

Review

Human Factors in AI-Driven Digital Solutions for Increasing Physical Activity: Scoping Review

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Abstract

Background: Artificial intelligence (AI) has the potential to enhance physical activity (PA) interventions. However, human factors (HFs) play a pivotal role in the successful integration of AI into mobile health (mHealth) solutions for promoting PA. Understanding and optimizing the interaction between individuals and AI-driven mHealth apps is essential for achieving the desired outcomes.

Objective: This study aims to review and describe the current evidence on the HFs in AI-driven digital solutions for increasing PA.

Methods: We conducted a scoping review by searching for publications containing terms related to PA, HFs, and AI in the titles and abstracts across 3 databases—PubMed, Embase, and IEEE Xplore—and Google Scholar. Studies were included if they were primary studies describing an AI-based solution aimed at increasing PA, and results from testing the solution were reported. Studies that did not meet these criteria were excluded. Additionally, we searched the references in the included articles for relevant research. The following data were extracted from included studies and incorporated into a qualitative synthesis: bibliographic information, study characteristics, population, intervention, comparison, outcomes, and AI-related information. The certainty of the evidence in the included studies was evaluated using GRADE (Grading of Recommendations Assessment, Development, and Evaluation).

Results: A total of 15 studies published between 2015 and 2023 involving 899 participants aged approximately between 19 and 84 years, 60.7% (546/899) of whom were female participants, were included in this review. The interventions lasted between 2 and 26 weeks in the included studies. Recommender systems were the most commonly used AI technology in digital solutions for PA (10/15 studies), followed by conversational agents (4/15 studies). User acceptability and satisfaction were the HFs most frequently evaluated (5/15 studies each), followed by usability (4/15 studies). Regarding automated data collection for personalization and recommendation, most systems involved fitness trackers (5/15 studies). The certainty of the evidence analysis indicates moderate certainty of the effectiveness of AI-driven digital technologies in increasing PA (eg, number of steps, distance walked, or time spent on PA). Furthermore, AI-driven technology, particularly recommender systems, seems to positively influence changes in PA behavior, although with very low certainty evidence.

Conclusions: Current research highlights the potential of AI-driven technologies to enhance PA, though the evidence remains limited. Longer-term studies are necessary to assess the sustained impact of AI-driven technologies on behavior change and habit formation. While AI-driven digital solutions for PA hold significant promise, further exploration into optimizing AI's impact on PA and effectively integrating AI and HFs is crucial for broader benefits. Thus, the implications for innovation management

involve conducting long-term studies, prioritizing diversity, ensuring research quality, focusing on user experience, and understanding the evolving role of AI in PA promotion.

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KEYWORDS

machine learning; ML; artificial intelligence; AI; algorithm; algorithms; predictive model; predictive models; predictive analytics; predictive system; practical model; practical models; deep learning; human factors; physical activity; physical exercise; healthy living; active lifestyle; exercise; physically active; digital health; mHealth; mobile health; app; apps; application; applications; digital health; digital technology; digital intervention; digital interventions; smartphone; smartphones; PRISMA

Introduction

Physical activity (PA) has been recognized as a cornerstone of a healthy lifestyle since it has demonstrated numerous benefits for both physical and mental well-being [1,2]. Engaging in regular PA has been associated with preventing and managing a range of health conditions, including obesity, diabetes, cardiovascular disease, and multiple sclerosis [2,3]. However, the global population's engagement in regular PA is often low, with many individuals failing to meet the recommendations necessary for health benefits. This persistent challenge necessitates innovative approaches to motivate and facilitate increased PA participation, and mobile health (mHealth) technologies have emerged as a promising avenue for intervention [4].

The availability of mobile devices and the increasing mobile penetration provide an unprecedented opportunity to leverage mHealth solutions to promote PA [5,6]. Mobile technologies offer persuasive and ubiquitous systems. Equipped with built-in sensors that can monitor and encourage PA in real time, they can facilitate sending personalized reminders and motivational messages [7-10], which have been proven to significantly increase PA [10-12]. However, the effectiveness of mHealth interventions in promoting PA has been limited by the challenge of sustaining engagement over the medium and long term. Mönninghoff et al [13] found that mHealth “can foster small to moderate increases in PA,” and the effects are even maintained long-term, but “the effect size decreases over time.” This is where the integration of artificial intelligence (AI) holds immense promise. AI technology has the potential to deliver effective interventions to promote PA [11,14].

AI can enrich mHealth solutions by offering personalized, adaptive, and tailored interventions that cater to individual preferences and needs. For example, an optimal exercise plan for an individual can be suggested by AI algorithms to help maximize the long-term health utility of the user [15]. This level of customization has the potential to enhance user experience (UX), which in turn could result in increased motivation to engage in PA. Motivation is a critical factor in driving behavior change, especially when adopting and maintaining a physically active lifestyle. AI can also gamify fitness by setting challenges, goals, and rewards, motivating users to increase PA through points, competition, and achievements [16]. Moreover, research indicates that the human-likeness of conversational agents increases adherence to chatbots [17] and compliance with their recommendations [18].

In this context, human factors (HFs) play a pivotal role in the successful integration of AI into mHealth solutions aimed at promoting PA. Understanding and optimizing the interaction between individuals and AI-driven mHealth apps is essential for achieving the desired outcomes [19]. HFs, in the context of AI, involve considerations related to human cognition, behavior, and ergonomics, which are crucial for designing effective and user-friendly mHealth interventions. Bergevi et al [20] explored users' perceptions of acceptability, engagement, and usability of mHealth solutions that promote PA, healthy diets, or both. They concluded that mHealth services targeting increased PA “should be personalized, dynamic, easily manageable, and reliable.” This study is distinguished from their work by focusing on AI-driven digital solutions.

This research underscores the critical role of PA in promoting overall health and well-being while highlighting the persistent challenge of low engagement in regular PA globally. It emphasizes the potential of mHealth technologies, augmented by AI, to effectively motivate and facilitate increased PA participation. By leveraging AI, mHealth solutions can offer personalized, adaptive interventions tailored to individual preferences and needs, thereby enhancing the UX and motivation. However, the successful integration of AI into mHealth solutions relies on understanding and optimizing HFs, encompassing cognition, behavior, and ergonomics, to ensure effective and user-friendly interventions. Specifically, this study aims to address the following research question, what are the key HFs influencing the effectiveness and adoption of AI-driven digital solutions aimed at promoting PA? Our objective is to review and describe the current evidence on the HFs in AI-driven digital solutions for increasing PA.

Methods

Overview

We have conducted a scoping review to capture current evidence on HFs in AI-driven digital solutions for increasing PA. A scoping review is a systematic approach used to map and synthesize existing literature on a broad topic, providing an overview of key concepts, sources, and knowledge gaps. Our review followed the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) [21].

Search Strategy

We have searched for publications including keywords related to PA (ie, “physical activity;” “exercise;” “active lifestyle;” “sedentary behaviour;” “inactivity;” “resistance training;”

“exergaming;” “walking;” “swimming;” “jogging;” “climbing”), artificial intelligence (ie, “artificial intelligence;” “AI;” “machine learning;” “deep learning;” “natural language processing;” “neural networks;” “sentiment analysis”), and human factors (ie, “usability;” “task performance;” “satisfaction;” “workload;” “human errors;” “user perception;” “cognitive factors;” “mental model;” “context awareness;” “automation bias;” “teamworking;” “user experience;” “acceptance;” “acceptability;” “task analysis;” “handover;” “patient interaction;” “human factors;” “ergonomics”) in their titles and abstracts. No language or year limitations were used. The full search strategy can be found in [Multimedia Appendix 1](#).

Textbox 1. Inclusion and exclusion criteria.

Inclusion criteria

- Primary studies that described an artificial intelligence (AI)-based digital solution
- AI-based digital solutions aimed at increasing physical activity
- Publications that reported results from testing the AI-based solution related to physical activity behavior

Exclusion criteria

- Publications that did not meet all 3 inclusion criteria

All references were uploaded to EndNote (version 20.6; Clarivate) [22] and Rayyan (Qatar Computing Research Institute) [23]. After duplicates were removed, 2 authors (EG and DL) independently assessed the eligibility of the remaining publications by checking their titles and abstracts. Two additional authors (KD and OR-R) checked the full text of the eligible papers after the title and abstract screening. After the full-text screening, the selected papers were included in a qualitative synthesis.

Data Items and Data Extraction

Two authors (KD and OR-R) extracted the following data: bibliographic information (publication year and country); study characteristics (study design, type of evaluation, research methods, primary and secondary measures, materials, and theoretical foundations); population (number of participants, age, and gender); intervention (intervention design, duration, and follow-ups); comparison (control group or groups and pre-post evaluation or other); outcomes (primary and secondary outcomes); and AI-related information (technology type, main purpose, platform, and HFs).

OR-R identified and assigned codes representative of the main purpose of the AI model implemented in each of the systems studied. The 3 main purposes of the AI models implemented in the studied systems were identified as personalization, communication, and human activity recognition. Personalization

The data search was performed on August 29, 2023. The database search was done by a single author (EG) and covered PubMed, Embase, and IEEE Xplore. Another author (DL) carried out a search on Google Scholar and selected the first 100 entries. Finally, DL used a snowballing approach to identify additional relevant studies cited in only the included publications.

Eligibility and Selection Process

Inclusion and exclusion criteria are presented in [Textbox 1](#).

includes all AI models analyzed whose main purpose was to adapt the digital solution or intervention to the patient’s needs, conditions, and preferences. The second group includes models that enabled a communication pathway with patients. Finally, human activity recognition includes all models that enable the detection of user behaviors, particularly PA. OR-R and KD reviewed the assigned codes and created a classification of these by consensus.

Certainty of the Evidence

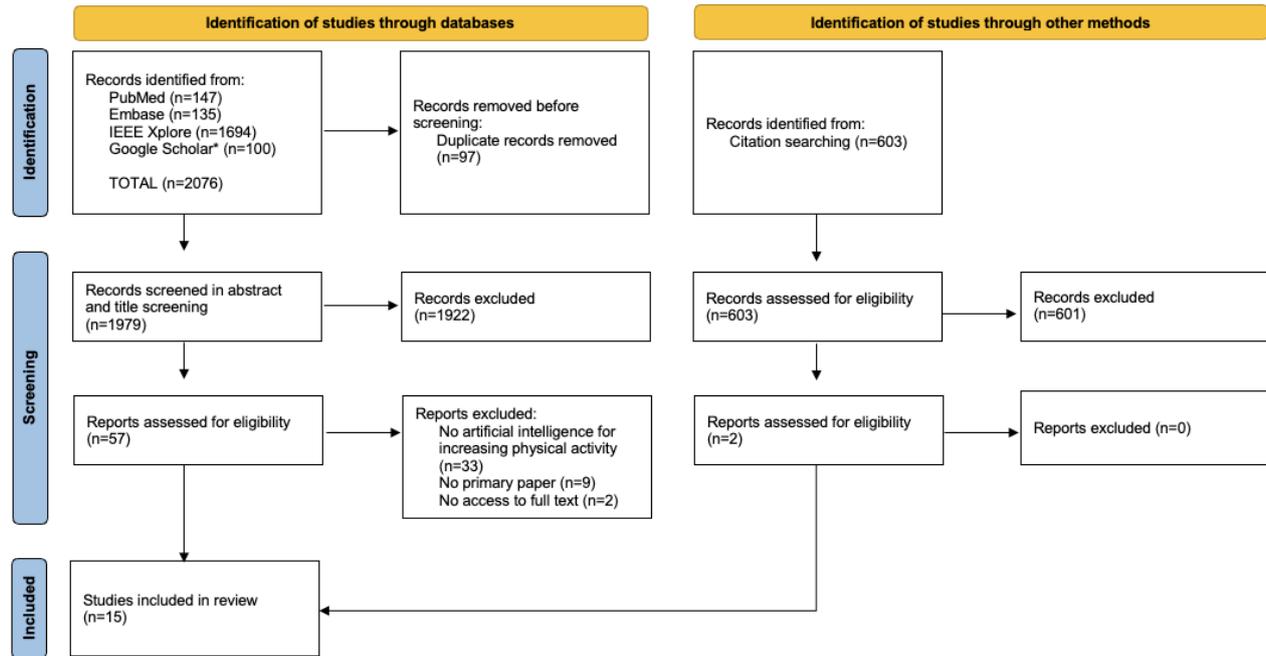
The certainty of the evidence on the outcomes was assessed by a single author (EG) by drawing on the GRADE (Grading of Recommendations Assessment, Development, and Evaluation) criteria [24] and verified by the rest of the coauthors.

Results

Study Selection

A total of 2076 articles were identified in the data search. After removing duplicates, 1979 titles and abstracts were screened for eligibility. Of those, 13 publications met the inclusion criteria [25-37]. The snowballing approach identified 2 additional publications [38,39]; therefore, the final number of publications included in this review was 15 ([Figure 1](#) shows the PRISMA [Preferred Reporting Items for Systematic Reviews and Meta-Analyses] flowchart).

Figure 1. Flowchart diagram of the selection process.



* Only 100 first entries chosen

The list of publications excluded during the full-text search and the reasons for their exclusion are reported in [Multimedia Appendix 2](#).

Description of the Included Publications

The 15 included articles were published between 2015 and 2023. Countries of origin of these studies were: United States (n=3) [25,26,36], Australia (n=2) [32,38], South Korea (n=2) [29,35], the Netherlands (n=1) [31], Italy (n=1) [27], Belgium and Italy (n=1) [30], Thailand (n=1) [37], and Taiwan (n=1) [33]. A total of 3 publications did not specify in which country the study was performed [28,34,39].

Regarding the study design, 8 publications followed a quasi-experimental approach [26-29,32,35,38,39], 5 were randomized controlled trials [25,30,33,36,37], and 2 were exploratory studies [31,34].

Only 4 of the 15 included publications explicitly mentioned their theoretical foundations. The following theoretical approaches were cited in these 4 publications: the Fogg Model for behavior change [25,31], Capability, Opportunity, and Motivation model of Behavior [32]; learning theory [25], social cognitive theory [25], and the Transtheoretical Model [39].

The main technical characteristics of the 15 included publications are presented in [Table 1](#).

Table 1. Main technical characteristics of the included artificial intelligence (AI)-based solutions.

Author and year	AI tech type	AI purpose	AI techniques	System platform	Human factors
Rabbi et al (2015) [25]	RS ^a	Personalization	Gaussian mixture model	MyBehavior (Mobile app)	User experience
Rabbi et al (2018) [26]	RS	Personalization and HAR ^b	Data clustering algorithm and sequential decision-making algorithm (multiarmed bandit)	MyBehaviorCBP (Mobile app)	Acceptability
Fadhil et al (2019) [27]	CA ^c	Communication	Fine state machine and multi class support vector machine	Chatbot stand-alone	Acceptability
Davis et al (2020) [28]	CA	Communication	Unknown	IBM Watson digital assistant AI software running on Slack	User experience
Luštrek et al (2021) [30]	RS	Personalization and HAR	Random forest	App with wristband	Acceptability, attitude, and performance expectancy
Joo et al (2021) [29]	RS+HAR	Personalization and HAR	Feature point extraction and part affinity fields (machine learning technology with top-down segmentation)	Weelo (web-based fitness program)	Satisfaction, usability, and usefulness
Pelle et al (2021) [31]	RS	Personalization and proposes challenging, achievable, and tailored goals	Machine learning compromising a dynamic model (contextual multiarmed bandit approach)	A stand-alone mobile health app	Usability
To et al (2021) [32]	CA	Personalization and communication	Unknown	DialogFlow (Google), Fitbit Flex, and messenger app	Usability and acceptability
Lin et al (2022) [33]	RS	Personalization and provides a personal training program	Decision tree	AIoT ^d , mobile app, and web application	Usability
Park et al (2022) [34]	HAR	HAR	Convolutional neuronal networks	Mobile app	Satisfaction, acceptability, and task performance
Seok et al (2022) [35]	RS	Communication	Large-scale modular behavior networks with inferred contexts and probabilistic model and Russel's arousal-variance model	TouchCare system: wearable watch, touchpad sensors, TouchCare app, and context-aware AI	Satisfaction
Bates et al (2023) [36]	RS	Personalization and real-time feedback on form and resistance for each task in the training program	Unknown	Tonal AI (commercially available product)	Satisfaction
Thiengwittayaporn et al (2023) [37]	RS	Personalization and patient disease stage	Decision tree classification	Mobile app	Satisfaction
Maher et al (2020) [38]	CA	Communication and personalization	Unknown	IBM Watson	Acceptability

^aRS: recommender system.

^bHAR: human activity recognition.

^cCA: conversational agent.

^dAIoT: artificial intelligence of things.

AI-Driven Technology and HFs

The most common AI technology type was recommender systems, described in 10 of the 15 included publications [25,26,29-31,33,35-37,39]. In addition to the recommender system, one of these publications also included computer vision [29]. Conversational agents were the second most used AI technology, as described in 4 publications [27,28,32,38]. One

of them was integrated into a social media platform, namely Slack [28]. One study tested human activity recognition [34]. Details of the AI technology, systems, or platforms used in the included studies are summarized in Table 1.

Regarding the considered HFs, the most commonly evaluated were acceptability [26,32,34,38,39] and satisfaction [29,34-37], both reported in 5 publications. Usability was the next most

considered and evaluated HF, as reported in 4 papers [29,31-33]. Usefulness was assessed in 2 publications [26,29]. Other considered and evaluated HFs were engagement [38], UX or individual perception [25], and task performance [34].

The studies that resulted in increased PA and had a moderate certainty of evidence were chatbot systems with integrated recommender systems. Although the usability of some of those systems was considered poor [32], they were perceived positively. Several papers gained interesting results regarding HFs. Given the variety of systems, a generalization for all 15 studies is difficult.

The automated collection of data needed for personalization and recommendation is an important aspect. In total, 5 systems involved fitness trackers [26,30,32,35,38] to enable automated data collection. They can be grouped into mobile-based activity tracking using movement sensors in the phone [25], dedicated fitness trackers [30,32,38], specifically an accelerometer in the wristband [30], Fitbit Flex 1 activity tracker (Fitbit LLC) [32], and Garmin Vivofit4 tracker (Garmin) [38], and smartwatches [35]. Rabbi et al [25] concluded that automated data collection would be useful. The studies involving chatbots concluded that users have high expectations regarding the chatbot’s knowledge and capabilities [28]. Human likeness is reported as a success factor of such systems. Relevant aspects leading to the efficacy of the system include the human-like qualities of the chatbot and the personalization of the suggestions [28,32,39], that is, chatbots or digital assistants should have a personality, have humor, be able to act with spontaneous behavior, and in a diverse, nonrepetitive manner [28,32]. They should provide the correct answers. For successful recommendations, it is essential to learn the personal preferences of users so that suggestions can be made that fit into personal routines and lifestyles [39].

Even a combination of human agents and digital agents was reported to be better accepted than pure virtual support [27]. Beyond that, access to a system anywhere and anytime is well

perceived [31]—and this is reflected by the fact that most systems included in this study are delivered as mobile apps (instead of desktop apps). Exercises and recommendations are successful in this setting when they can be easily integrated into the daily lives of the users [31].

Population, Interventions, and Comparison

A total of 899 individuals participated in the included publications. Of those, 60.7% (546) were female participants. The reported average ages of these participants ranged from 18.7 to 84.4 years. In total, 6 out of the 15 studies tested their solutions on participants with mean ages of around 50 years or older [28,31-33,37,38], while 6 studies predominantly included participants with a mean age of 40 years or younger [25,27,29,34,36,39]. Two studies did not specify the gender or age of participants [30,35].

The intervention of the included studies lasted between 2 and 26 weeks.

Prepost evaluations were carried out in 6 of the publications to evaluate the impact of the AI-driven intervention [26,29,32,35,38,39]. In 4 publications, control groups were used to assess the impact [25,30,34,36]. In 5 of the publications, the comparison methods used to assess the impact of the AI-driven intervention on increasing PA were not clearly reported [27,28,31,33,37].

Outcomes and Certainty of the Evidence

The effectiveness of AI-driven technologies for increasing PA was shown in 5 publications [28,32,36,38,39]. Three of these publications tested conversational agents [28,32,38], while the other 2 focused on recommender systems [36,39]. The analysis, based on GRADE guidelines, found moderate certainty in the evidence supporting this statement. Further details about the proven effect of these studies and the certainty of the evidence on these findings are reported in Table 2.

Table 2. Certainty of the evidence (artificial intelligence for increasing physical activity [PA]).

Outcome	Effect	Participants (studies)	Certainty of the evidence (GRADE ^{a,b})	Comment
<ul style="list-style-type: none"> Increased number of steps, distance walked, or time spent on PA Follow-up: mean 9.4 weeks 	<ul style="list-style-type: none"> Increased walked distance [36] exceeded step goal [28] more steps [32] increased walking minutes [39] increased time spent on PA [38] 	<ul style="list-style-type: none"> n=260 (3 pre-post studies, 1 RCT^c, and 1 observational study) 	B: moderate	We have a moderate level of confidence that the actual impact closely aligns with the estimated effect.
<ul style="list-style-type: none"> Change in PA behavior and abilities to perform behavior Follow-up: mean 13.3 weeks 	<ul style="list-style-type: none"> Feeling more stimulated to engage in PAs [30] change in walking behaviors [25] improved behaviors related to PA [35] improved ability to do sports [37] 	<ul style="list-style-type: none"> n=98 reported (number not explicitly reported in 2 studies) 3 RCTs, 1 pre-post study 	D: very low	We have a very low level of confidence in the estimated effect.

^aGRADE: Grading of Recommendations Assessment, Development, and Evaluation.

^bScale of 4 degrees, where A denotes the highest quality and D denotes the lowest quality.

^cRCT: randomized controlled trial.

In total, 4 of the included articles also showed that AI technologies have an effect on changing PA behavior (ie, feeling more stimulated to engage in PAs, change in walking behavior, improved behavior related to PA, or improved ability to perform PA) [25,30,35,37]. All these publications were recommender systems [25,30,35,37] and found a positive effect of AI-driven technology on changing PA behavior. However, the analysis, based on GRADE guidelines, found very low certainty evidence supporting this statement.

Discussion

Principal Results

In this scoping review, we aimed to identify and describe the current evidence on HFs in AI-driven digital solutions for

increasing PA. The results showed that the most common AI technology used in digital solutions for PA was recommender systems, followed by conversational agents. User acceptability and satisfaction were the most commonly evaluated HFs in the included studies. Some studies also evaluated the usability of AI-driven digital solutions for PA.

We have identified studies that provide evidence that AI-driven digital technologies have the potential to increase PA (eg, number of steps, distance walked, or time spent on PA). Furthermore, AI-driven technology, particularly recommender systems and chatbots, seems to have the potential to influence changes in PA behavior. Although these studies offer valuable insights by demonstrating positive outcomes through various AI-driven technologies for enhancing PA, the evidence is still very limited. The main findings are presented in [Table 3](#).

Table 3. Summary of main findings.

Included in review	Findings (N=15 studies; covering a total of 899 study participants)
Interventions duration	<ul style="list-style-type: none"> Interventions lasted between 2 and 26 weeks
Used AI ^a technologies	<ul style="list-style-type: none"> Recommender systems (described in 10/15 studies) Conversational agents (described in 4/15 studies) Human activity recognition (described in 1 study)
Human factors	<ul style="list-style-type: none"> Acceptability (evaluated in 5/15 studies) Satisfaction (evaluated in 5/15 studies) Usability (evaluated in 4/15 studies) Usefulness (evaluated in 2/15 studies) Engagement (evaluated in 1 study) User experience (evaluated in 1 study) Task performance (evaluated in 1 study)
Effectiveness of AI-driven technologies for increasing PA ^b	<ul style="list-style-type: none"> Moderate evidence: AI-driven digital technologies have the potential to increase PA (eg, number of steps, distance walked, or time spent on PA) Very low evidence: Recommender systems and chatbots, seems to have the potential to influence changes in PA behavior

^aAI: artificial intelligence.

^bPA: physical activity.

Comparison With Previous Work

In the included studies, we recognized several benefits of AI integrated into digital solutions for increasing PA, such as the ability to adapt the solution to the patient's physical capacity, current activity, and psychological profile [8,11,30]. AI can monitor activity and inactivity and predict bodily occurrences, which is especially relevant for older people [40]. AI can also simulate the role of a personal trainer, provide guidance, form correction, and motivation [37] through voice- or text-based interactions. Users can receive real-time feedback and support during their workouts [8,10] which would be difficult to achieve with non-AI digital solutions. AI algorithms can analyze user data such as fitness levels, health conditions, and preferences and provide personalized exercise recommendations [11]. The activities or other suggestions are tailored to the specific needs and goals of the user, increasing the likelihood of adherence. Real-time feedback can be shared with the user. Previous studies found that activity tracking combined with real-time, personalized text messages can significantly increase PA and

further affirm text messaging as an effective health behavior modifier [10-12]. However, in our review, researchers concluded that their solution did not achieve sufficient adherence to the exercise program [28,30]. The entire potential of personalization techniques has not yet been implemented in the solutions, as Luštrek et al [30] concluded that personalization, simplicity, ease of use, and avoiding information overload could be improved.

AI algorithms can continuously learn from user interactions and feedback to refine and improve the UX. This iterative process leads to more effective and engaging solutions over time. For example, the continuous interaction that chatbots can provide was reported to be useful in helping users increase regular PA and in helping them stay motivated to participate in PA [32]. Studies have already found that the human-likeness or anthropomorphisms of a chatbot increase the likelihood that users comply with the chatbot's recommendations [18]. Roy and Naidoo [17] found that human qualities like warmth and

competence are contributing to a positive UX and possibly to an increased adherence to the digital solution [17].

We only found 5 studies involving sensors to measure PA [26,30,32,35,38]. Dedicated fitness trackers seem to be more prominent to be involved in solutions increasing PA. Mobile-based activity tracking and smartwatches were only implemented in one solution. A reason might be that users prefer to use systems they already use; that is, integration with existing tools like fitness trackers is desired by users, as found by Wang et al [41]. The landscape of wearables and sensors that could be used for PA tracking is much larger than was found in our research [42]. The integration of sensors with AI could help analyze the data streams and promote an increase in PA [43]. Additionally, it could assist in monitoring PA among individuals affected by health conditions [44-46]. We hypothesize that existing research focuses on sensors that are well-known, not very intrusive, and therefore probably more accepted by users of solutions for increasing PA.

AI can gamify the fitness experience by setting challenges, goals, and rewards. Users are motivated to increase PA by earning points, competing with friends, or unlocking achievements. Xu et al [16] found in their review that gamification interventions could increase PA participation. Interestingly, none of our included studies explicitly reported about gamification elements.

Do We Have Enough Evidence on AI's Effectiveness in Increasing PA?

In total, 5 of the included studies provide moderate evidence of AI's effectiveness for increasing PA [28,32,36,38,39]. However, these studies involve short interventions lasting from 6 to 12 weeks. Hence, the significant effect might be influenced by this brief follow-up period, similar to other mHealth interventions [13]. The estimated time needed to form habits of complex behaviors such as exercise behavior is 12 weeks [47]. Thus, longer intervention studies are needed to assess the potential long-term effectiveness of AI-driven technologies for increasing PA.

Out of the 260 participants in these 5 studies [28,32,36,38,39], 72.3% (188) of them were women, and the majority were aged between 40 and 50 years. Further studies are needed to investigate the effects of these AI-driven technologies on participants with different sociodemographic characteristics, as well as those with health conditions for which exercise aids in managing the disease and preventing complications [1,2,4].

There is very limited and low-quality evidence supporting the impact of AI-driven technologies on changing PA behavior and the ability to perform such behavior [25,30,35,37]. In these cases, the durations of the interventions varied, ranging from as short as 3 to 4 weeks [25,37], to as long as 20 to 26 weeks [30,35]. Similar to previous cases, the majority of participants in these 4 studies were women, comprising 83.7% (82/98) reported participants. While research indicates that gender is one of the factors influencing the use of health-related technologies [48,49], technologies aimed at increasing PA should be tested, personalized, and accessible for all demographic groups.

What Is the Role of HFs on the AI-Based PA Solutions?

Most of the included AI-based PA systems showed positive results in terms of HFs related to their use. However, no study aimed to evaluate how the AI component could independently influence HFs such as user acceptance, perceived ease of use, or perceived usefulness. Many studies used AI techniques to personalize the PA system based on the authors' assumptions about the persuasive power of personalization that could lead to greater motivation and thus result in greater intention to use, adoption, and engagement. However, no study has tested these hypotheses. In this regard, more research is still needed to identify the role of AI components in HFs affecting PA systems. In addition, no study has focused on whether the inclusion of AI could lead to a change in the role of HFs, as has been the case with traditional technologies.

Limitations

There were some identified limitations in this scoping review. Even though we did not have a language limitation in the search strategy, all the included studies were in English. Therefore, we could have missed relevant AI-driven solutions published in other languages. The included studies were mainly from diverse high-income countries, restricting generalization to low- and middle-income countries. In addition, the studies included in the scoping review had an intervention period of a maximum of 26 weeks, showing only the short-term effect of the AI-driven solutions. All studies were included in the review, irrespective of the assessed quality of the evidence. However, the results of the included studies were reported separately according to the quality of the evidence, minimizing misinterpretation of the data.

Conclusions

This study synthesized current evidence on the effectiveness and potential of AI-driven digital solutions for increasing PA. Although the included studies offer valuable insights by demonstrating positive outcomes through various AI-driven technologies for enhancing PA, the evidence is still very limited. While some studies demonstrated moderate evidence of AI's effectiveness in increasing PA, these interventions were typically short-term. Longer-term studies are necessary to assess the sustained impact of AI-driven technologies on behavior change and habit formation. Additionally, further research is needed to investigate the effects of AI-driven interventions on diverse populations, including individuals with varying sociodemographic characteristics and conditions. Moreover, the evidence regarding the impact of AI-driven technologies on changing PA behavior remains limited and of low quality. There is a need for rigorous studies to evaluate the effectiveness of these interventions, particularly in terms of their ability to induce long-term behavior change. Furthermore, while most AI-based PA systems demonstrated positive results in terms of UX, there is a lack of research focusing on the independent influence of AI components on HFs, such as user acceptance and perceived usefulness. Additionally, more investigation is required to understand how the inclusion of AI may alter the role of HFs in PA systems compared to traditional technologies.

In conclusion, while AI-driven digital solutions hold significant promise for promoting PA and improving public health outcomes, addressing these limitations and challenges will be crucial for maximizing their effectiveness and accessibility.

Continued research efforts in these areas are essential for advancing our understanding of the role of AI in PA promotion and ensuring the development of evidence-based interventions that benefit diverse populations.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Full search strategy.

[\[DOCX File , 16 KB-Multimedia Appendix 1\]](#)

Multimedia Appendix 2

Excluded papers in full text eligibility phase.

[\[DOCX File , 22 KB-Multimedia Appendix 2\]](#)

Multimedia Appendix 3

PRISMA checklist.

[\[PDF File \(Adobe PDF File\), 84 KB-Multimedia Appendix 3\]](#)

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Abbreviations

AI: artificial intelligence

GRADE: Grading of Recommendations Assessment, Development and Evaluation

HF: human factor

mHealth: mobile health

PA: physical activity

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

PRISMA-ScR: Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews

UX: user experience

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