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Review

Users' Expectations of Smart Devices during Physical Activity—A Literature Review

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Abstract: Background: The field of smart devices and physical activity is evolving rapidly, with a wide range of devices measuring a wide range of parameters. Scientific articles look at very different populations in terms of the impact of smart devices but do not take into account which characteristics of the devices are important for the group and which may influence the effectiveness of the device. In our study, we aimed to analyse articles about the impact of smart devices on physical activity and identify the characteristics of different target groups. Methods: Queries were run on two major databases (PubMed and Web of Science) between 2017 and 2024. Duplicates were filtered out, and according to a few main criteria, inappropriate studies were excluded so that 37 relevant articles were included in a more detailed analysis. Results: Four main target groups were identified: healthy individuals, people with chronic diseases, elderly people, and competitive athletes. We identified the essential attributes of smart devices by target groups. For the elderly, an easy-to-use application is needed. In the case of women, children, and elderly people, gamification can be used well, but for athletes, specific measurement tools and accuracy may have paramount importance. For most groups, regular text messages or notifications are important. Conclusions: The use of smart devices can have a positive impact on physical activity, but the context and target group must be taken into account to achieve effectiveness.

Keywords: physical activity; exercise; wearables; activity trackers; smart device

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1. Introduction

1.1. Background

Stimulating physical activity is a very important part of improving health. When planning investments in programmes to promote physical activity, it is important to consider the factors that influence participation in sports. For example, gender may play a role in sporting habits [1]. However, when examining the development of sporting habits, it is important to highlight the role of adolescent influences such as parental attitudes, fitness, academic achievement, gender, and financial background [2,3]. In addition, the importance of housing conditions should be emphasised and has been highlighted in several studies [4,5].

Community support, facilitation of access, and participation in sports clubs can play a major role in improving sporting habits [6]. However, the SARS-CoV-2 outbreak in 2019 had a major impact on community activities and could have had a significant impact on sporting habits, especially if they were community- or team-based [7]. One study has shown that coaching can have a positive impact on individuals' attitudes towards sports during this period [8]. However, it should also be noted that the use of this method by individuals would require significant human resource capacity. To overcome this, Internet of Things (IoT) devices could be used to provide remote supervision in sports coaching [9,10].

The need to measure physical activity has existed for decades, but prior to the advent of wearable measurement devices, this was done using self-report questionnaires, which were not accurate [11–14]. The first wearable devices used to measure physical activity were mainly based on acceleration, measuring speed, duration, number of steps, and stride length, while more advanced devices categorised movements into categories such as sitting, standing, and walking [15–17]. These devices were usually attached to the limbs or waist and performed no function other than measuring physical activity [17]. The objective metrics they provide reduce the subjectivity inherent in survey methods and can be used in large groups [18,19]. Accelerometers can also be used in younger as well as older populations [20–24]. Furthermore, they can be used regardless of gender, even to detect sex differences [25,26]. Heart rate monitoring is valid enough to be used to create broad physical activity categories (e.g., very active, somewhat active, sedentary) but lacks the specificity needed to estimate physical activity in individuals [27].

As devices have evolved, physical activity meters have become more compact and convenient. The most commonly used devices are smartwatches, smart bracelets, and smartphones. Newer devices are capable of simultaneously measuring parameters such as exercise, activity intensity, respiratory rate, cardiac output (ECG), and body surface temperature [28]. Physical activity energy expenditure (PAEE) and different intensity profiles measured with such devices can be linked, providing a framework for the personalisation of wearable devices [29]. However, there is currently a need to improve the accuracy of measurements [30–32].

The use of wearable devices to monitor physical activity is predicted to grow more than five-fold in half a decade [29]. With the advances in wearable technology and the increasing demand for real-time analytical monitoring, devices will undergo significant development in the future through materials science, integrated circuit construction, manufacturing innovation, integrated circuit fabrication, and structural design [33]. By monitoring new parameters, measurements for physiological and health purposes will be possible, allowing professionals to make diagnoses and treatment decisions, thereby improving healthcare and supporting research [34]. The effectiveness of wearable smart devices can be improved not only by the development of new measurable parameters and accuracy but also by the inclusion of new technologies such as virtual reality or artificial intelligence analysis in the future [35,36].

1.2. Objectives

The use of smart devices can therefore be a good way to increase physical activity. However, as many factors influence sporting habits and thus the measures to promote sports, we need to carry out thorough research to prepare real interventions. A considerable amount of literature on the subject has become available, particularly in recent years. To establish the basis for further research, studies on smart devices and physical activity between 2017 and 2024 were collected by searching two major literature databases (PubMed, National Library of Medicine, National Center for Biotechnology Information, Bethesda, Maryland, USA and Web of Science, Clarivate, Philadelphia, Pennsylvania, USA, London, United Kingdom) and then organising the results through a suitable filtering process. This study can help in designing practical research and learning about previous research. This article aims to present the latest research on the use of smart devices during physical activity and identify the target groups, the impact of the usage of devices with different options, and the expectations of the populations studied. This can contribute to a better design of research on physical activity and smart devices.

2. Materials and Methods

2.1. Searching Strategy, Inclusion and Exclusion Criteria

We searched in PubMed and Web of Science databases. In both databases, we ran the search on 25 March 2024 using the following search terms and relationships: (physical activity) AND (smart device) AND ((income) OR (sex) OR (age) OR (education)). We surveyed articles published from 1 January 2017 to 25 March 2024.

We used the two databases mentioned above because they are considered as scientific databases in the field of health and social sciences, and we can be sure that the publications published there have been properly peer-reviewed. We have also considered using open databases such as Google Scholar, but these yield tens of thousands of results for the queries we have used. Furthermore, such databases usually do not have the option to export the results to Excel or other files, so manually recording a large number of hits would be time-consuming. Other databases could of course be included in similar searches.

The keywords in the query were selected based on several scientific articles. We aimed to examine factors that influence both physical activity [37–39] and smart device usage [40] patterns. Taking into account several articles, the four factors included in our research (income, gender, age, and education) were found to be appropriate when examined from both perspectives.

The results of both database queries were input into automatically generated Excel spreadsheets, and the duplicates were removed. We included articles and reviews and excluded article commentaries and proceeding papers. We also did not include studies that we could not access through our institution. The filtering and selection process and the number of articles per step are shown in Figure 1. Papers were filtered by title and abstract, and the inclusion and exclusion criteria are shown in Table 1.

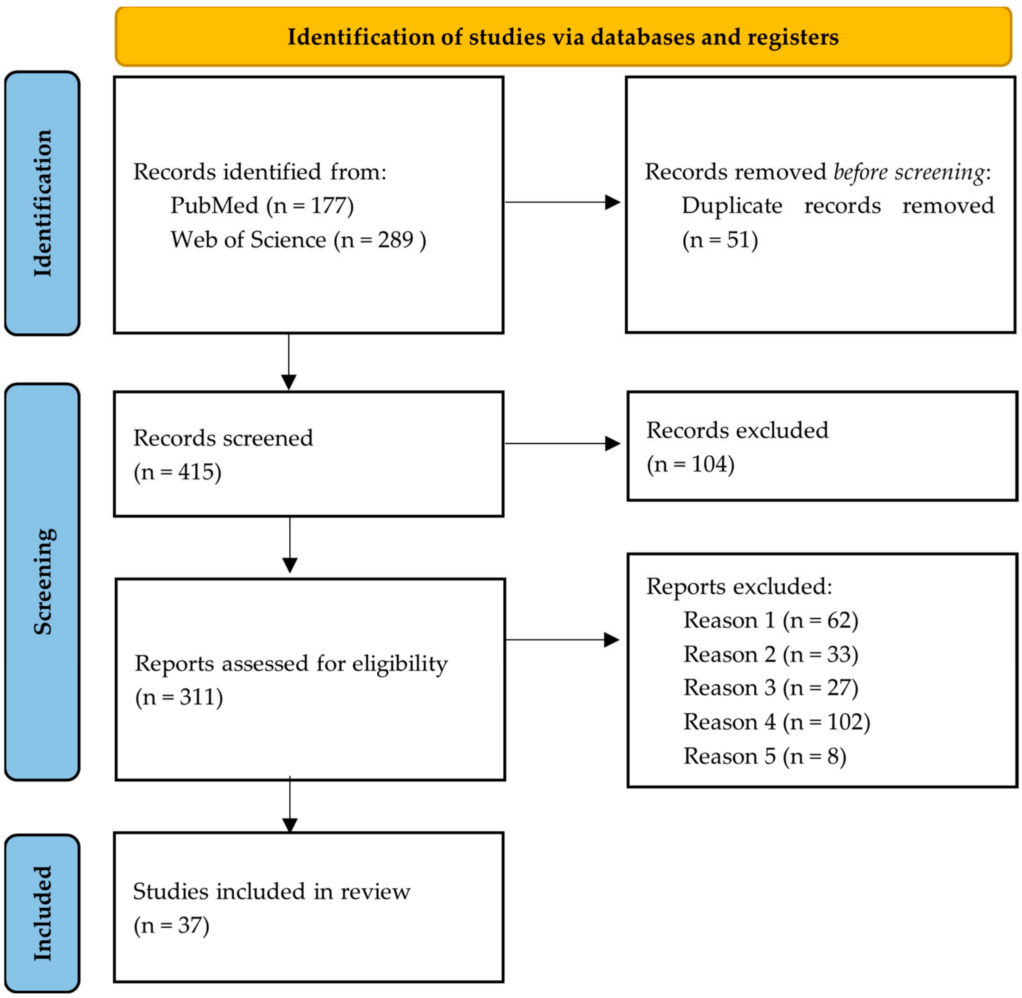

Figure 1. Article selection process based on PRISMA 2020 [41].

Table 1. Criteria for inclusion of relevant literature (own ed.).

Articles to be Included	Ineligible Articles
Measures the physical activity of a healthy sample using a smart device.	Reason 1: It is about the effects of an IT tool or technology, not a wearable device (e.g., smart home), and/or not specifically about encouraging physical activity.
Measures the physical activity of a group of patients using a smart device.	Reason 2: It is about a system to measure physical activity, but there are no concrete results yet (e.g., science-promoting articles, theories, study protocols, device designs, etc.).
The smart device helps to make school-based movement (e.g., PE lessons) more effective.	Reason 3: The research focuses on the accuracy of the technology, not on motivation and activity.
The smart device helps professional/competitive athletes to train more efficiently.	Reason 4: It examines the impact of using a smart device from a non-physical activity perspective (e.g., impact on sleep, cognitive function, aging, identification of a disease).
An attitude survey on the use of smart devices during physical activity is presented.	Reason 5: It is not a smart device, it is looking at the impact of social media, television, etc., on movement.
	Reason 6: Does not include any testing using an IT tool (e.g., prevention of harmful effects of IT, non-IT PA programmes).

The main criterion was to examine the impact of smart devices on physical activity. This was mainly examined in terms of sociodemographic indicators and motivation. It was important that physical activity was mainly considered as a health determinant in the studies processed. On this basis, we excluded papers from the analysis that examined the topic from a technological point of view, e.g., architecture or accuracy of the equipment. In addition, exclusion criteria were also applied if the study did not examine the use of smart devices from a physical activity perspective or did not present smart devices (e.g., it examined the impact of social media). Those articles that did not contain concrete results or were non-professional, rather science-promoting, were not further analysed. We also excluded studies that did not include any IT tools at all. Based on the criteria, the articles that could be included and the articles that were filtered out were marked, and we did not work with the excluded articles. After this, the results were then analysed from a content perspective.

2.2. The Selection Process

The search returned 177 results for PubMed and 289 for Web of Science. In the selection process, 51 duplicates were deleted, and 104 articles were not available through our institution or were of the wrong type of scientific paper. After the exclusion criteria were applied, only 37 articles were further processed.

3. Results

3.1. Main Findings and Citation

Table 2 shows all the articles we have processed. The table shows each article's serial number, reference number, author abbreviation, title, journal, and year of publication. We have also summarised the main findings of the studies. In the next three columns, we display the citation count of the article, the average of the journal's impact factor, and the citation count of the article normalised by the journal's impact factor. In the last column, we display the period for which the average impact factor was calculated.

Table 2. Summary table of the articles included in the study, their main findings, and their average citations (own ed.).

No.	Article	Findings	Total Number of Citation	IF	Normalised Citations * Cited/IF	Notes
1.	[42] Moore et al. Older adults' experiences with using wearable devices: Qualitative systematic review and meta-synthesis *JMIR mHealth and uHealth*, 2021	The value of wearable devices is determined by the balance between motivation, device features, ease of use, purpose, and user experience, and therefore a supportive framework needs to be built to encourage and align user preferences.	31	5.	5.44	5 years
2.	[43] Yen, H. Y. Smart wearable devices as a psychological intervention for healthy lifestyle and quality of life: a randomized controlled trial *Quality of Life Research*; 2021	Individuals who wore and frequently checked their watches were more prone to altering their exercise habits. Such behaviours can be positively impacted by the design of a device that is convenient and comfortable for the user.	13	4.4	2.95	5 years
3.	[44] Chong et al. Analysis of Health Management Using Physiological Data Based on Continuous Exercise *International Journal of Precision Engineering and Manufacturing*; 2021	The three-subject study found that the combination of a smartwatch and a smart scale increased maximum heart rate (BPM), improving adaptation to exercise. In addition, this combination reduced body weight, thus improving the subjects' body mass index (BMI).	2	1.9	1.05	5 years
4.	[45] Beltrame et al. Extracting aerobic system dynamics during unsupervised activities of daily living using wearable sensor machine learning models *Journal of Applied Physiology*; 2018	Research shows wearable devices effectively measure blood oxygen levels, providing insights into individual adherence to healthy lifestyles and assessing changes in aerobic system dynamics, including cardiorespiratory fitness and overall health index.	30	3.6	8.33	5 years
5.	[46] Golbus et al. Wearable device signals and home blood pressure data across age, sex, race, ethnicity, and clinical phenotypes in the Michigan Predictive Activity & Clinical Trajectories in Health (MIPACT) study: a prospective, community-based observational study *The Lancet Digital Health*; 2021	Researchers found variations in blood pressure and heart rate linked to sex, age, race, and ethnicity using smartwatch data; men had higher blood pressure, while those 65 and older had lower heart rates, and women and older individuals took fewer steps and walked less.	28	31	0.91	5 years
6.	[47] Ye & Ma The effects and patterns among mobile health, social determinants, and physical activity: a nationally representative cross-sectional study *AMIA Annual Symposium Proceedings*; 2021	A nationally representative survey in the USA explored sociodemographic factors affecting the impact of smart devices on physical activity, with approximately half of respondents not using them, but notably, many users were younger; for wearables, women, higher-educated and higher-income individuals, and those in relationships showed more usage inclination.	29	-	-	no IF data
7.	[48] Ruiz-Cárdenas et al. Validity and reliability of an iPhone App to assess time, velocity and leg power during a sit-to-stand functional performance test *Gait & Posture*; 2018	This study was based on data collected from 48 individuals using an iPhone app. Here, activity scores from the app were moderately or very strongly associated with age and grip strength, but not with walking speed.	33	2.4	13.75	only 2022
8.	[49] Hartwig et al. A monitoring system to provide feedback on student physical activity during physical education lessons *Scandinavian journal of medicine & science in sports*; 2019	Based on systematic literature reviews, the study revealed that activity levels in physical education classes fall short of WHO recommendations, suggesting that providing feedback to teachers and students could boost activity, though it found accelerometers inaccurate and recommends pedometers instead.	25	4.1	6.10	only 2022
9.	[50] Dong et al. Design and Development of an Intelligent Skipping Rope and Service System for Pupils. *Healthcare*; 2021	The research showed that despite limited instruction, skipping rope can be a fun exercise for students, especially with gamification, highlighting the importance of social support and the need for parental guidance; however, many parents express concerns about smart devices, which could affect children's development.	38	3	12.67	5 years
10.	[51] Lee et al. Temporal association between objectively measured smartphone usage, sleep quality and physical activity among Chinese adolescents and young adults *Journal of Sleep Research*; 2021	The study found a positive association between the use of social networking sites, instant messaging apps, multimedia, and overall smartphone usage with increases in step count and moderate-intensity physical activity. Importantly, the study utilised objective measures, rather than relying on self-report questionnaires, to gather data.	16	4.4	3.64	only 2022

Table 2. *Cont.*

No.	Article	Findings	Total Number of Citation	IF	Normalised Citations * Cited/IF	Notes
11.	[52] Ráthonyi et al. Wearable Activity Trackers Usage among University Students *European Journal of Contemporary Education*; 2019	Among over 500 university students surveyed, approximately 26% reported using a wearable device; users showed a significant increase in exercise days compared to non-users, with 70.6% of smartwatch wearers reporting a positive impact on activity, while 42.1% of wristband users reported increased activity.	8	1.6	5.09	4 years
12.	[53] Yen et al. Smart Wearable Device Users' Behavior Is Essential for Physical Activity Improvement *International Journal of Behavioral Medicine*; 2021	Research conducted on smartwatches revealed that individuals who wore and frequently checked their watches were more inclined to modify their exercise routines.	29	2.7	10.74	5 years
13.	[54] Gonze et al. Use of a smartphone app to increase physical activity levels in insufficiently active adults: Feasibility Sequential Multiple Assignment Randomized Trial (SMART) *JMIR research protocols*; 2020	A Brazilian study aimed to modify the habits of physically inactive adults by establishing a daily step goal. After 24 weeks, individuals who initially did not respond to the intervention demonstrated a positive increase in step count after transitioning to a new group utilising an app equipped with gamification features.	41	1.8	22.21	4 years
14.	[55] Polo-Peña et al. Influence of gamification on perceived self-efficacy: gender and age moderator effect *International Journal of Sports Marketing and Sponsorship*; 2020	The effectiveness of utilising gamification to promote regular exercise is greater among women compared to men, and also more pronounced among older users than younger ones.	30	3.5	8.49	4 years
15.	[56] Zarnowski et al. Use of Mobile Apps and Wearables to Monitor Diet, Weight, and Physical Activity: A Cross-Sectional Survey of Adults in Poland *Medical Science Monitor*; 2022	The study investigated mHealth technology adoption among Polish adults, highlighting the usage of mobile apps and wearables for tracking diet, weight, and physical activity; findings indicated 23.2% used wearables for activity monitoring, 14.4% owned smart scales, and 16.3% used mobile apps for activity tracking, with factors such as younger age and healthy lifestyle habits associated with adoption, indicating potential for promoting health and reducing disparities.	40	2.6	15.35	5 years
16.	[57] Kim et al. Physical Activity Pattern of Adults With Metabolic Syndrome Risk Factors: Time-Series Cluster Analysis *JMIR mHealth and uHealth*; 2023	The study examined individuals with metabolic syndrome risk factors, identifying two distinct physical activity patterns (early bird and night owl) for weekdays and weekends, categorising participants into stable and shifting groups based on activity patterns, revealing age-related differences and emphasising the potential of TADPole clustering and age in understanding physical activity behaviours.	40	5.7	7.02	5 years
17.	[58] Paré et al. Diffusion of the digital health self-tracking movement in Canada: results of a national survey *Journal of medical Internet research*; 2018	A Canadian survey collected data on various demographics and health-related parameters, with 66.20% of respondents regularly monitoring health metrics; digital self-monitors tend to be young or adult, healthy, employed, university graduates, and high-income earners, but a significant portion of individuals with chronic conditions avoid using such devices.	43	7.6	5.66	5 years
18.	[59] Zhai et al. Smartphone accelerometry: A smart and reliable measurement of real-life physical activity in multiple sclerosis and healthy individuals *Frontiers in neurology*; 2020	Monitoring assists clinicians in tracking disease progression or rehabilitation across various clinical conditions and empowers patients to self-monitor their condition. When paired with motivational and educational tools, it can enhance physical activity levels regardless of the underlying diseases.	45	3.4	13.24	only 2023
19.	[60] Aminorroaya et al. Use of Smart Devices to Track Cardiovascular Health Goals in the United States *JACC: Advances*; 2023	The study explored smart device usage for health goal tracking among US individuals with cardiovascular disease (CVD) or risk factors, finding that 46% of adults and 42% with CVD or risk factors used such devices, with usage linked to younger age, gender, race, higher education, and higher income, yet disparities among older and low-income groups underscore the necessity for digital health interventions to mitigate cardiovascular risk management disparities.	31	-	-	no IF data
20.	[61] Bentley et al. The use of a smartphone app and an activity tracker to promote physical activity in the management of chronic obstructive pulmonary disease: randomized controlled feasibility study *JMIR mHealth and uHealth*; 2020	The study evaluated an mHealth app aimed at assisting COPD patients. It emphasised the necessity of providing training for utilising the technology, considering the circumstances, motivations, and abilities of the participants, and highlighting the significance of effective communication with healthcare professionals.	88	5.7	15.44	5 years
21.	[62] Sokolovska et al. Impact of interval walking training managed through smart mobile devices on albuminuria and leptin/adiponectin ratio in patients with type 2 diabetes *Physiological Reports*; 2020	The study examined the effects of interval walking training with smart device support on type 2 diabetes patients, showing significant reductions in albuminuria and leptin/adiponectin ratios over four months, with slight improvements in HbA1c levels, yet adherence to the exercise plan remained low, possibly due to lack of reminder features in the app.	5	2.5	2.00	only 2022

Table 2. *Cont.*

No.	Article	Findings	Total Number of Citation	IF	Normalised Citations * Cited/IF	Notes
22.	[63] Patel et al. Effect of behaviourally designed gamification with social incentives on lifestyle modification among adults with uncontrolled diabetes: a randomized clinical trial *JAMA network open*; 2021	In a diabetic patient population, gamification was explored as a motivational tool, resulting in a notable increase in physical activity over a one-year period. This effect was observed when gamification was implemented to amplify support or competition, yet not cooperation.	49	14	3.55	only 2023
23.	[64] Hauguel-Moreau et al. Smart bracelet to assess physical activity after cardiac surgery: A prospective study *PloS one*; 2020	Among heart surgery patients, 61% found smart bracelets significantly beneficial for their recovery, with 41% reporting lifestyle changes and 77% continuing use post-rehabilitation, highlighting the importance of standardised design and functionality for such devices.	23	-	-	no IF data
24.	[65] Frith et al. Changes in patient activation following cardiac rehabilitation using the Active+ me digital healthcare platform during the COVID-19 pandemic: a cohort evaluation *BMC health services research*; 2021	The study found that remotely monitored cardiac rehabilitation led to increased PAM scores in high-risk patients, with no change in medium and low-risk groups, along with decreases in resting systolic blood pressure and waist circumference; participation in standard rehabilitation with Active+me improved patient skills, knowledge, and confidence in managing their condition.	32	3.5	9.14	5 years
25.	[66] Ormel et al. Self-monitoring physical activity with a smartphone application in cancer patients: a randomized feasibility study (SMART-trial) *Supportive care in cancer*; 2018	A study examining the effect of a smartphone app on cancer patients' physical activity levels over 12 weeks found significant improvement by week 6 compared to baseline, yet no significant difference was observed between week 6 and week 12 measurements.	45	3.5	12.86	5 years
26.	[67] Van Blarigan et al. Feasibility and Acceptability of a Physical Activity Tracker and Text Messages to Promote Physical Activity During Chemo-therapy for Colorectal Cancer: Pilot Randomized Controlled Trial (Smart Pace II) *JMIR cancer*; 2022	Patients undergoing chemotherapy received smartwatch and SMS interventions, with 63% expressing satisfaction, 68% reporting motivation to exercise, 74% finding the frequency (1–3 days) ideal, and 79% preferring morning and evening SMS delivery.	29	28	1.04	only 2023
27.	[68] Van Blarigan et al. Self-monitoring and reminder text messages to increase physical activity in colorectal cancer survivors (Smart Pace): a pilot randomized controlled trial *BMC cancer*; 2019	In an experimental study, 21 individuals receiving smartwatch notifications and text messages showed increased daily physical activity by an average of 13 min compared to a control group, despite a declining response rate to the messages over time.	28	4.3	6.51	5 years
28.	[69] Hardcastle et al. A randomized controlled trial of Promoting Physical Activity in Regional and Remote Cancer Survivors (PPARCS) *Journal of Sport and Health Science*; 2024	The study evaluated the impact of combining wearable technology with health coaching on physical activity levels among breast and colorectal cancer survivors in regional and remote areas of Australia, showing a significant increase in moderate-to-vigorous physical activity favouring the intervention group, indicating the effectiveness of this approach in enhancing activity levels for non-metropolitan cancer survivors.	57	12	4.67	only 2023
29.	[70] Passos et al. Wearables and Internet of Things (IoT) Technologies for Fitness Assessment: A Systematic Review *Sensors*; 2021	The study found that wearable technologies are used to monitor athletes' internal and external workload, employing physiological condition monitoring, activity recognition, and tracking techniques, with their primary advantage being objectivity through quantifying the impact on athletes.	66	4.1	16.30	5 years
30.	[71] Wiesner et al. Technology adoption, motivational aspects, and privacy concerns of wearables in the German running community: field study *JMIR mHealth and uHealth*; 2018	Among the group surveyed, 73.0% reported using technology to monitor activity during events or exercise, with male distance runners and younger runners (aged 16–29 years) showing greater inclination toward using tracking devices; additionally, 42.0% of those using wearable technology expressed no concern about the device manufacturer sharing their data without consent.	42	5.7	7.37	5 years

Table 2. *Cont.*

No.	Article	Findings	Total Number of Citation	IF	Normalised Citations * Cited/IF	Notes
31.	[72] Pobiruchin et al. Accuracy and Adoption of Wearable Technology Used by Active Citizens: A Marathon Event Field Study *JMIR mHealth and uHealth*; 2017	The results of a German survey in 2016 showed that most participants (75%) of a sport competition used smart devices to exercise, with a lower proportion of women and older athletes using smart devices to exercise.	33	5.7	5.79	5 years
32.	[73] Giménez-Egido et al. Using smart sensors to monitor physical activity and technical–tactical actions in junior tennis players *International Journal of Environmental Research and Public Health*; 2020	The study of junior tennis players using sensor-equipped rackets revealed a reliance on fundamental stroke techniques and preferred sides during matches, highlighting a reluctance to explore beyond their comfort zone and emphasising the need for enhanced practice of these specific strokes within the studied population.	60	3.8	15.84	5 years
33.	[74] Barricelli et al. Human Digital Twin for Fitness Management *BioMed Research International*; 2020	SmartFit generates accurate predictions regarding athletes' conditions and offers valuable recommendations for coaches to implement optimisation of athletes' behaviour.	159	-	-	no IF data
34.	[75] McCaskey et al. Making more of IT: enabling intensive motor cognitive rehabilitation exercises in geriatrics using information technology solutions *BioMed Research International*; 2018	The research was targeted at IT tools for senior people and their motor and cognitive rehabilitation, also mentioning the positive effects of gamification. It is highlighted that by using such programmes and games, older people can interact socially with other people, which also affects physical activity.	166	-	-	no IF data
35.	[76] Jang et al. Impact of a wearable device-based walking programs in rural older adults on physical activity and health outcomes: cohort study *JMIR mHealth and uHealth*; 2018	In a study of elderly individuals in rural areas, coaching combined with smart device usage for 6 months, followed by 6 months of self-management, led to increased activity levels, highlighting the importance of coaching compared to studies solely relying on smart devices.	33	5.7	5.79	5 years
36.	[77] Fioranzato et al. Improving Healthy Aging by Monitoring Patients' Lifestyle through a Wearable Device: Results of a Feasibility Study *International Journal of Environmental Research and Public Health*; 2021	Involving patients with type 2 diabetes and their healthcare providers, the study found that 75% of patients expressed satisfaction levels above 80% with the device's features, with weak correlations observed between health professionals' perceptions and patient parameters, particularly in collaboration dimensions and web interface ease of use, along with average step count and sleep duration.	25	-	-	no IF data
37.	[78] Hvalič-Touzery et al. Benefits of a Wearable Activity Tracker with Safety Features for Older Adults: An Intervention Study *Public Health*; 2022	The study in Slovenia investigated integrating wearable activity monitors and telecare for older adults, finding that activity trackers effectively encouraged physical activity, while safety features were deemed crucial for all participants, regardless of health or activity level.	95	1.7	55.88	5 years

*—The number of citations was normalised to the average impact factor of the journal for the period in the Notes column.

3.2. Citation of the Articles

Articles with a normalised citation above 15 were considered strong. The most cited article is reference No. 37 with a value of 55.88, which is very high. This is followed by article No. 29, which has a much lower normalised citation count of 16.3. Article No. 32 is also considered outstanding with 15.84, as are article No. 20 with 15.44 and article No. 15 with 15.35.

In the normalised Impact Factor table (Table 2), the first six highlighted articles can be classified into two large groups. On the one hand, the articles deal with applications used by athletes (articles No. 29 and 32). Another group deals with mobile measuring devices used in everyday life, precisely with cases in which the measurement is evaluated by specialists (articles No. 37, 13, 15, 20). In both cases, there is no individual monitoring of the processes, but specialists are involved through communication.

3.3. Definition of Target Groups and Their Geographical Location

The studies have been processed from a content point of view. During the content processing of the articles, four main groupings were implemented according to the group targeted by the study of the impact of smart devices:

- Physical activity stimulation in a group of healthy people;
- Smart devices and physical activity of patients;
- Examining the impact of smart devices on the performance of competitive athletes;
- Smart devices for health protection among the elderly.

Figure 2 shows how many articles mentioned a target group. An article could have addressed more than one of the target groups we have identified, so adding up the number of articles gives a higher number than the number of articles included in the study. Most of the studies were carried out on healthy people (23 studies). After that, the most common target group was elderly people (16 papers), followed by patients (13 articles) and competitive athletes (5 studies).

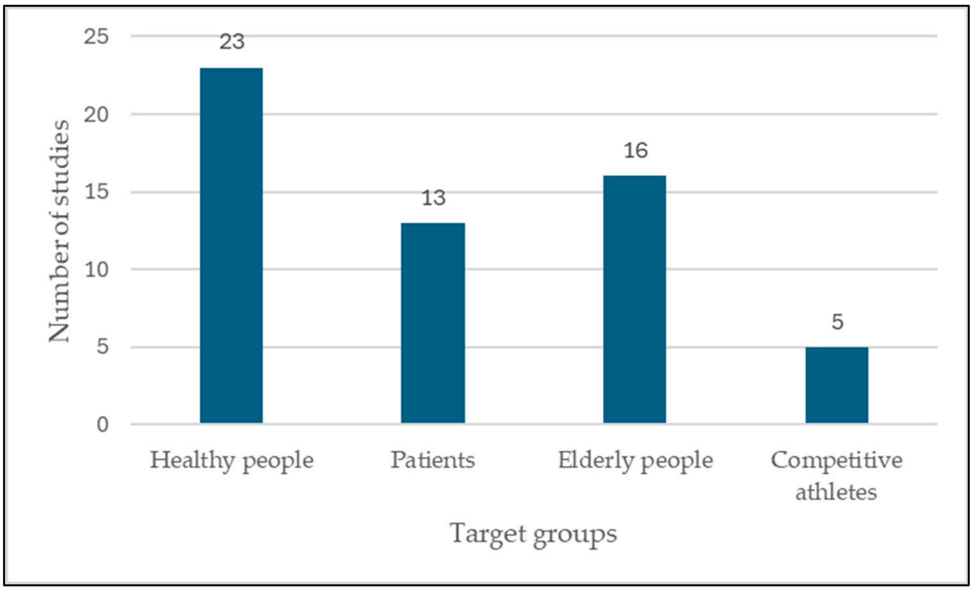

Figure 2. Number of studies by target groups mentioned.

Looking at the studies, we found a very heterogeneous picture in terms of geographical location (Figure 3). In terms of country distribution, the country with the largest number of studies was the United States of America (six studies). Germany had three studies. Two studies per country were conducted in Australia, Spain, the Republic of Korea, Italy, Canada, the United Kingdom, and China. France, Taiwan, Hungary, Brazil, Latvia, Poland, Slovenia, and the Netherlands were mentioned in one article per country. In this case, some articles described research carried out in several countries, and some articles, mainly review articles, did not specify the country. The number of occurrences added together also does not match the number of articles included in the research. Our findings were therefore mostly related to the Americas and Europe.

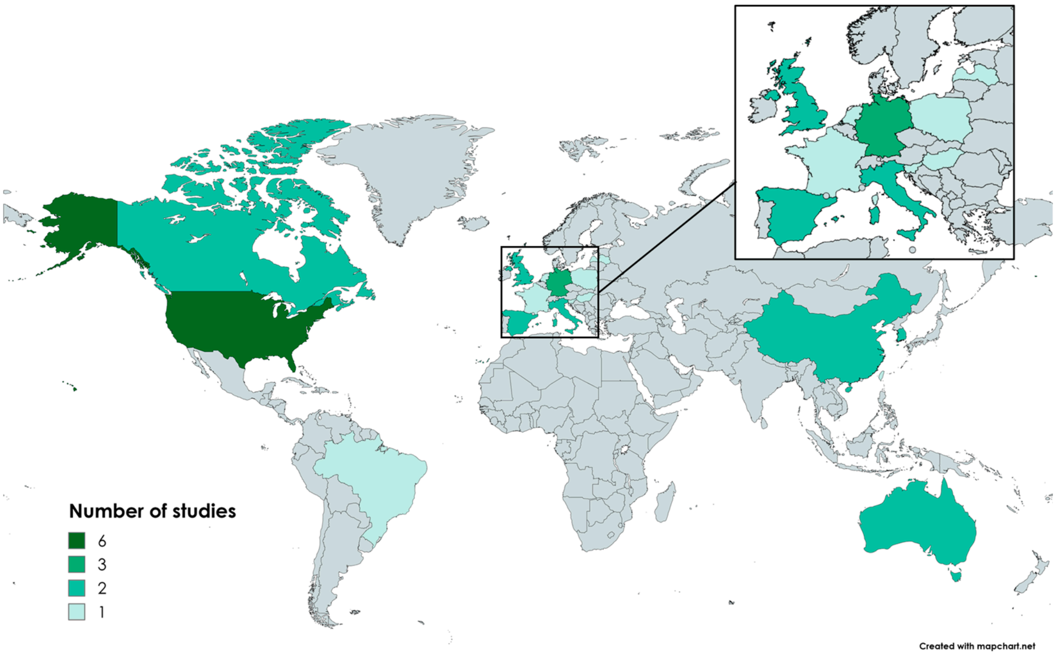

Figure 3. The geographical location of the target groups of the studies (own ed.).

3.4. Most Frequently Used Devices and Keywords

We also looked further at the type of smart device that each research study focused on (Table 3). This showed that most studies favoured smartwatches, smart bracelets, and smartphones. This may be because most people have access to these devices, so the research did not require additional investment, and users were more comfortable with their own devices. Smartwatches and smart bracelets are very similar in both appearance and function; although smart bracelets may have fewer features, they are also cheaper, so it is understandable that we found similar results in terms of their usage. Five studies did not specify the type of smart device used; these were generally review-type articles. Fifteen studies also used other devices such as accelerometers, GPS trackers, and smart scales. If we aggregate the number of devices, used the result is more than 37, which was the number of studies examined. This is because there were several cases where more than one wearable device was used in a study.

Table 3. Distribution of studies by type of smart device studied (own ed.).

Type of Smart Device Used				
Smartwatch	Smart bracelet	Smartphone	Any wearable device	Other
12	12	12	5	15

While analysing the scientific articles, we also observed the diversity of keywords, so we aggregated the keywords and their occurrence in the studies. A total of 161 keywords that occurred 208 times were identified. We then aggregated the keywords that differed only in conjugation. The most frequent keywords and their occurrence are shown in Table 4. It can be observed that the most frequent keyword, "Physical activity" (which we also used when preparing the queries), was used in the articles only 11 times. The second most common was the related word "Exercise", followed by "Wearables", "Wearable device", "Smart device", and "Activity trackers", which also showed similarities. Finally, the terms "Mobile health" and "Digital health" were included in the table with three occurrences each. Other keywords, many of which are synonyms of these terms (e.g., mobile health—mHealth), occurred one or two times and are not marked in the table.

Table 4. Most common keywords by number of occurrences (own ed.).

Keyword	Occurrence
Physical activity	11
Exercise	9
Wearables	7
Wearable device	6
Smart device	5
Activity trackers	4
Mobile health	3
Digital health	3

From these data, we can conclude that the use of keywords in scientific articles is very varied, often with only conjugation or phrasing differences, but this is a significant factor when we are running searches. The citability of an article can be greatly influenced by the chances of finding it when searching individual databases, so authors may want to assess the most commonly found keywords that fit the topic when creating an article and use them in the publication.

3.5. Target Groups' Expectations, Expected Characteristics

Twenty-one of the scientific articles examined what each of the target groups expected from the tools or what features were important to them. These are presented in Table 5.

Table 5. Target groups and their expectations of smart devices (own ed.).

Expectations # / Groups &	Healthy People	Patients	Competitive Athletes	Elderly People	Articles &
Accuracy	**	*	***		[49,59,70,73,74]
Prediction			**		[70,74]
Gamification	* (1) * (2)			*	[50,55,75]
Data protection			* (3)	*	[71,78]
Customisability		**			[61,67]
(Custom) notifications		***			[62,67,68]
Easy to use	**	***		**	[47,54,61,76,77]
Number of measurable parameters	*				[58]
Achievable goals	*				[54]
Coaching		*		**	[69,75,76]
Competition	*	*			[47,63]
Rewarding	*				[47]
Small size			*		[70]
Energy consumption			*		[70]

The number of asterisks denote the number of articles in which a particular attribute was considered important (*—1 article; **—2 articles; ***—3 articles). # The expectations or preferences that have been set for the tools. & Articles that highlighted the given parameter. (1) One article specifically singled out women and the elderly from the population for the effectiveness of gamification. (2) One article specifically singled out children from the population for the effectiveness of gamification. (3) One article specifically highlighted older people playing competitive sports in terms of data protection.

Device features are also important because users' needs and the supporting structure surrounding the device—often overlooked aspects—are crucial to long-term adoption [42].

The attitude of users influences the outcome of the use of the tools. Subjects who wore and checked their watches more often were more likely to change their exercise habits. So overall, it is not the smart device per se but the attitude towards the device and movement that is significant. These attitudes can be positively influenced by the design of a device that is convenient and comfortable for the user [43].

We have made additions concerning gamification. One article suggests that this method is particularly effective for older people and women, while another suggests that it is effective for children. Some of the studies analysed did not include any indication of the characteristics that users would prefer in relation to smart devices. This usually requires qualitative measurement, but most of the studies used quantitative data and did not use qualitative questionnaires or interviews, so it was not always possible to highlight these important characteristics in the articles.

4. Discussion

4.1. Stimulating Physical Activity among Healthy Individuals

In the target group of healthy people, the expectations of smart devices were as follows: Accuracy and ease of use were the most important, both mentioned in two articles. In addition, the number of measurable parameters, achievable goals, the possibility to compete with others, and rewards were also important, with one occurrence each. We also have to mention three subgroups in this respect, children, elderly, and women. In all three cases, gamification proved to be an even more useful feature. The reason for this, in our opinion, may be that gamification can provide them with the greatest experience and thus have a significant motivational effect (Table 5).

4.2. Smart Devices and Physical Activity of Patients

For the target group of patients, ease of use and the delivery of messages and notifications were the most important factors; the latter should be personalised where possible. The second most important parameter was therefore personalisation. The reason for this may be that not all devices are uniformly suited to the patients' special conditions, as each patient's condition is different, even if they have the same disease. However, it should also be mentioned that too much personalisation may be at the expense of ease of use, which was also an important factor in this target group. In addition, we can highlight accuracy, coaching, and competition as other important requirements (Table 5).

4.3. Improving the Performance of Athletes

For athletes, not too many expectations have been set. However, accuracy was clearly the most important, as it is more important for them to have accurate results from movement-related measuring tools so that they can draw the right conclusions about their performance. Data security is also an important factor for them, as this is sensitive business data for professional athletes. The possibility of forecasting is also an essential built-in element as it can help athletes to improve their results and plan a suitable training programme. It is important that the size of the device is small and the power consumption is low as this is the target group that would use these devices the most, and comfort and frequency of charging are essential for long-term use (Table 5).

4.4. Stimulating Activity among Elderly People

For senior people, ease of use and coaching were the main expectations for smart devices. We found two articles on each. These are not surprising findings, as external support and ease of use of devices can be of high importance for elderly people. Another important parameter for them is data security, and in addition, gamification emerged as a factor influencing usage. This may have a positive impact on motivation, as gamified devices can motivate older people to exercise regularly and use smart devices in this way (Table 5).

5. Conclusions

The existing literature predominantly examines the impact of smart devices on physical activity within the United States and Europe, highlighting substantial citation rates but also a wide variation in keyword usage. The most frequently used keywords were physical activity, exercise, wearables, wearable device, smart device, activity trackers, mobile health, and digital health. To enhance accessibility, we propose refining and standardising keyword selection.

Our review identifies various factors influencing smart device impact, including demographics such as age, gender, income, education, and marital status, suggesting tailored interventions based on target populations: healthy individuals, patients, competitive athletes, and the elderly.

Effective interventions hinge on intrinsic motivation, with healthy people benefiting from regular notifications or text messages, while the elderly require user-friendly interfaces and gamification strategies. Patients need notifications and easy-to-use, customisable devices. Athletes prioritise accurate data collection and predictive capabilities from smart devices. Additionally, heightened attention to data protection is warranted, given both user concerns and potential risks associated with data collection.

On the basis of normalised impact factor, the most cited articles focus on athletes and mobile measuring devices used in everyday life, in cases where the measurement is evaluated by professionals.

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