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Data absenteeism in digital health technology research for older adults: a systematic review

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Abstract

Background Digital health technologies are increasingly used to address healthcare challenges among older adults, yet concerns exist about data absenteeism—the underrepresentation of socioeconomically disadvantaged groups. This systematic review examines how data absenteeism affects digital health technology interventions for older adults, focusing on three research questions: (a) participant profiles; (b) implementation characteristics; and (c) metrics for assessing intervention effectiveness.

Methods Following PRISMA guidelines, we searched ten databases (MEDLINE, Embase, CINAHL, PsycINFO, SPORTDiscus, WOS, IEEE Xplore, Scopus, PubMed, and ScienceDirect) through September 30, 2022. Eligible studies included peer-reviewed articles in English that evaluated health outcomes of mobile applications, wearables, or exercise games (exergames) interventions. Two independent researchers conducted screening and data extraction, with disputes resolved by a third researcher.

Results Of 14,661 identified studies, 58 met inclusion criteria. Key findings revealed: (a) limited reporting of participant demographics, with only 32.8% reporting education levels, 3.4% reporting income, and 17.2% reporting racial composition; (b) predominance of exergames (75.9%) over health apps (10.3%) and wearables (10.3%); (c) concentration of studies in technologically advanced regions, with 70.7% having sample sizes under 50 participants; and (d) diverse outcome measurements including physiological metrics (67.2%), mental and emotional well-being metrics (51.7%), activity-lifestyle metrics (31.0%), and technology acceptability metrics (22.4%).

Conclusions This review examines patterns in digital health interventions for older adults, revealing limitations in demographic reporting, geographical concentration of studies, and varied approaches to outcome measurement. Future research should address these findings through: (a) enhanced demographic data collection, with particular attention to socioeconomic factors; (b) increased implementation across diverse geographical and cultural contexts; and (c) integration of physical, mental, and social health measurements. These improvements would support the development of digital health solutions that effectively serve diverse older adult populations.

Keywords Digital health, Data absenteeism, Socioeconomic disparities

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Introduction

There is a proliferation of digital health technologies such as wearable monitors, telemedicine platforms, and AI-powered diagnostic tools in response to the rising healthcare challenges of a rapidly aging population. These technologies not only facilitate the health monitoring and management process for older adults but also play a significant role in reducing loneliness and bolstering mental well-being [1, 2]. Health apps, such as *Medisafe*, ensure medications are taken promptly, track dosage levels, and provide valuable insights about each drug [3]. Meanwhile, mental well-being apps like *MoodPrism* offer guided sessions aimed at diminishing anxiety, improving sleep, and nurturing a sense of tranquility [4]. Wearable devices like *Fitbit* and *Garmin* are instrumental in tracking daily activities, monitoring heart rate, and motivating individuals to maintain regular physical exertion, crucial for heart health and joint flexibility [5]. Many of these wearables also encompass features that enable users to socially connect with family and friends, acting as a buffer against feelings of isolation [6]. Such research has shown that integrating health technologies into the daily lives of older adults can significantly improve their physical and mental health, leading to an advanced solution to healthy aging.

Despite the widespread adoption of digital health technologies to improve the physical and mental well-being of older adults, digital health technology interventions still suffer from issues surrounding *data absenteeism*, which may render the interventions ineffective. Data absenteeism refers to the omission or significant underrepresentation of data stemming from socioeconomically disadvantaged groups within health databases [7]. Such omissions compromise the comprehensiveness and representativeness of these databases, subsequently limiting our ability to develop and deploy equitable health interventions tailored to the needs of all demographic groups [7]. When examining the utilization of wearable fitness tracker interventions among older adults, it is important to consider that a significant portion of older adults from low-income backgrounds may not have access to such devices due to cost constraints. Consequently, the health data generated by these devices primarily represents more affluent segments of the older population, excluding a substantial proportion of seniors who may be at a higher risk of experiencing health disparities [8]. Furthermore, if the number of steps taken or heart rate measurements from these devices universally applies to seniors can result in ineffective interventions or even worsen health inequalities. Seniors from different socioeconomic backgrounds may have varying levels of physical activity, which cannot be accurately captured through a one-size-fits-all approach [7].

In examining digital health technology interventions among older adults, a critical question emerges: How pervasive is data absenteeism in digital health interventions among older adults? The issue of data absenteeism, a key obstacle to equal health outcomes for older adults, necessitates a thorough review of current digital health technologies interventions. Such a review will not only deepen our understanding of the issue but also guide future research directions. This study concentrates on the utilization of health apps, wearables, and exercise games (exergames), which are the predominant and popular forms of technological interventions aimed at improving health and quality of life for older adults [9, 10]. Health apps are software applications on smartphones intended to encourage health-related behaviours [11]. Health wearables, on the other hand, are electronic devices worn on the body that track various health metrics [10]. Lastly, exergames are interactive video games designed to stimulate physical activity, contributing to fitness and overall well-being [10]. Our review aims to examine the prevalence and impact of data absenteeism within digital health technology interventions targeting older adults. We anchored our examination on three research questions (RQs) of existing health apps, wearables, and exergames interventions:

> ***RQ1:*** *What characterizes the profile of older adults in health apps, wearables, and exergames interventions?*

> ***RQ2:****How are various types of health apps, wearables, and exergames employed and implemented within digital health technology interventions?*

> ***RQ3:****What metrics are employed to assess the effectiveness of health apps, wearables, and exergames interventions among older adults across different domains?*

Methods

Search strategy

We employed a systematic review method to address the research questions. This approach analyses and synthesizes existing research studies within a specified scope range, ensuring a structured and evidence-based approach to answering specific research questions while minimizing bias [12]. To ensure transparency and minimize potential biases, we followed the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) [13]. We selected ten databases: *MEDLINE, Embase, CINAHL, PsycINFO, SPORTDiscus, WOS, IEEE Xplore, Scopus, PubMed*, and *ScienceDirect* due to their extensive coverage of literature at the intersection of health technology and various disciplines. The systematic review covered all publications from January 1966 through September 30, 2022. The search terms for each database (as seen in Appendix A) were collaboratively decided through discussions between the authors and librarians from the hosting university.

Selection criteria

To comprehensively organize the relevant literature, the inclusion criteria were defined as follows: (a) full-text, peer-reviewed journal articles; (b) articles in English; (c) articles in which the intervention was health apps, wearables, and exergames; (d) studies that measure health outcomes; and (e) studies targeting participants aged 50 years and older. The World Health Organization's active aging policy framework recognizes that the aging process begins before traditional retirement ages, with preventive health interventions being most effective when initiated during the "pre-elderly" period (ages 50–64) [14]. This aligns with our study's focus on digital health technology interventions that aim for early adoption and sustained engagement. Our exclusion criteria of studies were: (a) usage of apps, wearables, and exergames that were unrelated to human health or healthcare; (b) those that were focused on the development of health apps, wearables, and exergames; (c) research that used health apps, wearables, and exergames solely for data collection or non-interventional purposes; and (d) those in categories such as conference papers, commentaries, viewpoints, research proposals, or theses.

Data extraction and risk of bias assessment

Following the removal of duplicate studies, we conducted a systematic screening process based on titles and abstracts. To establish a rigorous screening protocol, three researchers independently assessed the first 50 studies to ensure consistent interpretation of the inclusion criteria. We validated the reliability of this assessment through an intercoder reliability test, which demonstrated strong agreement among researchers (Cohen's kappa = 0.96). Upon confirming this high level of consistency, two researchers proceeded to evaluate the eligibility of all remaining studies independently. Any disagreements or uncertainties in study selection were resolved through consultation with a third researcher.

In line with PRISMA 2020 guidelines [15], we considered two types of risk of bias: risk of biases in the results of included studies and risk of bias due to missing studies. As our review did not aim to assess intervention effectiveness or conduct meta-analysis, the first type of risk was not applicable. To mitigate the risk of missing studies, we collaborated with our university library to refine our search strategy, ensuring comprehensive coverage of relevant literature. Additionally, we chose not to exclude studies based on quality metrics to avoid potentially masking important patterns of data absenteeism. As this review aimed to comprehensively map the current landscape of digital health technology interventions and identify patterns of data absenteeism, we focused on ensuring reliable data extraction through our systematic dual-coder approach with third-party arbitration. This rigorous process further ensured the reliability of our findings and mitigated potential biases in data extraction and interpretation.

Data analysis approach

In this study, we employed a two-stage analytical process combining descriptive and inductive thematic analyses [16]. First, we utilized a standardized data extraction sheet in Microsoft Excel to systematically organize data obtained from the chosen studies. Using the Population, Intervention, Comparison, and Outcome (PICO) framework [12, 17], we conducted descriptive analysis by categorizing the included articles. Our codebook encompassed various dimensions, such as article identification (e.g., author, title, publication year, and journal), participant characteristics (e.g., age, gender, health status, socioeconomic status), intervention particulars (e.g., type of health technologies, duration, purpose, implementation settings, and countries), comparison groups, and reported outcomes.

Following this initial descriptive categorization, we conducted an inductive thematic analysis to identify emerging patterns and themes across the studies. This process involved three main stages. In the first stage of open coding, two independent researchers read through the extracted data, identifying and coding key concepts. The second stage involved theme development, where related codes were grouped into potential themes. In the third stage of theme refinement, themes were reviewed and refined through iterative discussion between researchers. Example of the coding process in our thematic analysis: In examining mental health outcomes, when a study reported "Older adults showed decreased feelings of loneliness and improved mood after participating in the exergame program with other community members," we initially coded this as "reduced social isolation." This code was then grouped with other related codes such as "improved emotional state" and "enhanced social connections," which ultimately contributed to our final theme of "mental and emotional domain metrics." To ensure the reliability of our findings, two independent researchers independently coded the included studies, resolving any discrepancies through consensus discussions. This dual analytical approach allowed us to systematically categorize the explicit content of the studies while also uncovering underlying patterns and relationships that informed our understanding of data absenteeism in digital health technology interventions.

Results

In our study, we initially reviewed a substantial collection of 14,661 studies across ten predefined electronic databases up to September 30, 2022. Through an automatic screening process, we filtered out duplicates and unrelated studies, narrowing our focus to 7,951 studies. Further screening based on titles and abstracts reduced this number to 236 relevant articles. After an in-depth examination of these articles, we identified 58 studies that met our specific inclusion criteria (see Fig. 1).

The 58 studies spanned from the early 2010s, with a significant increase in research noted towards the end of that decade and continuing into the early 2020s. This trend highlights the growing interest in this area of study. Our results offered a characteristic profile of older adults interacting with health apps, wearables, and exergames interventions (see Table 1). We also provided insight into how these health technologies interventions are implemented, such as their geographical distribution, implementation contexts, and overall outreach. Additionally, our examination identified specific health metrics assessing the effectiveness of these interventions, which included primary physiological measures, mental and emotional metrics, activity and lifestyle indicators, and engagement and adherence to health technologies.

Profiles of older adults in health apps, wearables, and exergames interventions

RQ1 asked about the profiles of older adults in digital health technology interventions, and our findings

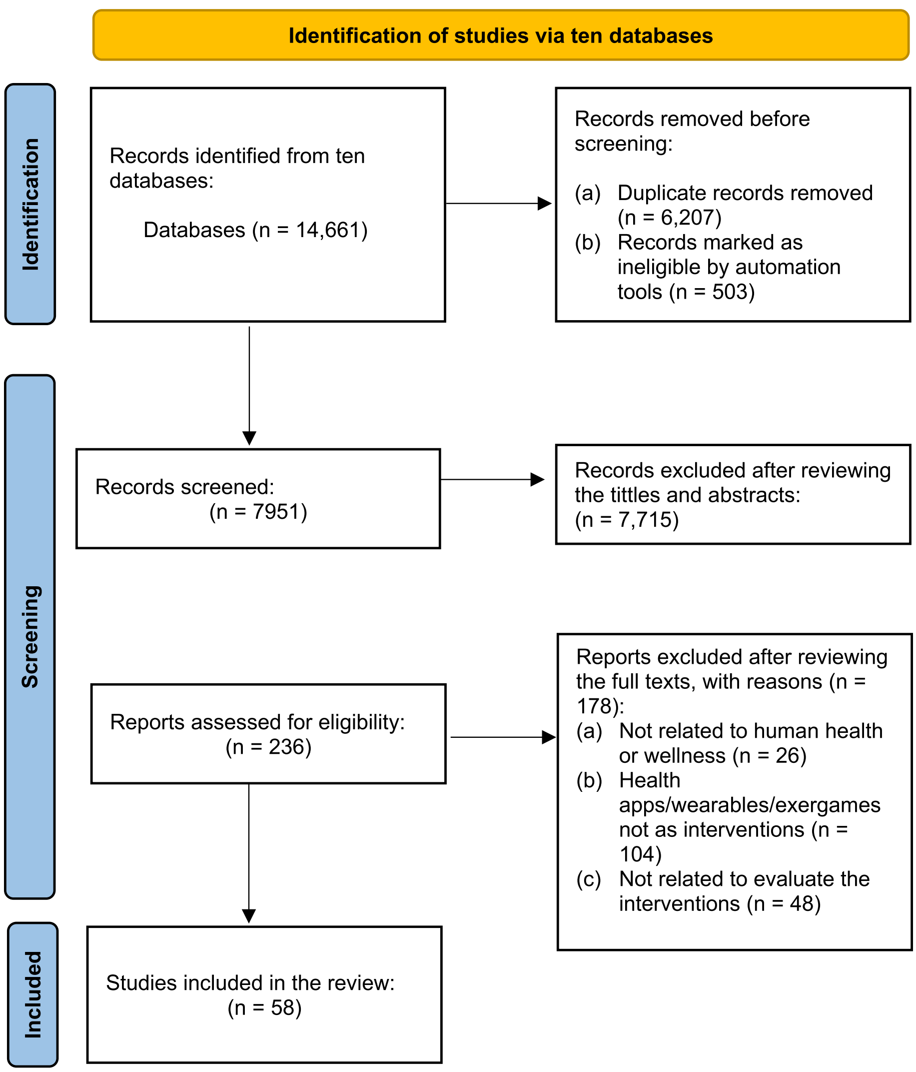

Fig. 1 Flowchart of the systematic review

Table 1 Characteristics of the selected studies

Characteristics	n	Percentage
Year		
2010	1	1.72%
2011	1	1.72%
2012	2	3.45%
2013	2	3.45%
2014	1	1.72%
2015	1	1.72%
2016	5	8.62%
2017	5	8.62%
2018	8	13.79%
2019	3	5.17%
2020	7	12.07%
2021	12	20.69%
2022	10	17.24%
Type of interventions		
Health apps	6	10.3%
Health wearables	6	10.3%
Exergame	44	75.9%
Health app & wearable	1	1.7%
Health wearable & exergame	1	1.7%
Race		
Majority > = 50%	9	15.5%
Majority < 50%	1	1.7%
Not mentioned	48	82.8%
Education		
Mentioned	19	32.8%
Not mentioned	39	67.2%
Income		
Mentioned	2	3.4%
Not mentioned	56	96.6%
Geographical distribution		
Africa	1	1.7%
Australia	2	3.4%
East Asia	14	24.1%
South Asia	1	1.7%
West Asia	1	1.7%
Southeast Asia	2	3.4%
North America	14	24.1%
South America	5	8.6%
Middle East	1	1.7%
Western Europe	15	25.9%
Eastern Europe	1	1.7%
Not mentioned	1	1.7%
Implementation settings		
Community	34	58.6%
Clinical	22	37.9%
Online	2	3.4%
Sample sizes		
Less than/equal to 50	41	70.7%
51—150	14	24.1%
151–500	2	3.4%
> 500	1	1.7%
Duration		
< 6 weeks	18	31.0%
6—12 weeks	30	51.7%
12 weeks – 6 months	4	6.9%
6—12 months	4	6.9%
Over 12 months	2	3.4%

categorized five primary demographic attributes: education; income; gender; and race. In terms of education, 19 studies (32.8%) detailed participants' educational backgrounds. Among these, six studies reported a predominance of participants holding advanced degrees (bachelor's degree or higher), whereas only one study predominantly featured participants with intermediate education levels (high school diploma or equivalent). Additionally, five studies provided data on average years of education, with two reporting an average exceeding 12 years, and the other three indicating less than 12 years. Income, a significant socioeconomic factor, was less frequently reported. A mere 3.4% of the studies offered insights into participants' income levels. One study categorized participants based on a monthly income threshold of USD 20,000, while another presented data around an average income near the minimum wage. The distribution of gender was relatively balanced across most of the studies. Out of 58 studies, 50 (86.2%) included both male and female participants. However, gender-specific research was also conducted: 6 studies (10.3%) were exclusively focused on female participants, and 2 (3.4%) were only focused on male participants. Race, often a critical factor in sociological research, appeared to be less emphasized in these studies. While some studies mentioned nationality, only 10 (17.2%) provided a detailed racial or ethnic composition of their participants. Of these, 9 (15.5%) primarily included participants from the racial majority of the study's geographical area.

Types and implementations of health apps, wearables, and exergames interventions

RQ2 sought to understand the utilization and implementation of health apps, wearables, and exergames in interventions. We examined the types of health app, wearables, and exergames, as well as the geographical distribution of these digital interventions, the contexts in which they were deployed, and their overall reach.

Types of health apps, wearables, and exergames

In exploring the use of health apps, wearables, and exergames, we found exergames to be the most popular, used in 75.9% ($n=44$) of studies. The usage of Wii Fit platform was prevalent, along with Xbox 360 Kinect, Nintendo Switch, and some custom-developed games. Health apps were next in line, featured in 10.3% ($n=6$) of studies, followed by wearables in 6.9% ($n=4$). Some studies combined apps and wearables ($n=3$, 5.2%), but wearables paired with exergames were rare ($n=1$, 1.7%). Most apps were custom designed for the studies, contrasting with the general consumer products like Fitbit or Xiaomi watches used as wearables.

Geographical distributions

The use of health apps, wearables, and exergames was global, but with a concentration in technologically advanced countries. In the Americas, 32.7% ($n=19$) of studies were conducted, with most in North America ($n=14$, 24.1%) and a few in South America ($n=5$, 8.6%). Asia hosted 31.0% ($n=18$) of the studies, primarily in East Asia, with a few in South and Southeast Asia. Europe had 27.6% ($n=16$) of studies, mostly in Western Europe, and a few in Eastern Europe. There were also studies in the Middle East ($n=1$, 1.7%), Africa ($n=1$, 1.7%), and Australia ($n=2$, 3.4%), with one study not specifying the location.

Implementation settings

In our study, we distinguished three implementation settings: community; clinical; and online. Community settings, used in 58.6% of the studies ($n=34$), involved interventions in everyday environments like neighborhoods or community centers, offering authentic contexts but with the challenge of varied, non-standardized conditions [18, 19]. In contrast, 37.9% of the studies ($n=22$) used clinical settings, providing controlled, uniform conditions in healthcare facilities, which enhances internal validity but may limit the generalizability to less structured environments [18]. Additionally, two studies (3.4%) were conducted online, introducing a different mode of intervention delivery.

Intervention outreach

Our examination of the scope of the intervention focused on two key components: the sample sizes incorporated in the studies and the durations over which these interventions were administered. In terms of outreach, most studies had small sample sizes, with 70.7% ($n=41$) involving less than 50 subjects, likely due to many being preliminary studies. Only a few studies ($n=14$, 24.1%) had larger groups, and just one ($n=1$, 1.7%) had more than 500 participants. The duration of the interventions in our study varied: 18 studies (31.0%) were less than 6 weeks, 30 (51.7%) lasted between 6 and 12 weeks, 4 studies (6.9%) had interventions ranging from 12 weeks to 6 months, 4 (6.9%) extended up to 6 months or a year, and 2 (3.4%) exceeded a year.

Metrics for assessing health apps, wearables, and exergames intervention effectiveness

In addressing RQ3, our study identified four primary domains for assessing intervention effectiveness: physiological metrics, mental and emotional well-being metrics, activity and lifestyle metrics, and technology acceptability and usability metrics.

Physiological Metrics

Physiological metrics focus on objective measurements of bodily functions, with 67.2% ($n=39$) of studies examining these outcomes. Balance assessment emerged as the most common parameter (37.9%, $n=22$), followed by BMI measurement (25.9%, $n=15$), and gait analysis (22.4%, $n=13$). Cardiovascular parameters were frequently measured, with heart rate monitored in 19.0% ($n=11$) of studies and blood pressure in 15.5% ($n=9$). Less frequently measured parameters included waist circumference (5.2%, $n=3$), heart rate variability (3.4%, $n=2$), and specific clinical indicators such as forced expiratory volume (FEV1) and glycated hemoglobin (HbA1c) (1.7%, $n=1$ each).

Several studies reported significant physiological improvements. For instance, Padala et al. [20] conducted a randomized controlled trial with 30 older adults comparing Wii-Fit with walking, finding significant improvements in Berg Balance Scale scores in the Wii-Fit group (mean difference = 3.6 points; 95% CI = 2.3–4.8; $p<0.001$) after 8 weeks. In another investigation by Lee et al. [21], older adults using exergames showed significant improvements in both systolic blood pressure (-12.7 ± 7.4 mmHg, $p<0.001$) and diastolic blood pressure (-7.2 ± 5.3 mmHg, $p<0.001$) over a 3-month intervention. Additionally, Meekes and Stanmore [22] reported significant improvements in physical function through a 6-week Kinect intervention, with participants showing enhanced postural control (mean difference in sway = 4.3 cm, $p<0.05$) and functional reach (mean increase = 5.4 cm, $p<0.01$).

Mental and emotional well-being metrics

Mental and emotional well-being metrics assess psychological well-being and cognitive function, featured in 51.7% ($n=30$) of studies. Depression was most commonly measured (29.3%, $n=17$), using instruments such as the Geriatric Depression Scale (13.8%, $n=8$) and Patient Health Questionnaire-9 (8.6%, $n=5$). Cognitive function assessment was the second most frequent measure (27.6%, $n=16$), employing tools such as the Mini-Mental State Examination (MMSE). Health-related quality of life was examined in 15.5% ($n=9$) of studies, while fear of falling appeared in 15.5% ($n=9$). Less frequently measured outcomes included anxiety (8.6%, $n=5$) and fatigue (5.2%, $n=3$).

Studies demonstrated significant improvements across various mental and emotional parameters. For example, Choi et al. [23] investigated the effects of an exergame program on cognitive function among older adults, finding significant improvements in MMSE scores (mean difference = 2.8 points, 95% CI = 1.3–4.3, $p=0.002$) after a 12-week intervention. In another study, Rosenberg et al. [24] reported that participants using exergames showed substantial reductions in depressive symptoms measured by the Patient Health Questionnaire-9 (mean change = −1.3 points, 95% CI = −2.5 to −0.1, $p=0.035$) over 12 weeks.

Activity and lifestyle metrics

Activity and lifestyle metrics focus on assessing changes in health-related behaviors and habits, such as physical activity, nutrition, and substance use. These metrics provide valuable insights into the effectiveness of health interventions in promoting healthier lifestyles among older adults. Physical activity and mobility were the most frequently examined metrics in this domain, with 13 studies (22.4%) assessing changes in daily step counts or overall mobility. For instance, Lyons et al. [25] found that older adults using a Wii Fit intervention significantly increased their daily step count by an average of 1,950 steps (95% CI: 1,271–2,629; $p<0.001$) over a 12-week period. Nutritional habits and adherence to healthy eating patterns were examined in 3 studies (5.2%). In a 6-month lifestyle intervention using mobile health technology, Kim et al. [26] reported significant improvements in daily fruit and vegetable intake (mean difference: 1.1 servings/day; 95% CI: 0.6–1.6; $p<0.001$) among older participants. Smoking cessation and alcohol consumption reduction were each reported in 1 study (3.4%). Maddison et al. [27] found that a mobile phone-based intervention led to a significant reduction in the number of cigarettes smoked per day (mean difference: −4.5; 95% CI: −6.2 to −2.8; $p<0.001$) among older smokers over a 6-month period.

Technology acceptability and usability metrics

Technology acceptability and usability metrics were studied in 22.4% ($n=13$) of the reviewed research. These metrics assess user satisfaction, perceived benefits, ease of use, and user engagement with health technology interventions, providing valuable insights into the acceptability, usability, and overall user experience of these technologies for older adults. User satisfaction and perceived benefits were key aspects of technology acceptability. In a study by Vaziri et al. [28], older adults reported high satisfaction (mean score: 4.2 out of 5) and perceived benefits (mean score: 4.0 out of 5) after using a tablet-based fall prevention exercise program for 12 weeks. Ease of use, a crucial component of usability, was also examined in several studies. Steinert et al. [29] found that older participants rated a smartwatch-based physical activity intervention as highly user-friendly (mean score: 4.5 out of 5), contributing to better acceptability and engagement. User engagement measures how actively and consistently users interact with and adhere to the technology intervention. Game-based interventions often use game scores as a unique metric for measuring engagement, with higher scores indicating better adherence and a positive response to the intervention. Stanmore et al. [30] reported that older adults achieved high game scores (mean: 85% of maximum attainable score) in a 12-week Kinect-based exergaming intervention, demonstrating strong engagement and adherence.

Discussions and future directions

We conducted a systematic review of 58 studies examining data absenteeism in digital health technology interventions among older adults. Our findings provide valuable insights into the current state of digital health technology interventions, revealing which areas are well-researched and which remain neglected. Three significant findings emerged from our analysis: (a) the underrepresentation of low SES older adults in a variety of digital health technology interventions; (b) limitations in customized intervention types, geographical biases, and duration limitations; and (c) the need to go beyond initial successes to holistically understand health outcomes.

Understanding SES considerations in digital health research for older adults

Our analysis of digital health technology intervention studies reveals that demographic reporting is limited, with fewer than 20% of studies providing comprehensive demographic data including race, education, and income of participants. This limited reporting of socioeconomic indicators affects our ability to understand whether and how these interventions reach and benefit older adults across different socioeconomic backgrounds. Education level reporting is important because, as Hill et al. [31] showed, older adults with different educational backgrounds experienced varying levels of empowerment and barriers when using digital technologies. Similarly, income data documentation is valuable because even well-designed interventions may be inaccessible to lower-income groups. Barnard et al. [32] demonstrated that cost considerations significantly influenced older adults' experimentation with and adoption of new health technologies. Ethnic background data is also significant as cultural beliefs and practices have a strong influence on technology adoption and healthcare experiences. For instance, recent evidence shows that Black people often face challenges finding healthcare providers who share their background and experiences, leading to the development of culturally-specific digital health solutions. The *Health In Her HUE* app demonstrates this need—launched specifically to connect Black women to culturally relevant healthcare providers, it attracted significant funding due to high demand for culturally-sensitive digital health interventions [33]. While limited demographic reporting does not necessarily indicate the underrepresentation of any particular socioeconomic group, comprehensive demographic documentation remains crucial for understanding the reach and effectiveness of digital health interventions across different population segments.

The importance of considering SES in health research is well-established [8, 34]. For instance, studies by Fiscella and Tancredi [35] and Canedo et al. [36] showed those older adults situated in the lowest SES group faced a two-fold risk of chronic conditions such as diabetes and heart disease in contrast to their counterparts in the highest quintile. These health disparities extend beyond disease prevalence. Other research by Stepanikova and Oates [37] and Griffith et al. [38] highlighted the pronounced disparities in healthcare access, where older adults with lower SES encountered substantial barriers, and this often culminated in deferred treatments and suboptimal health outcomes. Understanding these SES-related health disparities becomes particularly relevant in the context of digital health interventions, as they represent a promising avenue for improving healthcare access and outcomes. However, the effectiveness of these interventions in addressing existing health disparities can only be evaluated when studies adequately document participants' socioeconomic backgrounds and experiences.

Most importantly, digital health interventions generate vast data repositories that could offer valuable insights into population health, behaviors, and preferences. However, without adequate demographic reporting, our understanding of how these interventions serve different socioeconomic groups remains incomplete. Lee et al. [39] found that older adults from lower SES backgrounds often reported feeling excluded or overwhelmed by digital health solutions, suggesting potential barriers to technology adoption. This raises important considerations about healthcare equity, which extends beyond mere access to encompass equal opportunity to benefit from medical and technological advancements [31]. This underrepresentation in digital health research has broader implications. Without adequate demographic data and diverse participant pools, digital health interventions risk reinforcing existing systemic biases. As demonstrated in other domains of health technology [31, 32, 39], when certain populations are consistently underrepresented in research and development phases, the resulting solutions may inadvertently perpetuate existing healthcare disparities by primarily serving the needs and preferences of more privileged groups. This creates a cyclical effect where digital health innovations, despite their potential for expanding healthcare access, may actually widen rather than narrow the healthcare accessibility gap for older adults across different socioeconomic backgrounds.

Navigating intervention types, geographical biases, and duration limitations

The second finding concentrated on the implementation of health apps, wearables, and exergames interventions. The first observation was the frequent deployment of commercial market products, like Xbox and Nintendo Switch, as platforms for interventions. While these platforms carry mass-market appeal, they were initially tailored for younger audiences [40]. Consequently, there might be challenges when repurposing these platforms for older adults. For example, imagine a popular game like "Dance Central" on Xbox. Designed for dynamic dance routines, it is a favorite among the younger demographic due to its upbeat tracks and animated visuals. However, when introduced to an older adult unfamiliar with fast-paced games, the hurdles can be multifaceted. The intuitive drag-and-swipe or press-and-hold for a younger user might be a novel, confusing gesture for an older person [41]. They might require more extended periods or additional sessions to acclimate to such interfaces. Such mismatches in design intentions versus user capability are evident in a study by Uzor and Baillie [42] where a decline in engagement rates among older adults was noticed while using an Xbox game. The inference suggests that the game's design, which was not tailored for older adults, possibly played a role in this decreased interest.

Another finding is the geographical distribution of health apps, wearables, and exergames interventions. These interventions come mainly from technologically advanced countries, a bias that threatens to obscure the unique challenges and experiences of less developed regions. For instance, differences in technological infrastructure, digital literacy programs, and economic resources across countries can significantly impact access to and familiarity with digital health technologies.

Systemic factors such as differences in technological infrastructure investment, digital education opportunities, and market penetration of consumer electronics can create disparities in technology adoption across different regions [43]. It is, therefore, questionable whether the experience of digital health technology interventions in developed countries can be applied in other regions. Furthermore, the settings of these interventions, whether clinical or community, influence their outcomes. Clinical environments, often with structured programs and supervision, can provide consistent data. However, community settings, as shown by Ni Scanaill et al. [44] have their own value. For example, a group of older adults trying out a new health app at a community center can provide unique insights into barriers and facilitators to technology adoption through discussion, mutual learning, and collective feedback. Such organic settings reveal real-world challenges and the actual sustainability of tech engagement.

The next concern is about the duration of these health apps, wearables, and exergames interventions. Most interventions last for only brief periods, often with modest sample sizes. Is it possible that an older adult enthusiastically tries a new health wearable for a week but then finds it cumbersome and shelves it afterward? Without long-term implementation, we are left with a potential iceberg scenario: we might only be seeing the tip in the form of initial enthusiasm, with a vast chunk of declining interest and engagement submerged out of view [45, 46].

Going beyond initial successes to understand holistic health outcomes

The third finding from our systematic review examined the distinct metric domains employed to assess intervention effectiveness. First, many studies demonstrated a restricted scope, typically focusing on singular health outcomes—either physiological (e.g., heart rate, BMI) or psychological (e.g., stress, mood levels). Despite identifying four predominant categories of health outcomes, most studies did not assess these domains simultaneously. This narrow approach risks providing an incomplete understanding of older adults' well-being [7]. An individual's well-being, particularly in the older adult demographic, comprises physical, mental, emotional, and social dimensions of health [47, 48]. The disproportionate focus on easily quantifiable metrics provides only a partial view of the broader health narrative. For example, while an individual might demonstrate improved cardiovascular health through regular exercise, cognitive challenges might remain unaddressed [48, 49]. This research trend often misses the increasingly recognized multifaceted nature of health as being central to overall well-being. To comprehensively evaluate digital health interventions, an approach that gives equal consideration to all health dimensions is essential.

Second, the prevalence of self-reported metrics has provided valuable insights into lifestyle and behavioral changes. Studies increasingly employ questionnaires to evaluate how health apps, wearables, and exergames affect older adults' daily routines and behaviors. While self-reported data may contain inherent biases—such as over- or underestimation of behaviors, memory lapses, or response bias to meet perceived researcher expectations [41, 50, 51]. —it offers crucial insights into participants' lived experiences. This qualitative data complements empirical measurements, providing a more comprehensive understanding of intervention impacts [9]. For instance, while physiological data such as heart rate or blood pressure provides objective measurements, it cannot capture the subjective experience of the intervention. A heart rate monitor might show improved cardiovascular metrics, but only self-reported data can reveal whether participants found the intervention enjoyable, sustainable, or beneficial to their daily lives. These personal perspectives are essential for understanding the real-world applicability and effectiveness of digital health interventions in older adults' daily routines [9].

Third, a critical oversight exists in measuring the long-term sustainability of digital health interventions. In the context of health technologies for older adults, initial adoption represents only the beginning of the journey. The challenge lies in ensuring continuous engagement with these tools beyond the formal intervention phase. Research across technological domains has documented a consistent 'drop-off' effect, where users initially embrace new technology with enthusiasm but gradually decrease their engagement over time [39, 52]. This pattern raises particular concerns in the context of health interventions for older adults, as it could significantly diminish the potential long-term benefits of these technologies [53, 54]. Without sustained engagement, initial progress—whether in physical mobility, mental well-being, or lifestyle habits—may regress to pre-intervention levels. For example, participants might show initial improvements in physical activity levels and mobility during the structured intervention period, supported by regular monitoring and guidance. However, post-intervention, without consistent support and motivation, these gained benefits often diminish. This trajectory underscores the importance of distinguishing between short-term intervention success and long-term behavioral change. To truly maximize the potential of digital health technologies for older adults, researchers and developers must prioritize creating interventions that maintain engagement beyond the initial novelty phase, ensuring that health improvements persist as sustainable, long-term changes rather than temporary achievements [54, 55].

Adapting digital health technologies for older adults in resource-constrained settings

While our review identified a concentration of digital health interventions in technologically advanced countries, adapting these technologies for resource-constrained settings requires careful consideration of both technological and user-specific factors. Based on existing research, we propose several evidence-based strategies to make health apps, wearables, and exergames more accessible to older adults across different technological contexts.

First, interventions should be optimized for available infrastructure. Studies have shown that older adults in resource-constrained regions often have limited access to advanced devices [44]. For health apps, this means developing versions that can function with limited processing power and storage. Huy and Thanh [56] demonstrated success with simplified health monitoring apps that could operate offline and sync data when connectivity was available in rural areas. Such adaptations are significant for ensuring technology accessibility in resource-limited settings. Cultural and technological adaptability is particularly important for older adult users. Recent evidence shows that digital health interventions are more successful when they are designed to align with local cultural values and practices. For example, *Health In Her HUE*'s success in connecting Black women to culturally sensitive healthcare providers demonstrates how digital health solutions can effectively serve specific community needs [33]. This includes not just language translation, but consideration of local health beliefs and practices.

For wearables and exergames, cost-effective alternatives to commercial devices have shown promise. Vaziri et al. [28] validated community-based models where multiple users share devices during scheduled sessions. This approach not only addresses resource constraints but also provides social support, which Hill et al. [31] identified as crucial for older adult engagement with digital health technologies. Implementation strategies should focus on sustainable integration into existing healthcare structures. Lee et al. [39] found that training local healthcare workers to support older adults with digital health technologies led to better long-term engagement than purely technological solutions. Community centers and senior facilities can serve effectively as technology hubs, providing supervised access to health technologies [57].

The challenge of maintaining long-term engagement is particularly significant in resource-constrained settings. Barnard et al. [32] identified that this challenge is amplified where technical support may be limited. These findings underscore the importance of developing sustainable implementation models that combine appropriate technology with robust support systems. Future digital health interventions for older adults in resource-constrained settings must, therefore, balance technological innovation with practical constraints, ensuring that solutions are not only accessible and affordable but also sustainable in the long term.

Limitations

Our systematic review has several important limitations that should be considered when interpreting the findings. Firstly, our restriction to English-language publications may have excluded valuable research from non-English-speaking regions, potentially introducing cultural or geographical biases. The selection of specific databases for our search strategy, combined with the inherent publication bias in systematic reviews, may have resulted in an overrepresentation of studies with favorable outcomes. Consequently, our findings might present an overly optimistic view of intervention effectiveness. Additionally, our focus on peer-reviewed literature meant excluding potentially valuable insights from grey literature, including conference proceedings, technical reports, and theses. The temporal constraints of our review period may have resulted in the omission of recent publications or ongoing studies relevant to our research questions, potentially affecting the comprehensiveness of our findings. Lastly, while we implemented rigorous data extraction procedures, the inherent complexity of systematic reviews may have introduced inconsistencies or biases that could influence our synthesis and interpretation of results.

These limitations suggest several directions for future research. Future studies should consider expanding the scope to include non-English language studies and grey literature. There is also a critical need for conducting longitudinal studies to assess the long-term effectiveness of digital health interventions. Furthermore, researchers should focus on developing standardized reporting protocols for demographic data in digital health research. Additional emphasis should be placed on investigating intervention effectiveness across diverse cultural and socioeconomic contexts. Finally, future research should explore innovative methodologies for measuring sustained engagement with digital health technologies. These future directions would address current knowledge gaps and strengthen the evidence base for digital health interventions among older adults.

Conclusion

While digital health technologies offer promising benefits, our findings emphasize that the path to creating effective and inclusive solutions requires careful consideration of these challenges. The evidence suggests that current digital health interventions, despite their potential, may inadvertently perpetuate healthcare disparities. To address this, future development of digital health technologies must prioritize inclusivity, considering diverse socioeconomic backgrounds, geographical contexts, and individual capabilities. The ultimate objective extends beyond technological advancement, it aims to ensure that digital transformation in healthcare serves all older adults equitably, regardless of their socioeconomic status or location.

Appendix A

Search strategy using MEDLINE database as an example

1 exp aged/ (3,439,986)

2 ("aged patient?" or "aged people" or "aged person?" or "aged subject?" or elders or elderly or seniors or "older adult?" or "older patient?" or "older people" or "older person?" or "older subject?" or "old age" or "older adulthood" or "late adulthood" or geriatric or senium).ab,ti. (685,279).

3 ("aged 64" or "aged 65" or "aged 70" or "aged 75" or "aged 80").ab,ti. (73,008).

4 1 or 2 or 3 (3,656,854).

5 exergaming/ (151).

6 ("active videogam*" or "active video gam*" or exergam* or "interactive physical and cognitive").ab,ti. (1291).

7 (xbox or kinect or wii or nintendo or "serious game?" or "serious play").ab,ti. (4350).

8 5 or 6 or 7 (5298).

9 wearable computer/ (1062).

10 activity tracker/ (1789).

11 smart glasses/ (231).

12 ("wearable?" or "wearable device?" or "wearable electronic? device?" or "wearable sensor?" or "wearable technol*" or "electronic skin" or "activity tracker?" or "fitness tracker?" or "physical fitness tracker?" or "personal fitness tracker?" or "smart device?" or "smart electronic? device?" or "smart glass*" or "google glass*" or "smartglass*").ab,ti. (25,573).

13 9 or 10 or 11 or 12 (26,638).

14 mobile application/ (18,968).

15 ("mobile app?" or "mobile application?" or "mobile phone app?" or "mobile phone application?" or "cellphone app?" or "cellphone application?" or "cell phone app?" or "cell phone application?" or "smartphone app?" or "smartphone application?" or "smart phone app?" or "smart phone application?" or "android app?" or "android application?" or "ios app?" or "ios application?" or "iPadOS app?" or "iPadOS application?" or "mobilehealth app?" or "mobilehealth application?" or "mobile health app?" or "mobile health application?" or "mhealth app?" or "mhealth application?").ab,ti. (18,980).

16 14 or 15 (27,722).

17 8 or 13 or 16 (57,811).

18 locomotion/ (80,354).

19 walking/ (79,493).

20 gait/ (64,004).

21 motor activity/ (46,620).

22 (locomot* or walk* or ambulat* or gait? or mobility or "motor activit*").ab,ti. (649,674).

23 18 or 19 or 20 or 21 or 22 (719,218).

24 mental health/ (182,289).

25 ("mental health" or "mental hygiene" or "mental well-being" or "mental wellbeing" or "mental wellness" or "mental care" or "mental condition" or "mental factor" or "mental help" or "mental state" or "mental status" or "psychic health" or "affective well-being" or "affective wellbeing" or "affective wellness" or "emotional well-being" or "emotional wellbeing" or "emotional wellness" or "eudaimonic well-being" or "eudaimonic wellbeing" or "eudaimonic wellness" or "hedonic well-being" or "hedonic wellbeing" or "hedonic wellness" or "psychological well-being" or "psychological wellbeing" or "psychological wellness" or "psychosocial well-being" or "psychosocial wellbeing" or "psychosocial wellness" or "social well-being" or "social wellbeing" or "social wellness" or "subjective well-being" or "subjective wellbeing" or "subjective wellness" or "well-being" or "wellbeing" or wellness).ab,ti. (440,935).

26 24 or 25 (492,747).

27 23 or 26 (1,194,748).

28 4 and 17 and 27 (2184).

Abbreviations

AI	Artificial intelligence
Apps	Applications
Exergames	Exercise games
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analysis
PICO	The Population, Intervention, Comparison, and Outcome framework
USD	United States Dollar
BMI	Body Mass Index
EQ-5D	EuroQol-5 Dimensions
SES	Socioeconomic status

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Authors' contribution
HB served as the lead author, overseeing project conceptualization, guiding the data collection process, and drafting the manuscript. JYW contributed to data collection and analysis. NBS and SGP provided expertise in formulating

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Data availability
The datasets analyzed during the current systematic review are available from the corresponding author (EWJL) upon reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

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Competing interests
The authors declare no competing interests.

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