

[c]*P*<.05.

[d]IDENT, extr.: Identified extrinsic motivation.

[e]INTROJ, extr.: Introjected extrinsic motivation.

Average Weekly Frequency Results

Weekly frequency was found to be statistically significantly associated with sex, activity level, and body type (*P*<.05) and not significantly related to the Pro version, fitness goal, or training schedule (Table 6).

Table 6. Average weekly training frequency relative to categorical variables levels. Multivariate analysis of variance (N=2771).

Variable	Mean (SD)	H[a]	η^2 [b]	*P* [c]
Sex		3.950	0.001	.04[d]
Female	1.82 (1.35)			
Male	1.9 (1.29)			
Pro version		0.122	-0.001	.78
No	1.94 (1.45)			
Yes	1.83 (1.21)			
Activity level		6.199	0.001	.04[d]
Inactive	1.83 (1.34)			
Active	1.85 (1.29)			
Very active	2.05 (1.31)			
Body type		8.324	0.002	.02[d]
Mid	1.77 (1.23)			
Thin	1.96 (1.37)			
Strong	2.02 (1.39)			
Fitness goal		4.363	<0.001	.11
Antiaging	1.79 (1.28)			
Gain	1.91 (1.28)			
Lose	1.85 (1.36)			
Training schedule		4.519	0.001	.10
Afternoon	1.82 (1.30)			
Morning	1.93 (1.32)			
Night	1.94 (1.30)			

[a]H: Kruskal-Wallis H value.

[b]$\eta 2$: eta squared.

[c]*P*: Kruskal-Wallis significance.

[d]*P*<.05.

For the sex variable, figures in the "male" group were statistically significant (*P*<.005; Dunn *r*=0.04) and higher than those for the "female" group. In the activity level variable, the "very active" group values were significantly higher (*P*<.05; Dunn *r*=0.05) than those in the "inactive" group. Neither the "active" versus "inactive" groups nor the "active" versus "very active" groups showed any statistically significant differences in weekly training frequency values. For the body type variable, values in the "thin" group were statistically significantly (*P*<.04; Dunn *r*=0.05) higher than those of the "mid" group. No statistically significant differences were found between the "mid" and "strong" groups, nor between the "strong" and "thin" groups, for weekly training frequency values. For more detail on multivariate analyses of variance results for weekly training frequency, please refer to Table 7.

Table 7. Post-hoc comparison of average weekly training frequency by categorical variable levels.

Variable	Comparison	U [a]	P value
Sex	• Female-male	• –1.988	• .04b
Pro version	• No-yes	• 0.349	• .73
Activity level	• Active-inactive • Active-very active • Inactive-very active	• 0.599 • –2.218 • –2.427	• >.99 • .08 • .04b
Body type	• Mid-strong • Mid-thin • Strong-thin	• –1.989 • –2.501 • 0.727	• .14 • .04b • >.99
Fitness goal	• Antiaging-gain • Antiaging-lose • Gain-lose	• –1.716 • –0.372 • 1.679	• .26 • >.99 • .28
Training schedule	• Afternoon-morning • Afternoon-night • Morning-night	• –1.824 • –1.508 • –0.379	• .20 • .40 • >.99

[a] U = standardized test statistic.

[b] $P<.05$.

After corrections for multiple comparisons, none of the explanatory numerical variables reflected statistically significant correlations with weekly training frequency.

Regarding types of motivation, only introjected extrinsic motivation correlated significantly with training frequency (r=0.17; $P<.05$), after corrections for multiple comparisons, with a moderate-low positive correlation. Intrinsic and identified extrinsic motivations showed close to no correlation with frequency (r=0.00 and $P>.05$ for both) (Table 5).

Adherence Results

Adherence was found to be associated with one of the categorical variables (Table 8). These differences were found in body type, which presented a highly statistically significant ($P<.005$; Dunn r=–0.06) difference between the groups "mid" and "thin". In particular, the values for the "mid" group were statistically significantly lower than those for the "thin" group. No statistically significant differences were found between groups "mid" and "strong," nor between "strong" and "thin," in adherence to the training program.

Table 8. Adherence, relative to categorical variables levels. Multivariate analysis of variance (N=2771).

Variable and group	Mean (SD)	H[a]	η^2 [b]	*P* [c]
Sex		1.479	0.000	.22
Female	54.02 (38.07)			
Male	54.35 (34.88)			
Pro version		3.260	0.000	.07
No	57.35 (39.85)			
Yes	52.35 (33.37)			
Activity level		2.394	0.000	.30
Inactive	53.76 (38.29)			
Active	53.91 (35.09)			
Very active	57.01 (35.39)			
Body type		7.322	0.002	.03[d]
Mid	52.1 (35.28)			
Thin	56.96 (37.32)			
Strong	52.01 (31.57)			
Fitness goal		2.960	0.000	.23
Antiaging	52.52 (34.7)			
Gain	55.34 (35.53)			
Lose	53.48 (37.37)			
Training schedule		2.843	0.000	.24
Afternoon	53.12 (35.66)			
Morning	56.05 (36.95)			
Night	53.61 (34.38)			

[a]*H*: Kruskal Wallis H value.

[b]$\eta 2$: eta squared.

[c]*P:* Kruskal-Wallis significance.

[d]$P<.05$.

No statistically significant differences were found between adherence and any of the groups in any of the remaining categorical variables (Table 9).

Table 9. Post-hoc comparison of adherence by categorical variables levels.

Variable	Comparison	U [a]	P value
Sex	• Female-male	• –1.216	• .22
Pro version	• No-yes	• 1.806	• .07
Activity Level	• Active-inactive • Active-very active • Inactive-very active	• 0.832 • –1.082 • –1.539	• >.99 • .84 • .37
Body Type	• Mid-strong • Mid-thin • Strong-thin	• –0.517 • –2.703 • –0.836	• >.99 • .02b • >.99
Fitness Goal	• Antiaging-gain • Antiaging-lose • Gain-lose	• –1.282 • –0.096 • 1.499	• .60 • >.99 • .40
Training schedule	• Afternoon - Morning • Afternoon - Night • Morning - Night	• –1.680 • –0.558 • 0.453	• .28 • >.99 • >.99

[a]*U*: Mann-Whitney standardized test statistic.

[b]*P*<.05.

For explanatory numerical variables, none reflected statistically significant correlations with adherence. Similarly, no types of motivation showed statistically significant correlations with adherence. Introjected extrinsic motivation rendered the highest (r= 0.14; P>.05) positive correlation, while intrinsic and identified extrinsic motivation showed little to no correlation (r=–0.00; P>.05, and r=0.02; P>.05, respectively; Table 5).

Summary of All Findings From the Inferential Analysis

A summary of all findings from the inferential analysis is presented in Table 10.

Table 10. Summary of statistically significant findings of the post-hoc inferential analyses.

Variable	Retention	Weekly training frequency	Adherence
Sex	Male>female	Male>female	—[a]
Pro version	Yes>no	—	—
Activity level	Active>inactive Very active>inactive	Very active>inactive	—
Fitness goal	Antiaging>lose Gain>lose	—	—
Body type	Mid>thin	Thin>mid	Thin>mid
Training schedule	—	—	—
Age	Positive correlation	—	—
BMI	Negative correlation	—	—
Subjective body fat	Negative correlation	—	—
Difficulty	Positive correlation	—	—
Enjoyment	Positive correlation	—	—
Intrinsic motivation	Positive correlation	—	—
Identified extrinsic motivation	Positive correlation	—	—
Introjected extrinsic motivation	—	—	—

[a]Not applicable.

Discussion

Summary of Key Findings

This study examined training behaviors among users of the MH fitness app and identified key factors associated with training behavior. Variables including adherence and retention were evaluated, with the latter having shown greater relevance in users long-term maintenance of training behavior. The main findings pointed at paid subscription and intrinsic motivation as being the most determinant factors to user retention. Other variables that correlated with retention included sex, body type, BMI, and fitness goal. In contrast, adherence was only linked to body type, while training frequency varied slightly by sex, activity level, motivation, and body type.

This piece of research involved 2771 individuals and is possibly one of the largest existing cohort studies of fitness app users to date. Previous large cohorts include the Konstanz Life Study with 1236 users of either fitness or nutrition apps [21]. Some systematic reviews have covered samples of 3555 participants from a total of 22 interventions (n=833 in the largest single study) [8] or 1622 total participants from 6 different studies [7]. Our work possibly also covers the longest time duration (18 months). Previous research has been 2-24 weeks [7], up to 5 months [22], or even 6 months in some cases [8].

Our sample figures fall within the "expected" ranges for a fitness app that offers high-intensity training, delivered electronically. Results are also in line with the systematic review by Stecher et al [8], which included participants between 10.6 and 61.5 years of age and found a mean of 39.6 (SD 6.5) years. Participants in this study presented some features worth noting, which were probably specific to our sample population. The majority (75.6%) of them were previously "active" or "very active." This was most likely due to the fact that all data registries were obtained from an app update (MH version 2.0) which, naturally, received many of its users from the previous version. This could also partially explain why 62% of our users were on the Pro version (paid subscription). MH always offered a free training program upon first registration, so the newest users would be expected to be on a free deal, while more experienced users would naturally progress to payment modes.

The studied sample primarily pursued "muscle gain" or "weight loss" fitness goals. A remarkably small (21.4%) percentage trained for "antiaging" purposes. We initially interpreted this finding as a sign that individuals were focusing mainly on "appearance," but this would have to be further investigated, as muscle gain [23,24], as well as weight loss [25], are also known markers of improved health [25] and consequently better aging.

Attrition Rates and Perceived Difficulty

It is well-established that attrition rates in mobile apps are extremely high. Meyerowitz-Katz et al [26], in their 2020 meta-analysis, stated that up to 98% of people only use apps for a short period of time. Our results fully align with this marked tendency, as we appreciated a remarkable drop in the number of training sessions within the first few weeks of enrollment. There was an observable decline of 69.3% by the end of the first month, a reduction of 77.5% by the end of month 2, and an 80.6% decline by the end of month 3. These figures strike even harder if we assume that many enrollments allegedly came from MH users who were transitioning from the old to the new version of the app. Participants in our study preferred "afternoon" (12:31-20:00 hours) training sessions and declared mean rates of session "difficulty" of 5.56, over a total of 10 points. The "difficulty" variable and its results need to be interpreted with caution. In our study, "difficulty" was an equivalent of perceived exertion, and it aimed to be indicative of how hard the session had felt to the user. However, this data were inquired once the user had not only finished the training but also finished the cool-down phase, and this could have led to respondents underrating the perceived exertion derived from the main block of training. Contrary to our expectations, difficulty in our sample showed a strong positive correlation to retention, which could be interpreted as a sign that challenge fosters engagement. Indeed, there is previous evidence that complex, vigorous, or hybrid activities correlate with intrinsic motivation [27], which commonly underlines activity retention. Regarding constructs of adherence, this finding could also reflect a self-selection bias, where more committed users are more likely to opt for challenging sessions, thus reinforcing their engagement over time.

Factors Influencing Training Frequency

Frequency of training seemed not to be related to factors such as age, BMI, declared enjoyment or perceived difficulty, subscription vs nonsubscription, declared fitness goal, or preferred training schedule. However, statistically significant differences were observed based on sex, previous activity level, motivation, and body type. Frequency of training was greater in the introjected motivation group, in males, in the very active vs inactive, and in the thin vs mid groups. One could argue that the controlled and external regulation of introjected motivation could explain the increased frequency observed in this group. This would partially align with previous research that points to the primacy of extrinsic motivation in exercise contexts [28]. The fact that introjected motivation seems to encourage higher training frequencies but no longer retention or higher adherence might be indicative of an enthusiasm that is not sustained over time. As to the user's previous activity level, while it seems logical that highly active individuals would train more often, this could be influenced by their prior engagement with the MH app or other forms of PA. If they were former MH users, their higher frequency could indicate loyalty, whereas if their activity stemmed from external sources, it is noteworthy that they also engaged frequently with the app. In contrast, inactive individuals may have felt overwhelmed by structured training. Previous research highlights differences in how beginners perceive social comparison and networking features in fitness apps, as well as how exercise proficiency affects adherence [29]. Additionally, attitudes toward PA significantly impact behavior, with Feng et al [30] showing that greater activity levels correspond to deeper integration and sustained engagement. Another possible explanation is that very active users may use more app features, enhancing their overall experience and leading to higher engagement [30]. Our results should, however, be interpreted with caution, since despite statistical significance, effect sizes were small to very small, which is indicative of them having limited practical implications.

Reflections on Adherence to mHealth Training

In our study, adherence did not correlate with age, sex, previous level of activity, declared fitness goal, being on a free plan versus subscription mode, training schedule, perceived difficulty, or enjoyment in sessions.

Only one statistically significant difference was found for adherence, and it was for the “thin” group, which showed higher adherence than the “mid” group. Both frequency and adherence in this study were correlated with “thin” body type, but in both cases the effect size was small, so the association may not imply high practical impact. Notably, no motivation type proved to be more relevant for adherence, in spite of several authors having pointed to the more autonomous regulations of motivation leading to increased adherence and persistence [31]. Recent evidence confirms that maintaining physical activity remains challenging for healthy adults, with persistent individual-level barriers (ie, lack of motivation, attitudes, and concerns about physical changes) [32]. Adherence results in our study ranged from 1.2% to 166.7%, which was an impactfully wide range. It is important to note that intensity and duration data were not consistently available across users, which limited our ability to construct the adherence measure. Adherence in this study was based only on training frequency, a limitation that highlights the need for more standardized and comprehensive adherence metrics in future app-based exercise research. These results brought us to the following insights. Adherence is rather a measure of precise forecasting, as it basically depends on the ability to foresee future behavior. In that case, several personal characteristics may come into play, which have not been assessed in this study, such as the concept of self-efficacy, ambition, the ability to plan in advance, or the ability to pursue goals. Similarly, in healthy adults, psychological factors such as self-efficacy, enjoyment, and planning were significant predictors of long-term adherence to PA, emphasizing the relevance of individual motivational and behavioral traits in sustained engagement [33]. In addition, a study identified lack of time, motivation, and fatigue as frequent barriers to PA in healthy young adults, while enjoyment and social support emerged as consistent facilitators [34]. We found the lowest adherence rates for those who trained 6 times per week, while the highest adherence values were for those who trained twice per week. Based on our results, individuals with lower frequency expectations managed better to fulfill their target plan and were, consequently, more adherent. Again, we see a disadvantage in how different researchers seem to measure and define adherence, in addition to the fact that electronically delivered interventions often lack a detailed reporting of it [35]. We note that in our study, adherence was based on training frequency (% of targeted versus actual), which naturally correlates both variables. In contrast, retention and adherence operate on different parameters, especially when the exercise program is nonprescribed, lacks external obligation, and has no set duration.

Retention as a Key Variable, Distinct From Adherence

In this study, retention correlated significantly with most study variables. There was higher retention in the male group, in subscribers, in “active” and “very active,” in “mid” body types versus “thin,” and also higher retention when the fitness goal was “antiaging” or “gain muscle” versus “lose weight.” “Pro version” users exhibited higher retention, aligning with previous research linking price to commitment [29,36,37], suggesting that subscription may indicate greater interest. The effect size for our finding was moderate-to-large, which points at subscription possibly being the most determinant factor in long-term training behavior. All other correlations had small to very small effect sizes. “Thin” body types, which had shown correlation with frequency and adherence, did not display higher retention, potentially reflecting an initial enthusiasm that wanes over time. The finding that “antiaging” goals led to higher retention than “lose weight” aligns with theories suggesting that health-oriented goals promote sustained engagement. However, the fact that “gain muscle” goals also outperformed “lose weight” in retention suggests that aesthetic-driven objectives may still play a role in long-term engagement, challenging this interpretation.

The study found that only intrinsic motivation had a statistically significant positive correlation with retention, while no such correlation was observed between intrinsic motivation and adherence. The distinction between retention and adherence is emphasized, as these concepts are considered distinct. In line with previous evidence [28,38-40], our study reflects that intrinsic and identified autonomously regulated motivations are the strongest correlated with retention. There is, however, previous evidence that points at extrinsic regulations of motivation as possibly the most important ones for exercise contexts [28,41]. We agree with Wilson’s statement that future research with larger sample sizes is recommended, considering potential variations in extrinsic motivation types [28] and a revision of the commonly accepted theory that intrinsic motivation is the most desirable to engage in and sustain exercise activities.

To translate our findings into practical applications, we suggest that fitness app developers consider tailoring features to specific user subgroups (ie, providing targeted support or content adaptations for users with a “mid” body type). Moreover, including motivational aspects that support intrinsic regulation, such as goal-tracking tools, personalized feedback, and autonomy-enhancing design, may further increase retention and adherence.

Strengths and Limitations

The present study focused on analyzing user training behavior by means of a cross-sectional study conducted on 2771 MH app users over a period of 18 months. To the authors’ knowledge, the largest study previously available was a cohort study conducted under the Konstanz Life Study, which followed a total of 1236 users of either fitness or nutrition apps [21]. Other revisions involved larger samples, such as that by Stecher et al [8], (with 3555 participants across 22 interventions) or He et al [7] (with 1622 participants from 6 studies). Previous studies followed participants for periods of 2 to 24 months [7,8,22].

Based on this evidence, our study could be the largest of its kind in sample size and follow-up period so far. Nonetheless, we acknowledge that broader meta-analyses may include larger cumulative samples and aggregated durations across multiple interventions and apps [26].

The use of real-world app data, combined with motivational surveys, provides valuable insights into user behavior, retention, and adherence patterns. Additionally, the study uses robust statistical analyses, including nonparametric tests and multiple correction methods, ensuring the reliability of the findings.

However, the research also has limitations. The cross-sectional design prevents establishing causal relationships between motivation, training behavior, and adherence. The dataset is limited to users of a single fitness app (MH), potentially restricting generalizability to other platforms with different features or user demographics. We obtained informed consent from 5858 users. Of those registries, 2771 were complete and eligible for analysis. This loss should be acknowledged as the fact that we only managed to merge motivation and training data for a total of 289 participants, which limits the statistical power of our motivation-related analyses. Finally, adherence was measured in terms of training frequency, which may not fully capture engagement in app-based fitness programs, highlighting the need for more nuanced adherence metrics in future research.

Conclusions

This study provides crucial insights into the exercise behavior and retention patterns of MH app users, highlighting key factors that influence user engagement. New insights are shared in regard to how motivation relates to training behavior with fitness apps. Clear differentiations are presented between adherence and retention, as conceptualized by the study authors. Fitness apps are a promising tool toward more active lifestyles, but we are yet lacking a sound understanding of related human behavior. Strategies such as gamification, goal-setting, or prompting are available to app developers to increase user engagement. However, longitudinal studies and mixed methods approaches are needed both to study causality and explore qualitative drivers to trainee behavior.

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Data Availability

The datasets analyzed during this study are available from the corresponding author on reasonable request.

Authors' Contributions

Conceptualization: BG-Z, JMA-M, JM, JJ-R
Data curation: OB-J
Formal analysis: AF-V, RP, JMA-M
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Methodology: AF-V, RP, BG-Z, MG-B
Project administration: JM
Supervision: JM, BG-Z, JJ-R
Validation: AF-V
Visualization: JM, JJ-R
Writing – original draft: AF-V, JM
Writing – review & editing: AF-V, RP, JMA-M, OB-J, MG-B, JM, JJ-R

Conflicts of Interest

None declared.

Multimedia Appendix 1

Complete description of the Mammoth Hunters dataset, including all variable categories and the full motivation survey used in the study.
[DOCX File , 20 KB - mhealth_v14i1e72201_app1.docx]

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Abbreviations

MH: Mammoth Hunters
mHealth: mobile health
PA: physical activity
SDT: self-determination theory
WHO: World Health Organization

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Designing a Self-Guided Digital Intervention for Self-Management of Shoulder Pain in People Living With Spinal Cord Injury: Tutorial on Using a Person-Based Approach

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Abstract

Shoulder pain is prevalent in people living with spinal cord injury. Technology and digital rehabilitation tools are increasingly available, but this has not yet included the provision of a self-guided exercise intervention focused on managing shoulder pain for people living with spinal cord injury. We drew on the person-based approach (PBA) to intervention development to design a Shoulder Pain Intervention delivered over the interNet (SPIN) to address this gap. However, in preparation for the design process, we found very few published examples of how the PBA had been operationalized. The aim of this paper is to provide a detailed explanation of our approach and how we operationalized the PBA in the design of SPIN to maximize relevance and engagement. Our design process followed the key PBA steps, combining additional evidence and theoretical components. Each step ensured that guiding principles were formulated and followed to maximize the probability that SPIN would be fit for purpose. We followed 3 steps: (1) we drew on themes from preparatory research (existing and primary) to identify the key behavioral issues, needs and challenges, and existing features to form the basis of SPIN design; (2) we formatted guiding principles that included articulating specific design objectives to provide a framework to identify system requirements; and (3) we selected and refined intervention features using existing literature, behavioral theory, and tools such as the "Behaviour Change Wheel." We have designed SPIN by incorporating a deep understanding of the users' needs and best available evidence to maximize engagement and positive outcomes. In this paper, we have made clear how we operationalized the PBA phases, including how existing evidence, theory, tools, and methods were leveraged to support the PBA process. In explicating our process, we have provided a blueprint to guide future researchers using this approach.

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KEYWORDS

person-based approach; self-guided; intervention design; behavioral analysis; spinal cord injury; shoulder pain; self-management; mHealth; mobile apps; smartphones; digital health; digital interventions

Background

Overview

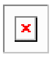
Shoulder pain is common in wheelchair users living with spinal cord injury (SCI) [1,2]. A lesion to the spinal cord can result in loss of innervation to muscles of the trunk and lower limbs. Consequently, many people living with SCI (pwSCI) rely on their upper extremities not only for performance of daily activities but also for locomotion. Shoulder pain can have a significant impact on their activity, reducing mobility, independence, and quality of life [1-5]. Digital and web-based interventions have increasingly been offered to pwSCI to promote exercise and physical activity [6-9]. These interventions minimize barriers to rehabilitation to address many health concerns, including managing their shoulder pain. Previous authors have found that in the general population, digital or web-based interventions can produce positive effects in various outcomes, such as physical activity [10,11].

Technology-supported exercise interventions for pwSCI with persistent shoulder pain are currently available, but they have some limitations. They either require ongoing input and monitoring from a clinician [12-15] or provide general self-management advice [13] but without enough guidance to allow for clear and structured exercise progression specifically for shoulder pain. Self-guided digital exercise interventions have been successfully implemented for people with knee osteoarthritis [16,17], dizziness [18,19], and breast cancer [20] and may be a viable option for pwSCI. Our recent systematic review and meta-analysis of self-guided digital physical activity and exercise interventions demonstrated positive effects on physical activity at both short- and longer-term follow-up, in people living with chronic conditions [21]. We also found that interventions that used behavioral strategies and were underpinned by a theoretical framework were more effective. This suggests that self-guided digital interventions have the potential to support pwSCI to manage their shoulder pain, but that the intervention would need to be designed systematically and intentionally.

We have designed Shoulder Pain Intervention delivered over the interNet (SPIN) as a self-guided digital intervention to give pwSCI who experience shoulder pain the ability to access and progress evidence-based exercises. The intervention guides pwSCI to monitor symptoms and improvement [22] to promote autonomy in the management of their condition. The aim of SPIN is to be an engaging program that is responsive to the needs of pwSCI who have shoulder pain.

To achieve this, we were guided by the person-based approach (PBA) in the design of SPIN [23]. The PBA follows 4 iterative phases of intervention development that include (1) planning which seeks a deep understanding of the perspectives and psychosocial context of potential users through iterative qualitative research, (2) design based on guiding principles that have been created from insights from the first phase, (3) development and refinements which are made through iterative user feedback, and (4) trialing to evaluate the effectiveness on outcomes and impact on behavior change to make any necessary adjustments. Due to its focus on the development of digital behavior change interventions, the intent and purpose of PBA align well with adjacent behavior change theory and tools such as the COM-B [24], "Behaviour Change Wheel" [25], and behavioral analysis [26]. Furthermore, the PBA process is sufficiently flexible to enable the use of these (and other) tools to achieve the aims and purpose of a given phase. Integrating behavioral science theory and evidence while keeping users' needs and contexts in focus has been found to maximize engagement and effectiveness of interventions [18,25,27-31]. This tutorial focuses on the first 2 PBA phases of planning and design. See Table 1 for an example of how our study was mapped onto the PBA.

Table . Mapping of person-based approach phases onto Shoulder Pain Intervention delivered over the Internet design.

PBA[a] description	Phase	This study	
		Purpose	Planned outcome
Use of primary and secondary *qualitative evidence* to understand users' behavioral and psychosocial needs and challenges in using the intervention		To determine *factors that need to be included* to *encourage or facilitate engagement* with this self-guided web-based exercise intervention	• A rich description of key *needs, challenges, and facilitators* of engagement in web-based tools and exercise for people living with SCI[b] who experience shoulder pain to *underpin the design phase's guiding principles and features*
Formulation of *key guiding principles* that capture the main intervention objectives as identified in the planning phase and that are continuously referred to throughout the development of the intervention		To design an *evidence-based, self-guided, web-based* intervention Exercise, behavioral support, and self-guided components to be included within the intervention features	• Intervention design objectives • Intervention features • First iteration of SPIN[c] prototype

[a]PBA: person-based approach.

[b]SCI: spinal cord injury.

[c]SPIN: Shoulder Pain Intervention delivered over the interNet.

We drew heavily on the existing PBA literature during the planning and designing stages of SPIN. However, the lack of access to detailed examples of how the PBA has been operationalized in practice made it challenging to translate the principles of this approach into reality. This is not a unique problem. Duncan and colleagues [32] noted that published work on the development of an intervention is frequently sparse because it is often included in the same publication as the reporting of a pilot or feasibility study.

Aim

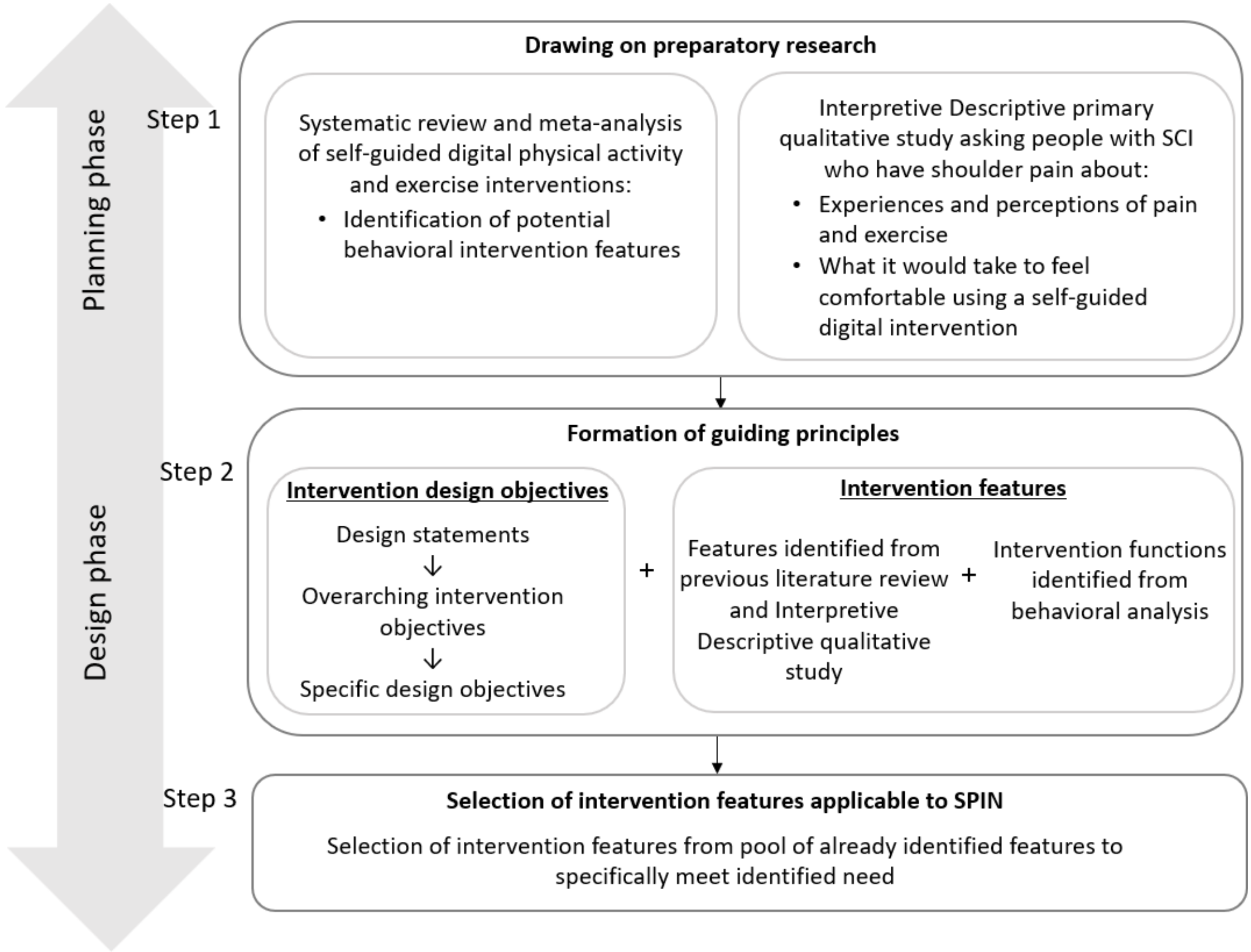
The aim of this paper is to make clear how the principles of the PBA were operationalized in intervention design and the development of SPIN. We have illustrated our use of the PBA framework by outlining the detailed and explicit steps involved in the translation of the evidence, theory, and person-based recommendations into intervention design. In doing so, we have built on the existing methodological framework and enabled others to draw on this approach in future intervention design and development.

Methods and Outcomes

Overview

The planning and design phases of the PBA are described below, along with an overview of how they were operationalized in the design of SPIN. Figure 1 provides an overview of the SPIN design process and the components involved. Each step and its subsequent outcome have been described in detail in the sections that follow.

Figure 1. Overview of Shoulder Pain Intervention delivered over the Internet design steps and components. SCI: spinal cord injury; SPIN: Shoulder Pain Intervention delivered over the interNet.



Step 1: Drawing on Preparatory Research

Methods

This initial phase of the PBA draws on qualitative research, including interviews and focus groups, to gather in-depth insights into the psychological, social, and emotional factors that influence the users' behavior. The goal is to identify the underlying motivations, beliefs, and barriers that may affect engagement with health interventions [23]. In the context of SPIN, this preparatory research included: (1) a systematic review and meta-analysis investigating the effectiveness of self-guided digital physical activity and exercise interventions [21] and (2) an Interpretive Descriptive qualitative study exploring the perceptions of pwSCI who have shoulder pain, on the use of a self-guided digital intervention to help them manage their shoulder pain [33].

Outcome

The review identified several self-guided digital physical activity and exercise interventions. Data extraction included identifying discrete intervention features and categorizing them using a purpose-built template (Multimedia Appendix 1), based on a synthesis of key literature [27,34-40]. Using this template, we extracted possible behavioral intervention features relating to qualities such as customizability, the provision of instruction, feedback and monitoring, tailoring, reminders and prompts, goals and planning, social support, and rewards and threats. We also noted the success of interventions using features that supported behavior, particularly self-regulation. This informed an initial pool of possible intervention features for SPIN that were reviewed later in Step 2.

The Interpretive Descriptive qualitative study identified themes that represented an evaluative process pwSCI go through when considering using a self-guided digital exercise intervention: *Should I use it?*, whether I believe it will work for me right now; *Can I use it?*, whether I can operate the intervention competently and confidently; and *Will I use it?*, whether it will be responsive to my unique needs and keep me coming back. These formed the basis of the design statements in Step 2.

Conceptual representations of possible behavioral intervention features identified from the review were used as probes and images during data collection in the Interpretive Descriptive qualitative study. These were used to prompt discussion about what could help pwSCI to engage in a self-guided digital intervention. The pwSCI discussed ways in which these concepts and specific features may support them. These perspectives were extracted from the audio recordings and tabulated to support the identification of behavioral intervention features in Step 2.

Step 2: Formation of Guiding Principles

Overview

The guiding principles in the PBA are formulated by synthesizing key insights from the planning phase (Step 1) into intervention design objectives and corresponding intervention features that address users' specific needs, preferences, and behavioral barriers [23]. Yardley and colleagues [23] contend that staying true to the identified needs of the people who will use the intervention, throughout the design process, increases intervention relevance, engagement, and effectiveness. In our design of SPIN, we followed several stages to ensure the key context-specific behavioral needs and challenges identified in the Interpretive Descriptive qualitative study remained the focal point during intervention design.

Intervention Design Objectives

Yardley et al [23] suggest generating intervention design objectives to support the creation of the guiding principles but do not expand on how these may be identified. Below, we describe the method we followed to produce intervention design objectives through the creation of design statements, overarching intervention objectives, and specific intervention design objectives.

Design Statements

Methods

We created design statements by using the 3 themes constructed in the Interpretive Descriptive qualitative study. We first reframed each theme into a design statement, giving consideration to how each could be reflected in the design of the intervention. To do this, we reworded the themes to move from a question (*Should I use it?*) into a design statement (*I should use it if…*) and then added conditions applicable to each design statement. Each condition reflected key elements from the qualitative findings, resulting in person-centered conditions to be met in the design process. This process provided depth and context to inform the design of SPIN and ensured the next step would be underpinned by the perspectives of the future users of the intervention, in this case, pwSCI.

Outcome

The Interpretive Descriptive qualitative study themes, design statements, and key conditions for success are presented in Table 2.

Table . Translation of themes to design statements and conditions of success.

Interpretive Descriptive qualitative study theme	Reframed to: design statements	Conditions for success
Should I use it?	I should use it if:	• I believe it will work for me • There is evidence of credibility • There is a clear indication that it is suitable for me • It resonates with my current attitude toward exercise, support situation
Can I use it?	I can use it if:	• I can use it competently • I can use it confidently • It can be tailored and adapted to my unique needs • I can use it safely, without causing more harm • I have the belief that I could use it, given the resources and capacity I have • I have the right support to use it
Will I use it?	I will use it if:	• It is responsive to my unique needs • It encourages me to progress when I am ready • I feel supported to use it • I can see progress as a consequence of using it • It keeps me coming back

Overarching Intervention Objectives

Methods

Next, we articulated the overarching intervention objectives. Succinctly describing the intervention objectives allows a snapshot of the key characteristics of the intervention [23]. We, therefore, clearly articulated how SPIN is distinctive and different from other interventions, reflecting the specific behavioral issues, needs, and challenges it must address.

We developed the intervention objectives iteratively, repeatedly revising the wording with reference to the original research question and design statements, and with input from the research team and stakeholders. Stakeholders included pwSCI, a clinician with experience in SCI rehabilitation, a clinician who was also a pwSCI and a representative of a relevant nongovernmental organization. Each iteration strived to reflect the essence of the needs expressed by the participants with wording that represented what ideal uptake and use of this self-guided digital exercise intervention could look like. The overarching intervention objectives were then used as a reference point for later design and development phases.

Outcome

Referring to the design statements and overall research aim, the overarching intervention objectives for SPIN were to:

1. Be tailored to users' specific and unique needs so they can relate to it and trust it and so that it can be responsive to their changing needs while using SPIN; and
2. Enable users to use it competently and confidently within their capabilities and support systems in a way that is safe and motivating.

Specific Design Objectives

Methods

Once the overarching intervention objectives were formulated, we created the specific design objectives underpinned by the design statements. We developed a working definition, incorporating the key conditions for success for each specific design objective, to ensure clarity in interpretation. These were then reviewed against the overarching intervention objectives, making sure they supported the overall objectives of SPIN. We continued to refine them as the design process progressed, during our planned discussion forums.

Outcome

Tables 3-5 each refer to a different theme. Specific design objectives and working definitions are presented in the first 2 columns; intervention functions and features are discussed in later sections.

Table . Guiding principles from the theme *Should I use it?*.

Design objectives that address identified needs, issues, and challenges	Working definition	Intervention functions	Intervention features that address the design objectives
To help users relate to and trust the program	The program will give users confidence in the source, message, and value of the program. The program is credible and legitimate and promotes trust.	• Education • Training • Modeling • Enablement • Persuasion	• Development team details (names, credentials, and contact info) • Endorsements • *Testimonials* (source matching for social comparison) • Evidence for shoulder pain exercises • How user data will be used or stored • Professional polished interface and function
To reassure users it will be clear who the program is suitable for, giving users confidence that the program is right for them and at what stage it is right for them	The program will guide users through a process to be able to screen for and identify if they are suitable to use the intervention and to promote trust and confidence that this is a safe and robust process.	• Education • Training • Modeling • Enablement • Persuasion	• Screening questionnaire/questions (that will exclude those unsuitable) • Monitoring questions at each exercise event and tracking this information • *FAQ*[a] *section* • Contact information for the team
To provide a sense of potential that it will work for them	The program will help users identify with it and the potential that it may have for them, in their current situation.	• Education • Training • Modeling • Enablement • Persuasion	• *Testimonials* (image with text, video, and quotes) of people in different "stages" of readiness or different situations. • FAQ section addressing suitability of different situations "Is this right for me?" or "How do I know this is right for me?" or "Questions I can ask to make sure this is right for me?"

[a]FAQ: frequently asked question.

Table . Guiding principles from theme *Can I use it?*.

Design objectives that address identified needs, issues, and challenges	Working definition	Intervention functions	Intervention features that address the design objectives
To promote a sense of safety when using the program	The program will ensure exercises are at the appropriate difficulty level and will be responsive to changes in user presentation to ensure that they don’t significantly aggravate shoulder symptoms.	• Training • Environmental restructuring • Modeling • Enablement	• *Monitoring and tracking of shoulder pain* and exercise difficulty • Exercise selection based on user responses and a priori rules • Program-generated advice based on user responses, such as acknowledging concerns, referral to *FAQ*[a], evidence, health care provider
To promote user competence	The program will be easy to use by a range of users and in a range of circumstances, giving them a sense of confidence when using it in the context of their unique life situation.	• Training • Environmental restructuring • Modeling • Enablement	• Language at an appropriate reading level • Layout is clear and simple • Font size and buttons are large for reduced hand function • Minimal scrolling and clicking • Consistent screen layout • Clear signposts • Logical interface • Exercises presented in video and audio formats by pwSCI • Exercises presented in step-by-step processes • Exercises are planned to fit in with daily routine and normal digital device use • Tunneling of information (releasing information in small amounts, as the user progresses through “right amount, at the right time”) • Graded goal setting, implementation planning • *Tailored* and action feedback based on tracking • Praise for success • Advice or support if not yet succeeded • Digital use guidance when needed (help link)
To promote user autonomy	The program will give users a sense of control and ownership over the program and their progress through the program.	• Training • Environmental restructuring • Modeling • Enablement	• *Offering choice where possible: tailoring functions* in exposure matching-timing, intensity (when and how often) • *Reminders* • Excercise selection, timing of exercise • Intervention delivery • Tunneling of options into the most common choices • Suggestions or options for different situations

[a]FAQ: frequently asked question.

Table . Guiding principles from the theme *Will I use it?*.

Design objectives that address identified needs, issues, and challenges	Working definition	Intervention functions	Intervention features that address the design objectives
To promote a positive emotional experience	The program will incorporate positive autonomy-supportive language that invites, informs, and supports users to work through the program.	• Training • Environmental restructuring • Enablement • Modeling • Education • Persuasion • Incentivization	• Use of *positive language and tone* in inviting users to decide for themselves "some find it helpful." • Use of anecdotes to describe examples of success, decision-making • Acknowledging and addressing concerns about using the program, such as pain or carer support • Using *FAQ*[a] *section* • Use of useful/interesting/relevant/personal reminders • Positive or encouraging wording on feedback on progress toward the goal
To promote a sense of relatedness	The program will be relevant to the user by using communication and wording that is tailored to their self-identified preferences and personalized to their unique circumstances.	• Training • Environmental restructuring • Enablement • Modeling • Education • Persuasion • Incentivization	• Feedback as above (and that is immediately reciprocated when interacting with the intervention) • Competition with others, and/or • Cooperation with others • Social connection through the program's grouping • Initial "getting to know you" questionnaire to help with *tailoring ingredients* • Personalization: (1) identification (including username in correspondence), (2) raising expectation (including relevant information in correspondence that is based on users' responses to questions/input), and (3) contextualization (*wording, examples that are relevant to user*-exercises relevant for tetra vs para) • *Reminders* • *Testimonials* • Self-identified support
To help users maintain their exercise over the 12 weeks	The program will use a variety of strategies and features to encourage and support users to maintain engagement in their exercise for the duration of the program.	• Training • Environmental restructuring • Enablement • Modeling • Education • Persuasion • Incentivization	• Rewards (points or similar)/competition • Goal setting • Action planning • Communication that is *positive*, immediate, and useful and *tailored*

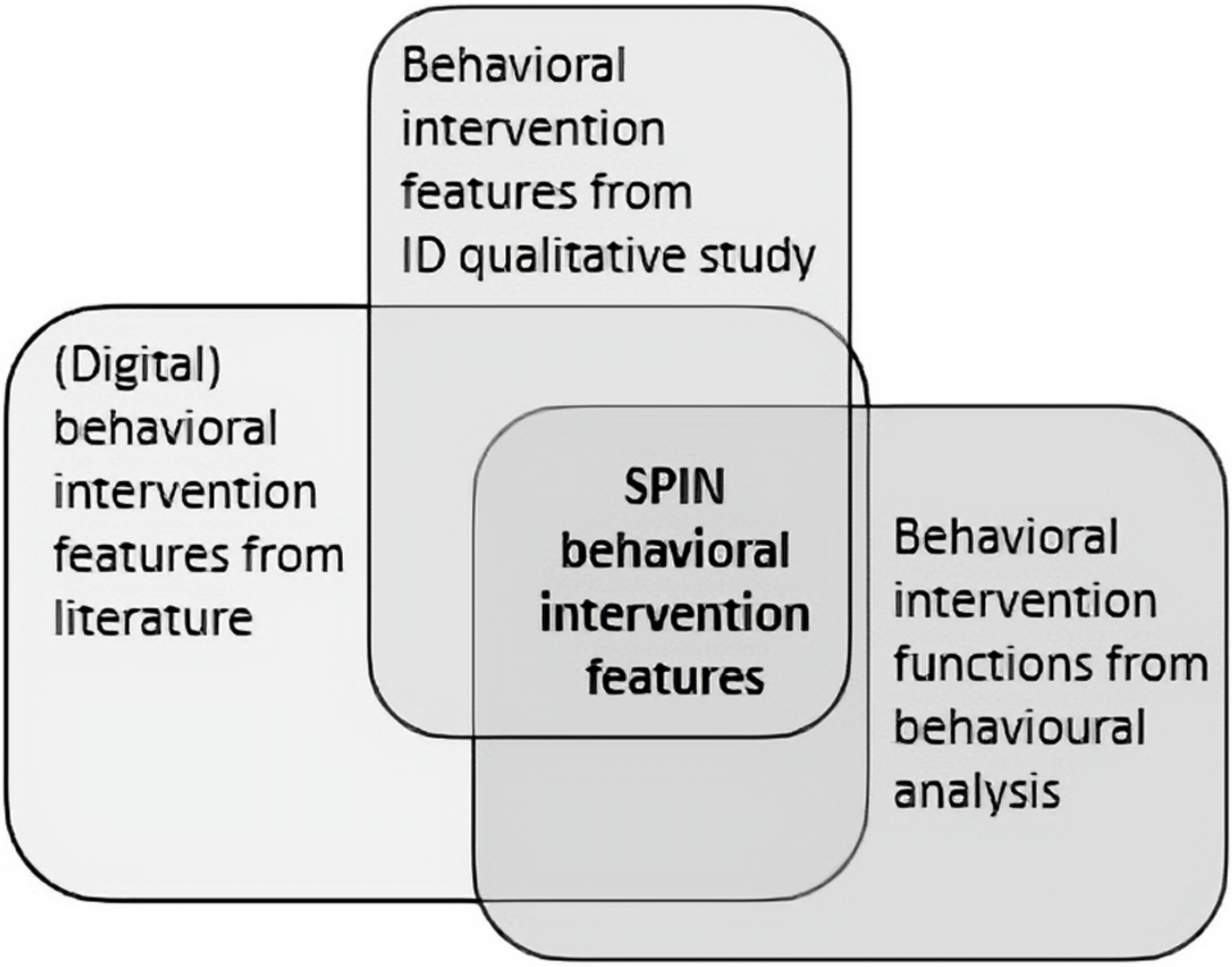
Design objectives that address identified needs, issues, and challenges	Working definition	Intervention functions	Intervention features that address the design objectives
To promote a sense of accountability	The program will provide features that encourage the user to return to the program and to continue with the exercises.	• Training • Environmental restructuring • Enablement • Modeling • Education • Persuasion • Incentivization	• Competition with others or with self • Support from others • Communication that is *positive*, immediate, and useful and *tailored* • Communication that is personalized • Rewards that are only released upon completion of a certain amount of exercise
To promote a sense of progree and engagement	The program will enable the user to understand their progress through a clear and simple tracking feature. This will be done in a way that encourages further progress and ongoing engagement with the exercise intervention	• Training • Environmental restructuring • Enablement • Modeling • Education • Persuasion • Incentivization	• Feedback and tracking • Choice in exercise selection • Personalization • *Tailoring*

[a]FAQ: frequently asked question.

Intervention Features

In the PBA, the guiding principles inform the intervention features by providing a framework for selecting and shaping features that directly support the specific design objectives, and to improve resonance, engagement, and acceptability of an intervention [23]. A range of evidence informed the selection of behavioral intervention features: (1) in our review, we identified a range of features used in digital interventions that have been associated with better health-related outcomes [27,34-36]; (2) we identified possible behavioral intervention design features from our Interpretive Descriptive qualitative study [33]; and (3) we identified behavioral "intervention functions" we were trying to achieve using a behavioral analysis as per Michie and colleagues' framework [26]. We then mapped these to the most relevant intervention features. Figure 2 represents the layers of evidence that informed SPIN's intervention features. We will describe each of these in detail below.

Figure 2. Layers of evidence that informed Shoulder Pain Intervention delivered over the Interjet's intervention features. ID: Interpretive Descriptive; SPIN: Shoulder Pain Intervention delivered over the interNet.



Identifying Behavioral Intervention Features From Previous Literature Review and the Interpretive Descriptive Qualitative Study

Methods

In Step 1, we had earlier identified potential behavioral intervention features for self-guided interventions that were identified from our systematic review and meta-analysis, using the specifically developed template, drawing from the CONSORT-EHEALTH checklist (V.1.6.1) [38]. See Multimedia Appendix 1 for a sample of our template showing sections used to record behavioral intervention features. For this current stage of the SPIN design, we also reviewed intervention features of publications that missed the strict inclusion criteria of the systematic review and meta-analysis but addressed digital delivery of physical activity or exercise intervention for possible relevant behavioral intervention features. We then integrated the data on specific features collected from our Interpretive Descriptive qualitative study. These data were categorized by proposed purpose and function and then mapped against the specific design objectives.

Outcome

There was overlap, resulting in some features identified as addressing more than one design objective. Many of the studies in the systematic review included digital behavioral intervention features that involved instruction on exercise or physical activity performance, self-monitoring of the exercise or physical activity behavior, goals and planning, and prompting. The results of the Interpretive Descriptive qualitative study and other reviewed literature suggested additional behavioral intervention features. Table 6 presents a summary of the behavioral intervention feature categories that we considered for SPIN, the design objective(s) they are related to, and the supporting evidence.

Table . Behavioral intervention feature categories supported by systematic review, Interpretive Descriptive qualitative study, and existing literature.

Design objectives	Behavioral intervention feature	Proportion of studies identified in systematic review and meta-analysis (out of 16 studies)	Identified in Interpretive Descriptive qualitative study	Identified in other literature not included in meta-analysis
Should I use it?	Ensuring personal relevance	16	✓	Horsch et al [41]
Should I use it?/Can I use it?	Use of credibility and trust-enhancing features	5	✓	Bossen et al [42]; Oinas-Kukkonen and Harjumaa [43]
Should I use it?/Will I use it?	Provision of information about actual users	2	✓	Morrison et al [34]
Can I use it?	Allowance of the user to control or adapt features	7	✓	McClure et al [44]
Can I use it?	Ensuring ease of use	6	✓	Carter et al [45]; Hurling et al [46]; Webb et al [27]
Can I use it?	Provision of information ‘just in time’ and in ‘just the right amount’	9	✓	Oinas-Kukkonen and Harjumaa [43]; Xu et al [47]
Can I use it?/Will I use it?	Use of goal setting	8	✓	Webb et al [27]; Willett et al [48]; Dugas et al [49]
Can I use it?	Use of demonstration of behavior	10	✓	Webb et al [27]
Can I use it?	Use of feedback of behavior	10	✓	Webb et al [27]; Dugas et al [49]
Can I use it?	Use of tailored feedback	10	✓	Morrison et al [35]; Dugas et al [49]
All	Use of tailoring based on a number of variables	5	✓	Morrison et al [34]; Couper et al [50]; Xu et al [47]; Oinas-Kukkonen and Harjumaa [43]; Figueiras and Neto [51]; Dugas et al [49]
Can I use it?/Will I use it?	Use of reminders	8	✓	Webb et al [27]; Lin and Wu [52]; Alahäivälä and Oinas-Kukkonen [53]; Dugas et al [49]
Can I use it?/Will I use it?	Use of self-monitoring features	9	✓	Morrison et al [34]; Glasgow et al [54]; Willett et al [48]
Can I use it? /Will I use it?	Use of positive tone and language	4	✓	Haines-Saah et al [55]
Can I use it? /Will I use it?	Use of text message	3	✓	Webb et al [27]
Will I use it?	Use of action/coping planning	5	✓	Webb et al [27]; Glasgow et al [54]; van Genugten et al [56]
Will I use it?	Use of facilitation of social comparison and support	2	✓	Webb et al [27]; Davies et al [57]; Perski et al [58]; Alahäivälä and Oinas-Kukkonen [53]; Xu et al [47]
Will I use it?	Use of rewards and incentives	1	✓	Khadjesari et al [59]; Schubart et al [60]; van Genugten et al [56]
All	Use of a combination and a number of features	14		Webb et al [27]; Meade et al [61]

Identifying Intervention Functions From a Behavioral Analysis

Methods

We included a behavioral analysis using the "Behaviour Change Wheel" and COM-B model as outlined by Michie and colleagues [26]. This is a theoretical framework that provides a systematic way of identifying the problem and analyzing the behavioral needs of a target behavior. The "Behaviour Change Wheel" can support intervention design by linking the identified behavioral needs to "intervention functions" through a mechanism of action.

Consistent with the guiding principles and specific design objectives, and for the purpose of this behavioral analysis, we reframed the 3 themes from the Interpretive Descriptive qualitative study into target behaviors: *Should I use it?*—Signing up to SPIN (Table 7); *Can I use it?*—Using SPIN (Table 8); and *Will I use it*?—Returning to SPIN over the 12 weeks (Table 9). The COM-B Model was then used to identify the capability (C), opportunity (O), and motivational (M) components required for each of these behaviors (B) to occur, referring to the specific design objectives. The questions "*what needs to happen for the target behavior to occur?*" and "*is there a need to change?*" facilitated the analysis process [26]. We used this process to identify (or "diagnose") the relevant COM-B components that need to be addressed for the target behavior to occur (see the Behavioral diagnosis of the relevant COM-B components in Tables 7-9).

Table . Behavioral analysis of target behavior: signing up to SPIN[a] (*Should I use it?*) for people living with spinal cord injury who have shoulder pain.

COM-B components[b]	What needs to happen for the target behavior to occur?	Is there a need for change?
Physical capability	Have the physical ability to access SPIN features and functions and use it	No change needed as SPIN will only be suitable for people who can physically access and use it
Psychological capability	Believe they have the capability to use SPIN	*Change* needed as pwSCI[c] will want reassurance that they have sufficient physical capability to use SPIN and/or that it is suitable for people with their level of physical ability
Psychological capability	Know that exercise can improve pain symptoms (or not make the condition worse)	*Change* may be needed as there may be fears or concerns that exercise could worsen pain symptoms
Physical opportunity	Have a device that can access SPIN	No change needed as SPIN will only be suitable for those people who have devices that can access SPIN
Social opportunity	Know about other pwSCI who have either benefitted from exercise for shoulder pain or are using SPIN	*Change* needed as pwSCI may not know about others who have benefitted from exercise to improve shoulder pain symptoms or who are using SPIN
Reflective motivation	Hold beliefs that exercising will reduce pain symptoms and/or improve activity	*Change* needed as pwSCI may be fearful that exercise may worsen pain symptoms
Reflective motivation	Believe that SPIN has been developed by a credible and trustworthy source	*Change* needed as pwSCI will want to assure themselves that SPIN has been developed by knowledgeable personnel who have experience in SCI[d] rehabilitation
Automatic motivation	Believe that SPIN will identify those that are suitable (and unsuitable) to use it	*Change* needed as pwSCI will want assurance that SPIN is appropriate for their circumstances and can be tailored for their needs
Automatic motivation	Need to feel that SPIN resonates (with current attitude toward exercise, support situation)	*Change* needed as pwSCI need to feel comfortable that SPIN is right for them at this time
Behavioral diagnosis of the relevant COM-B components	Psychological capability, social opportunity, reflective and automatic motivation need to change for the target behavior to occur	—[e]
Likely ”intervention functions” that link to COM-B	Education (psychological capability, reflective motivation), Training (physical opportunity), Modelling (social opportunity), and Persuasion (reflective motivation, automatic motivation)	—

[a]SPIN: Shoulder Pain Intervention delivered over the interNet.

[b]Behavioral diagnosis of the relevant COM-B components: psychological capability, social opportunity, reflective and automatic motivation need to change for the target behavior to occur.

[c]pwSCI: people living with spinal cord injury.

[d]SCI: spinal cord injury.

[e]not applicable.

Table . Behavioral analysis of target behavior: using SPIN[a] (*Can I use it?*) for people living with spinal cord injury who have shoulder pain.

COM-B components[b]	What needs to happen for the target behavior to occur?	Is there a need for change?
Physical capability	Have the physical ability to control and manipulate SPIN features and functions and related equipment and setup	*Change* may be needed as pwSCI[c] will want reassurance that they have sufficient physical capability to use the intervention and/or that the intervention is suitable for people with their level of physical ability
Physical capability	Have the additional support as required	*Change* may be needed with additional support for equipment setup and exercise support
Psychological capability	Believe they have the capability to use SPIN	*Change* needed as pwSCI will want reassurance that they have sufficient physical capability to use SPIN and/or that it is suitable for people with their level of physical ability
Psychological capability	Know how to navigate through the intervention	*Change* needed to clearly provide pwSCI with signposts and information to guide them through
Psychological capability	Know how to perform exercises safely	*Change* needed to ensure appropriate level of exercises is offered and explained to maximize safe exercising and to ensure that the program is responsive to changes in user presentation
Physical opportunity	Have a program that is usable and easy to follow	*Change* needed to ensure SPIN is easy to use and understand
Social opportunity	Haencouragement from peers	*Change* needed to ensure access to a community of users
Reflective motivation	Have confidence in one’s ability to use the intervention program	*Change* needed to provide a sense of ownership and control of the program, with positive reinforcement with use
Reflective motivation	Have belief the intervention will enable achievement of outcomes important to user	*Change* needed as users may not recognize the value of SPIN
Automatic motivation	Have experience of benefit from intervention and sense of progress	*Change* needed to provide consistent exercise opportunities
Behavioral diagnosis of the relevant COM-B components	Physical and psychological capability, physical and social opportunity, and reflective motivation need to change for the target behavior to occur	—[d]
Likely ”intervention functions” that link to COM-B	Training (physical capability, psychological capability), Environmental restructuring (physical opportunity), Modelling (social opportunity), and Persuasion (reflective motivation)	—

[a]SPIN: Shoulder Pain Intervention delivered over the interNet.

[b]Behavioral diagnosis of the relevant COM-B components: physical and psychological capability, physical and social opportunity, and reflective motivation need to change for the target behavior to occur.

[c]pwSCI: people living with spinal cord injury.

[d]not applicable.

Table . Behavioral analysis of target behavior: using SPIN[a] (*Will I use it?*) for people living with spinal cord injury who have shoulder pain.

COM-B components[b]	What needs to happen for the target behavior to occur?	Is there a need for change?
Physical capability	Have the physical ability to control and manipulate SPIN features and functions and related equipment and setup	*Change* may be needed as pwSCI[c] will want reassurance that they have sufficient physical capability to use the intervention and/or that the intervention is suitable for people with their level of physical ability
Physical capability	Have the additional support as required	*Change* may be needed with additional support for equipment setup and exercise support
Psychological capability	Believe they have the capability to use SPIN	*Change* needed as pwSCI will want reassurance that they have sufficient physical capability to use SPIN and/or that it is suitable for people with their level of physical ability
Psychological capability	Know how to navigate through the intervention	*Change* needed to clearly provide pwSCI with signposts and information to guide them through
Psychological capability	Know how to perform exercises safely	*Change* needed to ensure appropriate level of exercises is offered and explained to maximize safe exercising and to ensure that program is responsive to changes in user presentation
Physical opportunity	Have a program that is usable and easy to follow	*Change* needed to ensure SPIN is easy to use and understand
Social opportunity	Have encouragement from peers	*Change* needed to ensure access to a community of users
Reflective motivation	Have confidence in one’s ability to use the intervention program	*Change* needed to provide a sense of ownership and control of the program, with positive reinforcement with use
Reflective motivation	Have belief the intervention will enable achievement of outcomes important to user	*Change* needed as users may not recognize the value of SPIN
Automatic motivation	Have experience of benefit from intervention and sense of progress	*Change* needed to provide consistent exercise opportunities
Behavioral diagnosis of the relevant COM-B components	Physical and psychological capability, physical and social opportunity, and reflective motivation need to change for the target behavior to occur	—[d]
Likely ”intervention functions” that link to COM-B	Training (physical capability, psychological capability), Environmental restructuring (physical opportunity), Modelling (social opportunity), and Persuasion (reflective motivation)	—

[a]SPIN: Shoulder Pain Intervention delivered over the interNet.

[b]Behavioral diagnosis of the relevant COM-B components: physical and psychological capability, physical and social opportunity, and reflective motivation need to changefor the target behavior to occur.

[c]pwSCI: people living with spinal cord injury.

[d]not applicable.

Next, we mapped these components to established ‘intervention functions,’ using the “Behaviour Change Wheel.” Most relevant “intervention functions” were then identified from the matrix of links between COM-B and intervention functions [26]. The “Behaviour Change Wheel” uses the term “intervention function” in lieu of intervention “type” or “category” since the same intervention feature may address more than 1 function [26].

Outcome

Tables 7-9 present the target behavior for each design objective and what (if any) change is needed to occur based on the COM-B components. “Intervention functions” most likely to support behavior change have also been identified. For example, testimonials about positive experiences of using exercise to help with shoulder pain could be a form of modeling (providing an example for people to aspire to) and persuasion (using communication to induce positive feelings or stimulate action). This mapping process allowed each specific design objective to be checked to ensure it was supported by an appropriate “intervention function” and corresponding intervention feature. “Intervention functions” linked to the target behavior have been included in Likely “intervention functions” that link to the COM-B in each of the tables (Tables 7-9). The guiding principles tables (Tables 3-5) provide an overview of how these "intervention functions" map to the design objectives ("Intervention functions" column).

Step 3: Selection of Intervention Features Applicable to SPIN

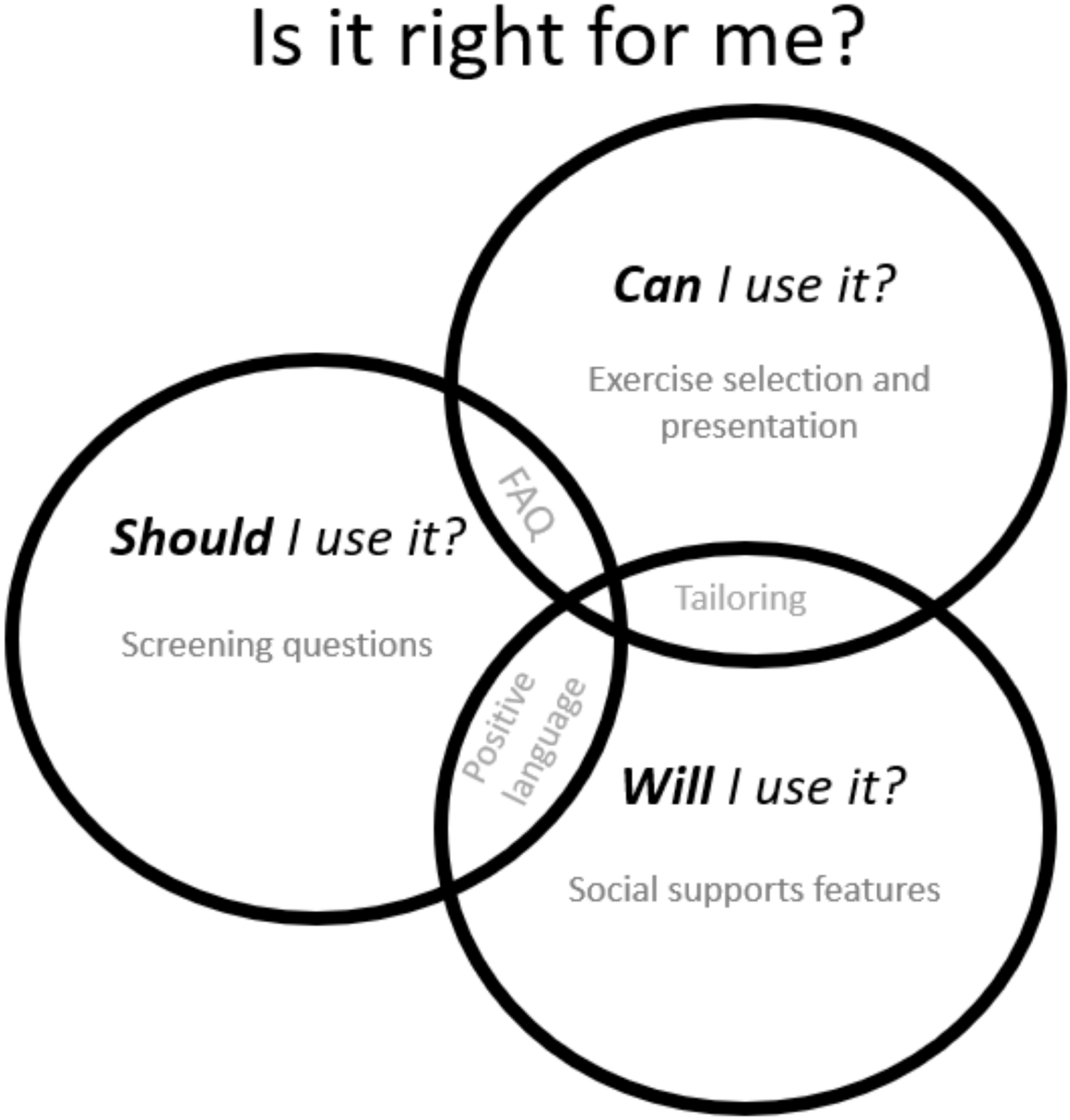
Methods

The design phase of the PBA involves identifying intervention features and content, guided by the previously formulated guiding principles, to ensure alignment with users' psychosocial contexts and to enhance relevance, acceptability, and engagement through iterative user feedback [23]. We were able to begin selecting specific SPIN intervention features once the behavioral analysis was complete. The behavioral intervention features previously identified (Table 6) were reviewed. We mapped those that we felt were contextually appropriate against the "intervention functions." Each was checked to ensure it supported the specific design objectives and the overarching intervention objective. VS completed this process in consultation with coauthors.

Outcome

Collectively, Tables 3-5 demonstrate a complete representation of the guiding principles of SPIN's proposed intervention features and functions, mapped back to the design objectives. Some intervention features address more than 1 intervention design objective. These features have been italicized in Tables 3-5. For example, having a forum for frequently asked questions may reduce barriers to starting the intervention and give users the information they need to progress. Having positive, encouraging language can attract users to start using the intervention and motivate them to continue with it. Other intervention features more clearly support only one of the intervention design objectives. Figure 3 schematically presents an example of how overlapping intervention features cohesively support SPIN's identified design objectives.

Figure 3. Schematic representation of overlapping intervention features.



Application of Our Design Steps to Future Intervention Design

We believe that by explicating how we used the PBA in the development of SPIN, we can support others to use the PBA in the design of interventions. Table 10 provides a summary view of our process and includes some questions that we hope will prompt other researchers to consider how they might operationalize the use of PBA in their work. The table provides an overview of key phases of PBA and possible timelines (column 1) and examples from SPIN (column 2), including tools and methods we drew on as complementary to PBA and which we found useful in operationalizing the approach. In column 3, we have included our reflections on the benefits of our approach. The final column has questions that we hope will serve as prompts for researchers and designers when using this approach.

Table . Operationalizing the person-based approach: our experience and future applications.

1. Key steps in the person-based approach	2. Methods we used to operationalize PBA[a] steps in the development of SPIN[b]	3. Strengths and opportunities of our approach	4. Questions to consider when planning this step
Step 1 (months 3 - 6) Identify key behavioral issues (access), needs (not feeling competent), and challenges the intervention must address	Interpretive Descriptive qualitative study to explore user perspectives of self-guided exercise intervention and what would help or hinder uptake of a self-guided digital exercise intervention. Used probes and images during data collection to help users visualize and provide feedback on possible intervention features.	Drawing on Interpretive Descriptive as a nested study within the PBA process helped to provide a robust framework to capture and make sense of user needs and preferences. Interpretive Descriptive is congruent with the goals of PBA and has the benefit of (1) being oriented toward translation from the outset, (2) prioritizing the production of clinically relevant insights, and (3) flexibility in methods so data collection and analysis could be tailored to the intended use of findings for intervention development.	Who are the users? What is the best way to understand their unique context and specific needs? Are there existing tools and methods available that would be fit for purpose to capture user needs and preferences? How is the information going to be used? How might your approach to capturing needs and preferences be optimized for this intended use? Does data already exist (systematic reviews and qualitative research) that can help inform this step?
Step 2 (months 6-9-12) Creating intervention design objectives that capture what is unique about your intervention and reflect the specifically identified user needs and challenges the intervention needs to address.	Translate themes from the Interpretive Descriptive study into design statements and conditions for success, drawing on the data from each theme.	Helped to reframe the themes into actionable statements. Provided an evidence-based framework to underpin intervention design objectives. Ensured that user needs and preferences will continue to be reflected in the design process.	How are user needs and preferences currently expressed? Can they be used to underpin design objectives in their current form, or do they need some further refinement/transformation?
Step 2 (months 6-9-12) Creating intervention design objectives that capture what is unique about your intervention and reflect the specifically identified user needs and challenges the intervention needs to address.	Two overarching objectives for SPIN were developed from the design statements and conditions of success. It was repeatedly revised, referring to the original research question and design statements, and with input from stakeholders.	Developing 2 overarching objectives, rather than 1, helped to make explicit 2 interrelated but distinct objectives. The intermediary step of developing design objectives from the qualitative study themes ensured that the objectives represent the essence of the needs expressed by the users. Refining with input from stakeholders helped to ensure the objectives remained resonant with the SCI[c] community. Articulating these objectives at the outset was a useful reference point to keep coming back to for all later design and development phases.	What is(are) the overarching intervention objective(s)? How will you ensure your overarching objective(s) remain(s) grounded by user needs and preferences? Who might need to be involved in the development of intervention objective(s)? How will you know if your intervention objective(s) adequately capture(s) the perspectives of future users?
Step 2 (months 6-9-12) Creating intervention design objectives that capture what is unique about your intervention and reflect the specifically identified user needs and challenges the intervention needs to address.	Specific design objective were identified, drawing on the design statements and overarching intervention objectives. Working definitions were formulated with reference to original data sources and in collaborative discussions as a research team.	The development of specific design statements provided a framework to identify design requirements (system requirements) and intervention features. Investing time to develop the working definitions as a team, with reference to original data sources, was important for clarity and shared understanding.	What process will you use to generate specific design objectives from your overarching design objective(s)? Who might need to be involved in that process? What data sources do you have that you can refer to so you can refine your specific design objectives?

1. Key steps in the person-based approach	2. Methods we used to operationalize PBA[a] steps in the development of SPIN[b]	3. Strengths and opportunities of our approach	4. Questions to consider when planning this step
Step 3 (months 6 - 12) Select and refine intervention features that support the specific design objectives.	Several methods were used to support the selection and refinement of intervention features for SPIN including: (1) extracting data on intervention features from a previous systematic review on self-guided exercise interventions, (2) reviewing relevant behavioral theory, (3) undertaking a behavioral analysis, and (4) drawing on persuasive system design.	Drawing on a multiplicity of methods in this step (1) ensured an evidence-based and theoretically informed approach and (2) enabled a systematic approach to ensure intervention features were those best suited to the behavioral needs of the SPIN user. A systematic approach to identifying intervention features and mapping them back to design objectives helps to imrove the credibility of intervention design. The outcome was a clear framework for SPIN intervention design that was a useful tool to support communication with design colleagues or software developers who were then bringing SPIN to form.	What data sources are available that can help you identify potential intervention features? What midrange theories are available that can help you identify potential intervention features? Are there existing tools and methods available that would be fit for purpose to help you identify intervention features which respond to user needs and preferences? Of all the potential intervention features, which are most likely to meet the design objective(s)? Who else should be involved in this process? How might you ensure that the outcome of this process can be an accessible and usable framework for others involved in intervention development?

[a]PBA: person-based approach.

[b]SPIN: Shoulder Pain Intervention delivered over the interNet.

[c]SCI: spinal cord injury.

Ethical Considerations

Ethics approval (Auckland University of Technology Ethics Committee-AUTEC 18/263) and participant consent were received for the earlier work [33] that informed this work.

Discussion

Principal Findings

This paper has described how we applied evidence, theory, and person-based approaches in the design of a self-guided digital intervention to help pwSCI manage their shoulder pain. We have detailed the processes of applying the PBA to the design of SPIN.

This builds on Yardley and colleagues' [23] collection of work. The PBA emphasizes a detailed, qualitative understanding of users' psychosocial contexts to inform intervention design. It adds value to user-centered design by addressing factors that influence behavior change, beyond just usability. The PBA complements theory- and evidence-based frameworks, such as the "Behaviour Change Wheel" [25] by tailoring interventions to the needs and preferences of specific populations. Despite growing evidence for the use of the PBA framework in intervention design [29-31,62,63], there is little available on its operationalization. To our knowledge, the detailed reporting of each step has not been available before.

In a recent systematic review on the effectiveness of self-guided digital exercise interventions, Stavric et al [21] found that interventions with theoretical underpinning had increased congruence with the intervention features leading to significant positive results. This is supported by findings from McEwan [64] who found that theory-based interventions resulted in more consistent significant improvements in physical activity. The pwSCI and shoulder pain who will use SPIN are likely to have minimal contact with a health care professional. Therefore, successful design required an understanding of how SPIN would meet their needs and how pwSCI would use it in daily life in a self-directed way. Engaging people and evidence in intervention design is supported by a range of researchers and designers [23,34,65]. Using a person-based approach, drawing on evidence from the people who will use the intervention, to derive the behavioral strategies has been shown to be effective in a variety of settings and methods of delivery [18,29,30,66,67].

Despite acknowledgment that interventions supported by theory and evidence maximize outcomes [68,69], there remains a paucity of full intervention description or design disclosure [70-73], making it challenging to explicate the link between theory and evidence and intervention features. A key tension we encountered was the limited availability of detailed examples of how the PBA had been operationalized in practice. This required us to make interpretive decisions when translating PBA principles into design elements, often without clear guidance. Additionally, balancing adherence to the PBA's iterative, user-focused process with practical constraints such as time, resources, and access to participants posed challenges. These limitations were compounded by the fact that we were largely self-taught in the application of both the PBA and behavioral analysis frameworks.

Michie and colleagues [74] recognized the challenges and lack of clarity around the purported mechanisms by which digital interventions work during an international workshop on developing and evaluating digital interventions to promote behavior change in health. DiLiberto and colleagues [75] support the importance of "insider accounts" of intervention implementation and argue that the same transparent reporting practice should apply to intervention design. Of the 16 self-guided interventions included in our systematic review and meta-analysis conducted in the planning phase [21], only 6 provided any reference to methods used to plan, design, and develop them [19,76-81]. Of these, there was little supporting detail on how the design was carried out and none of the included studies reported exploring the behavioral needs of the users before designing the intervention. Future researchers might benefit from greater transparency and reporting of the design phase, including more practical examples of operationalizing person-based and behavioral approaches. Considerations for mitigating these challenges include allocating sufficient time and resources for user involvement beyond the planning stage, documenting key design decisions, and seeking opportunities for peer collaboration to support methodological alignment and confidence.

Strengths

We have shown commitment to providing a robust and transparent process in the operationalization of the design phase of SPIN drawing on the PBA approach. This process included explicitly addressing the identified behavioral needs of the users and kept these central throughout the entire design process. The design of SPIN has demonstrated how we used evidence (from existing literature and from a previous Interpretive Descriptive qualitative study) and theory (from behavioral analysis, "Behaviour Change Wheel," and COM-B) to enhance the person-based process. This explicit and thorough process of planning and designing SPIN has provided a blueprint for intervention development when using PBA. It also addresses many of the limitations in the reporting on the development processes for existing self-guided digital exercise and physical activity-related interventions.

Limitations

Our operationalization of the PBA design phase reflects our interpretation of the PBA steps through available readings. We acknowledge there may be other perspectives and understandings. However, we believe that it is important to make our experiences visible to build on previous work and support future intervention design. Similarly, we relied on literature and online course instruction for support when we conducted the behavioral analysis using the COM-B. Being self-taught in both the PBA and behavioral analyses may mean that some aspects of our approach are not consistent with the original intent of these approaches. However, this is perhaps an artifact of the knowledge mobilization process, where the application of knowledge can change as knowledge changes hands. By offering transparency in our process, we hope that people can draw their own conclusions regarding the robustness of our approach. The design of SPIN did not include a logic model. Logic models typically include the main intervention components, how they relate to one another, which are meant to produce which effect, and include processes and expected outcomes. However, we did not believe a logic model would have been pragmatically useful as they assume causal relationships which may have restricted our thinking about solutions [82]. Our development process was underpinned by relationship building and community interaction, both of which are complex and require flexibility [83,84].

Future Steps of SPIN Using the PBA

With the proposed intervention features selected, SPIN wireframes have been constructed. Wireframes are images or screenshots that show how screens of a website or app are structured and how content is arranged. These have provided a visual representation of the product and an opportunity to comment on content, features, and organization without getting distracted by aesthetics. Further participant consultation and design refinement have occurred. Frontend and backend software programming will occur at a later phase. Reporting of these stages will follow in a subsequent publication.

Conclusion

The design of SPIN has incorporated a deep understanding of the users' needs and best available evidence by drawing on the PBA design process to maximize chances of engagement and outcomes. This paper has made visible the operationalization of each of the phases and can act as a blueprint to provide guidance to future researchers when using this approach.

Authors' Contributions

Conceptualization: VS, NMK
Methodology: VS, NLS, NMK
Supervision: NLS, NMK
Visualization: VS
Writing – original draft: VS
Writing – review & editing: VS, NLS, NMK

Conflicts of Interest

None declared.

Multimedia Appendix 1
Systematic review data collection template.
[XLSX File, 25 KB - mhealth_v14i1e66678_app1.xlsx]

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Abbreviations

PBA: person-based approach
pwSCI: people living with spinal cord injury
SCI: spinal cord injury
SPIN: Shoulder Pain Intervention delivered over the interNet

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