Health Wearable Tools and Health Promotion FREE

Arul Chib, Institute of Social Studies, Erasmus University of Rotterdam, Caining Li, Nanjing Normal University, and Sapphire Lin, SingHealth

https://doi.org/10.1093/acrefore/9780190632366.013.510
Published online: 22 November 2023

Summary

The application of wearable technology for health purposes is a multidisciplinary research topic. To summarize key contributions and simultaneously identify outstanding gaps in research, the input-mechanism-output (I-M-O) framework was applied to synthesize findings from 275 relevant papers in the period 2010–2021. Eighteen distinct cross-disciplinary themes were identified and organized under the I-M-O framework. Studies that covered input factors have largely been technocentric, exploring the design of various health wearables, with less emphasis on usability. While studies on user acceptance and engagement are increasing, there remains room for growth in user-centric aspects such as engagement. While measurement of physiological health indictors has grown more sophisticated due to sensitivity of sensors and the advancements in predictive algorithms, a rapidly growing area of research is that of measuring and tracking mental states and emotional health.

Relatively few studies explore theoretically backed explanations of the role of health wearables, with technocentric theories predicting adoption favored. These mainly focused on mechanisms of adoption, while postadoption use and health behavior change were less explored. As a consequence, compared to adoption mechanisms, there is an opportunity to increase our understanding of the continued use of wearables and their effects on sustained health behavior change. While a range of incentives such as social, feedback, financial, and gamification are being tested, it is worth noting that negative attitudes, such as privacy concerns, are being paid much more attention as well. Output factors were studied in both individual and organizational settings, with the former receiving considerably more attention than the latter. The progress of research on health wearables was discussed from an interdisciplinary angle, and the role of social scientists was highlighted for the advancement of research on wearable health.

Keywords: wearables, sensors, trackers, user behavior, health promotion, privacy, mHealth, I-M-O framework

Subjects: Behavioral Science and Health Education, Biostatistics and Data, Global Health

Introduction

Medical disciplines are increasingly integrating wearable technology into their systems (Amft, 2018). The rise of wearable health products (hereafter, "wearables") coincides with global healthcare challenges arising from certain demographic and lifestyle trends such as aging (Majumder et al., 2017) and self-management of chronic diseases (Brew-Sam & Chib, 2019).

Wearable health technologies are a subset of mobile information and communication technologies for health (mHealth). Wearables are characterized by being attached or embedded in the human body, constantly gathering and intermittently relaying data without necessity of user interaction, and providing medical information and health benefits (C. Li et al., 2020). These have the ability to provide continuous real-time monitoring of health-related parameters, adding a valuable dimension to the mHealth field (X. Li et al., 2017). Often used in conjunction with mobile health apps, which are designed to empower self-management of chronic disease and to facilitate patient–physician communication (Chib & Lin, 2018), wearables promise not only improved healthy lifestyles for individual consumers, but also enhanced service delivery processes for healthcare organizations.

The popularity of health wearables has been growing exponentially from the 2010s, with a global market volume of US$20.1 billion in 2021 and a revenue expected to exceed 83.9 billion by 2026 (Statista, 2022). However, despite the market growth as consumer adoption increases, there is a paucity of credible evidence that demonstrates their effectiveness in supporting individual health objectives, with even less evidence to confirm their efficacy in more critical clinical settings (Knowles et al., 2018). Moreover, existing knowledge of wearables is scattered across a range of disciplines, such as mobile computing, social science, and public health.

To provide a holistic understanding of wearables for health promotion, there is a need to synthesize existing knowledge in various research fields across various disciplines. The input-mechanism-output (I-M-O) framework (Chib et al., 2015) provides an integratory perspective for analyzing emerging transdisciplinary topics, having been used successfully in reviews of mHealth, both broadly (Chib et al., 2015) and specifically for mHealth apps (Chib & Lin, 2018). The I-M-O framework encompasses characteristics (*inputs*) of digital products, the underlying *mechanisms* of how they are adopted and used, and the effects (*outputs*) at both the individual and organizational level. As such, a review based on the I-M-O framework is relevant for technology development specialists, social scientists, interface designers, public health researchers, and policymakers.

A Look at Current Reviews in the Literature

Existing reviews on health wearables focus on a narrow scope of studies investigating a particular type of wearable technology or a specific health aspect consolidating academic evidence on technical features, user adoption, or the effectiveness of specific types of wearables. Focused on technical features of wearables by evaluating the feasibility and accuracy of a specific technology, Elgendi and Menon (2019) reviewed 22 papers and found that the use of electrocardiogram-wearable devices for detecting anxiety was unreliable. Another type of review looked at evidence of the effectiveness of wearables, finding consistent evidence about the effects of self-monitoring devices in increasing physical activity (Brickwood et al., 2019; C. Li et al., 2021). In the last type of review, reviewers investigated the acceptability of wearables, but these tended to focus on a specific target population for the sake of implementation. Generally, these reviews identified advantages and challenges regarding the introduction of wearables in specific settings, such as clinics (Sprogis et al., 2019) or various blue- and white-collar workplaces (Khakurel et al., 2018; Mardonova & Choi, 2018).

The academic evidence on wearables needs better consolidation due to the prevailing lack of holistic perspectives on this emergent research field. The input-mechanism-output (I-M-O) framework (Chib et al., 2015) is applied to categorize relevant studies into a pathway of three stages: input, mechanism, and output. Input factors are what that make a system work, mechanisms are how a system works, and output factors are the results from a system (Chib & Lin, 2018). Based on the I-M-O framework, theoretically relevant trends were identified, including the technological development of wearables, theoretical explanations of human behavior in adoption and use, and the extant evidence of effectiveness of wearables on individual health outcomes and organizational processes.

Methods

This review covers research on wearables in each stage of the input-mechanism-output (I-M-O) framework in detail, while a previous review looked at these 250 studies from a broader perspective across the stages (C. Li et al., 2020). Compared to the previous review, which mainly investigated the quantity distribution of wearables literature, this review further explores the progression of literature across every stage and delves into the related themes. The final dataset comprised 275 articles published between 2010 and 2021. Full-paper versions of these articles were obtained for analysis.

The initial search was conducted in databases of the Web of Science Social Sciences Citation Index (*n* = 967) and PsycINFO (*n* = 89) on August 27, 2019, using the following search terms and Boolean operators: ((wearable* OR fitness tracker* OR activity tracker*) AND (health*)). Only articles written in the English language were included. The search results across the two databases were combined, leading to a collection of 1,056 papers. Next, basic attributes of all 1,056 papers were screened. Duplicates (*n* = 47) and incomplete records (*n* = 46) were removed. Book sections (*n* = 9) and dissertations (*n* = 4) were similarly excluded as these were not peer-reviewed. After screening the titles and abstracts of the remaining 950 papers, we removed irrelevant papers that did not investigate wearables in health interventions (*n* = 477). In addition, conceptual articles (*n* = 100), study protocols (*n* = 30), and literature reviews (*n* = 93) were removed due to the absence of empirical evidence. Subsequently, to ensure an up-to-date dataset, a similar literature search procedure was conducted on December 31, 2021. Another 25 studies were identified through database updating. Figure 1 summarizes the selection process for the dataset.

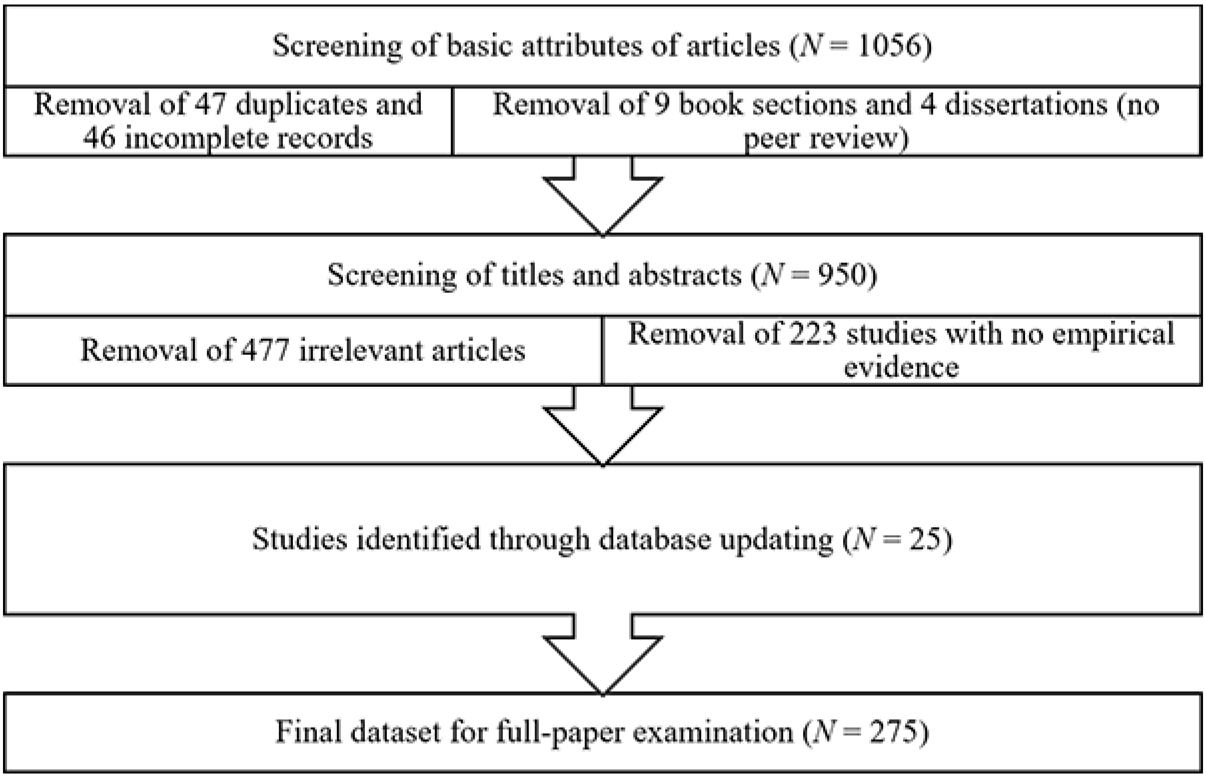

Figure 1. Steps in selection and formation of dataset.

For papers in the final dataset (N = 275), data were extracted using a standard form containing 23 fields including descriptions of the wearable technology, methods of the study, factors relating to the I-M-O framework, and the main conclusions of the study. All three reviewers met regularly to synthesize the findings.

Findings

Studies mainly emphasized inputs (n = 206), then outputs (n = 64). Least studied were theoretical mechanisms for adoption and use of wearables (n = 38). Eighteen themes arose from the studies, and these were further classified into eight categories under the input-mechanism-output (I-M-O) framework. Figure 2 provides a visualization of the stages, categories, and themes with a tree diagram. A preview of the identified themes is provided via a sample of 18 papers (one paper representing each theme for the sake of simplicity and representativeness), presented in Table 1.

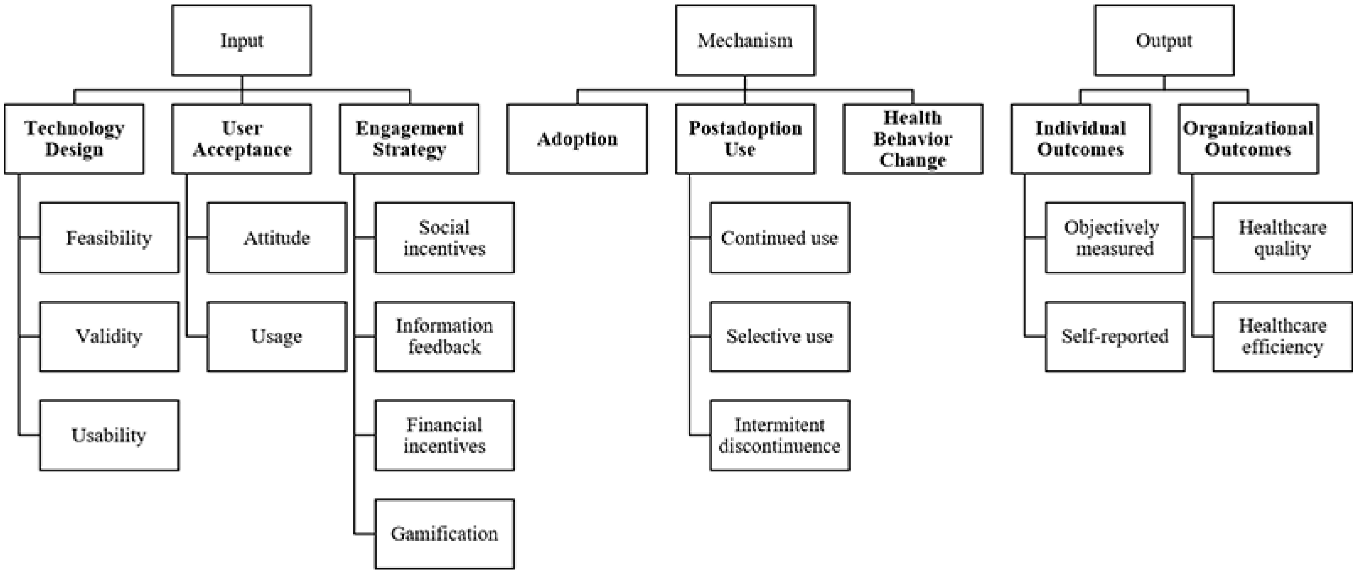

Figure 2. Dataset classified by the input-mechanism-output review framework.

Table 1. Preview of Selected Studies

Study	Category and Theme	Wearable(s)	Sample and Method	Findings
Thorpe et al. (2019)	Input: Technology design (feasibility)	Smartwatches	5 healthy people, 1-week field test	The proposed behavioral monitoring solution for extracting travel trajectories and mobility metrics was successful and could potentially support dementia care.
Hernando et al. (2018)	Input: Technology design (validity)	Apple Watch	20 healthy people, laboratory experiment	Apple Watch measurements had very good reliability and agreement with the Polar H7 (>0.9) in measuring heart rate variability parameters.
Liang et al. (2018)	Input: Technology design (usability)	Apple Watch, Samsung Gear S, Fitbit Surge, etc.	388 people, survey	The usability of wearable devices is similar across various brands. Perceived usability was unsatisfactory, suggesting the need for integration of more behavior change techniques.
Jiwani et al. (2021)	Input: User acceptance (attitude)	Fitbit	18 overweight older adults, focus group discussions	Participants reported favorable experiences of a Fitbit-based lifestyle intervention, such as increased knowledge of health behavior following the intervention, even under stressful life circumstances from COVID-19.
Friel and Garber (2020)	Input: User acceptance (usage)	Activity trackers	2,002 people, national web-based survey	Compared to current users, former users had lower body mass index, reported fewer medical conditions, shared data from device less often, and received the device as a gift more frequently.
Ronkko (2018)	Input: Engagement strategy (social incentives)	Jawbone UP24	8 vulnerable youths, 4-month intervention	Instant graphical feedback, sharing information, and being part of a social community can have a positive impact on lifestyle changes.

Study	Category and Theme	Wearable(s)	Sample and Method	Findings
Ginis et al. (2017)	Input: Engagement strategy (information feedback)	Wearable cue and feedback system	28 patients with Parkinson's disease and 13 healthy elderly, 6-week trial	Compared to continuous cueing and intelligent feedback, intelligent cueing is more suitable for assisting patients with Parkinson's disease during prolonged walking.
Chokshi et al. (2018)	Input: Engagement strategy (financial incentives)	Misfit Shine	105 patients with heart failure, 24-week trial	Loss-framed financial incentives ($2 could be lost per day for not achieving step goals) with personalized goal setting significantly increased physical activity among patients with ischemic heart disease using wearable devices.
Leinonen et al. (2017)	Input: Engagement strategy (gamification)	Polar Active	496 young men, 6-month RCT	Through game-based persuasion and rewards, MOPOrtal had a borderline positive effect on weekly time spent in MVPA. However, there was no effect on anthropometry or fitness, except reduced waist circumference in the most inactive men.
Farivar et al. (2020)	Mechanism: Adoption	Wearable technologies	280 North American seniors, survey	When seniors' subjective well-being is low, cognitive age increases seniors' intention to use the device.
Deranek et al. (2021)	Mechanism: Postadoption use (continued use)	Fitbit	59 adolescents, one-arm experiment	Intrinsic motivations including affiliation, revitalization, and health pressures positively predict sustained long-term use.
James, Deane et al. (2019)	Mechanism: Postadoption use (selective use)	Fitness wearable devices	619 people, MTurk survey	Based on the goal content theory, this study found that intrinsic exercise and body-focused extrinsic goals are associated with use of data management features; body-focused extrinsic and social extrinsic exercise goals are associated with use of exercise control features;

Study	Category and Theme	Wearable(s)	Sample and Method	Findings
				intrinsic exercise and social extrinsic exercise goals are associated with use of social features. Data and social features are associated with subjective vitality.
Shen et al. (2018)	Mechanism: Postadoption use (intermittent discontinuance)	Wearable health information systems	428 people, survey	Based on expectation-disconfirmation model, this study found that neutral disconfirmation exerts positive effects on neutral satisfaction and attitudinal ambivalence, both of which further have positive effects on intermittent discontinuance. Attitudinal ambivalence also has a positive and significant effect on neutral satisfaction.
Lehrer et al. (2021)	Mechanism: Health behavior change	Wearable devices	50 long-term users, interview	Based on self-leadership theory, this study finds that wearable use patterns of following and combining are associated with behavioral outcomes.
Kooiman et al. (2018)	Output: Individual outcomes (objectively measured)	Fitbit Zip	72 patients with type 2 diabetes, 13-week RCT	An online self-tracking program effectively improved physical activity in patients. While the intervention did not improve glycemic control, it did improve glycemic control in people who increased their step counts during the intervention.
Stiglbauer et al. (2019)	Output: Individual outcomes (self-reported)	Xiaomi Mi Band 2	80 students, 2-week RCT	The fitness tracker had a significant positive effect on users' perceived physical health, their sense of accomplishment, and health consciousness. When the accompanying app was used, the effects were more pronounced.

Study	Category and Theme	Wearable(s)	Sample and Method	Findings
Pickham et al. (2018)	Output: Organizational outcomes (healthcare quality)	The Leaf Patient Monitoring System	1,312 patients, 4-month RCT	The intervention group with wearables had significantly fewer hospital-acquired pressure injuries during intensive care unit admission than the control group.
McFarlane et al. (2018)	Output: Organizational outcomes (healthcare efficiency)	HAIL-CAT smartwatch	16 nurses, randomized within-subject experiment	There was 148% median faster nurse response after the onset of an important alarm/alert on wearable attention aid.

Note:. COVID-19 = coronavirus disease 2019; HAIL-CAT = Human Alerting and Interruption Logistics–Clinical Alarm Triage; MTurk = Amazon Mechanical Turk; MVPA = moderateto vigorous physical activity; RCT = randomized controlled trial.

Some papers studied issues that overlapped across various categories and stages of the I-M-O framework. This highlights the interdisciplinarity as differentiated objectives are addressed in single studies. However, the bulk of studies continue to function in individual categories (*n* = 243). The distribution of studies across different categories is shown in Table 2, which contains a matrix that depicts the number of papers under each theme.

Table 2. Number of Papers ($N = 275$) Sorted by the Input-Mechanism-Output Framework

Category		Stage							
		Input			Mechanism			Output	
		Technology Design	User Acceptance	Engagement Strategy	Adoption	Postadoption Use	Health Behavior Change	Individual Outcomes	Organizational Outcomes
I	Technology design	117							
	User acceptance		56						
	Engagement strategy			3					
M	Adoption	2			19				
	Postadoption use			1	1	7			
	Health behavior change						5		
O	Individual outcomes	2	5	18		1		33	

Category	Stage							
	Input			Mechanism			Output	
	Technology Design	User Acceptance	Engagement Strategy	Adoption	Postadoption Use	Health Behavior Change	Individual Outcomes	Organizational Outcomes
Organizational outcomes								3
I + M + O			2			2	2	
Total across categories	121	61	24	22	10	7	61	3
Total across stages	206			38 (1 paper addressed 2 categories)			64	

Note: The diagonal elements represent the numbers of single-theme papers, while the off-diagonal elements represent the numbers of multitheme papers. I = input; M = mechanism; O = output.

Input Factors: Current Status of the Development of Wearables

The largest proportion of existing literature of wearables addressed topics in the *input* stage (*n* = 206). First, technology design studies (*n* = 121) focused on the development and assessment of novel wearable sensors, algorithms, and integrated platforms for specific health-related purposes. These were mainly feasibility, validity, and usability studies. Second, user acceptance studies (*n* = 61) gauged the acceptance of relatively new wearable products from end-user perspectives, thereby providing guidance for design improvement. These surveyed user attitudes and usage patterns. Third, studies on engagement strategies (*n* = 24) explored user-centric designs that addressed various psychosocial factors to motivate engagement. Four of the engagement strategies identified were social incentives, information feedback, financial incentives, and gamification.

Technology Design (n = 121)

Technology design studies involved the development and assessment of wearable technologies. The three related themes were (a) feasibility (*n* = 89), which comprised proof-of-concept studies that tested novel devices, technological systems, and software; (b) validity (*n* = 31), which comprised studies validating the accuracy of the measurements from wearables in specific conditions and populations (these typically compared the measurements from wearables with gold-standard measurements from established medical equipment used in clinical settings); and (c) usability (*n* = 5), which entailed studies that explored how safe, comfortable, and easy to use wearables were for users.

We noticed that most wearable technologies were in the initial testing phase (feasibility and validity), while the usability studies were comparably limited. Much of the *input* research was conducted within the laboratory (*n* = 66) rather than in commercial settings (*n* = 55) with general consumers or in clinical settings with patients. The focus of input factor is on technology-centered characteristics rather than on end-user adoption characteristics.

Feasibility studies (*n* = 89) explored the use of wearables for mental health (*n* = 22) and physical health (*n* = 67). Over time, wearables are measuring mental health–related information more precisely. An initial study only discriminated stress from normal workload (Setz et al., 2010). Subsequently, measurements became more sophisticated, being able to distinguish between four types of mental state (depression, mixed state, hypomania, and euthymia) in persons with bipolar disorder (Valenza et al., 2014), then proceeding to measure continuous anxiety levels (Betti et al., 2018) and distinct types of emotional states (neutral, tenderness, amusement, anger, disgust, fear, and sadness; Martínez-Rodrigo et al., 2020).

Wearables for physical health have similarly progressed in sophistication over the years. Initially, wearable activity trackers solely provided binary information of active or sedentary behavior (Kelly et al., 2011). Later, with integrated heart rate sensors and accelerometers, wearables for monitoring aerobic activities were developed (Reiss & Stricker, 2014). In addition to monitoring the amount of activity, the quality of activity could be monitored, for instance, gait quality (Schwenk et al., 2015). Further, the performance of wearables for the classification of different activity types has been improved by incorporating signals other than motion, such as temperature (Lui & Menon, 2019).

In addition to directly measuring mental states and physical activity, studies have suggested the feasibility of wearables for reflecting high-level constructs of health-related status. For example, recent studies have proposed using calculations based on activity intensity and duration for predicting physical fatigue (Sedighi Maman et al., 2017) and using gait quality to reflect cognitive ability, thus supporting the diagnosis of dementia (Thorpe et al., 2019).

Likewise, validity studies (n = 31) tested novel wearables for measuring signals reflecting mental health (n = 4) and physical health (n = 27). Those focused on mental health tested the accuracy of the E4 wrist band (Menghini et al., 2019), Apple Watch 3 (Hernando et al., 2018), Fitbit Charge 2 (B. W. Nelson & Allen, 2019), and an integrated system (based on electrocardiogram, electrodermal activity, and electroencephalogram; Betti et al., 2018) for assessing mental status. These studies offered optimistic conclusions about wrist-mounted devices providing accurate estimations of stress in laboratory tests.

For physical health monitoring, validity examinations assessed the accuracy of wearables for measuring step counts (n = 13), sleep (n = 7), gait (n = 9), and electrocardiogram and respiratory signals (n = 1). Overall, the results were less conclusive. First, wearables for step counting produced valid measurements when the research population comprised healthy young people (Ferguson et al., 2015), but when the target population constituted patients with chronic diseases, a significant underestimation of steps was reported (Ummels et al., 2018; Wong et al., 2018). According to the results of validation tests, relatively large measurement errors appeared when wearables were used for measuring activity energy expenditure (Ferguson et al., 2015), walking distance (Compagnat et al., 2019), and activity intensity (Byun et al., 2018). Second, sleep measurement studies showed that consumer-level wearables had high accuracy in measuring total sleep time, but encountered limitations in monitoring deep sleep (de Zambotti et al., 2018) and performed poorly in detecting wake-up times after onset of sleep (J.-M. Lee et al., 2018). Third, studies showed that clinical-grade wearables provided a valid measurement of gait parameters (Fusca et al., 2018) and could capture fall risks with accuracy (Di Rosa et al., 2017). These studies on gait suggest that wearables show promise in the prevention of potential injury in high-risk populations such as older people with chronic diseases and those suffering from obesity. Fourth, one study designed an algorithm based on the unsupervised isolation forest model to reduce false alarms of arrhythmia (Xu et al., 2021).

Last, usability studies (n = 5) assessed how well users responded to the design of wearables. For instance, testing social communication coaching smart-glasses with users who had autism spectrum disorder suggested usability for a range of people of diverse ages and condition severity (Keshav et al., 2017). In another study, researchers confirmed that skin integrity was maintained in older adults who wore sensors for fall detection (Ferrari et al., 2012). Three other studies applied the System Usability Scale evaluation, with two suggesting that a wearable soft-robotic glove received high usability scores in supporting hand functions (Radder et al., 2018), and a smart work cloth proved usable as a workload risk assessment tool (Yang et al., 2018). The final study found that the usability scores of seven mainstream wearable devices were positively correlated with activity type identification function and negatively correlated with price and expandable new features (Liang et al., 2018).

In general, studies reported that users responded well to the physical forms of wearables. At the same time, usability varies between different wearables due to variation in human–computer interface design and other factors such as functions and financial costs.

User Acceptance (n = 61)

Studies on user acceptance involved agreeing with and approving wearables from the end-users' perspective. We noted two themes in this category: (a) attitudes (*n* = 55), from the viewpoints of either potential or actual users toward wearables; and (b) usage (*n* = 17), which comprises statistics of users' usage patterns. Most studies investigated attitudes, while only a small number of studies involved usage surveys.

Studies on attitude (*n* = 55) aimed to collect subjective user perceptions toward novel wearable products. According to surveys, wearable technologies were perceived as fun to use for some people (Naslund et al., 2016) and were also considered useful in terms of providing users with increased knowledge (Jiwani et al., 2021).

However, there were also negative attitudes toward wearables. The most frequently noted concern was the risk of privacy violation (Greenfield et al., 2016). Other concerns were related to stability and maturity of the technology, such as charging, synchronizing, compatibility, data accuracy (Grym et al., 2019), functional limitations (Ehn et al., 2018), and inopportune alerts and attention (Leonard et al., 2017). In addition, specific concerns existed among some populations. For instance, older people with technical anxiety often perceived wearables as difficult to use (Fang & Chang, 2016). Some employees were wary of the massive data trail that businesses could harness and repurpose for other goals (Mettler & Wulf, 2019). Clinicians had concerns about insufficient technical support, work overload, and the risk of patients becoming addicted to data regarding wearables in clinical settings (Bellicha et al., 2017).

Usage (*n* = 17) surveys found that the actual use behavior of wearables varied by consumer demographics and socioeconomic status. A survey in Australia showed that the use of trackers was lower in male, older, less-educated, nonworking, and inactive participants (Alley et al., 2016). A Canadian survey yielded similar results, finding that users of digital self-trackers were typically young, healthy, employed, university-educated, and with a higher annual family income (Paré et al., 2018). Regarding usage patterns, an exponential decay was observed in a study conducted in France; of 711 people receiving a Fitbit device, 562 were still tracking after 100 days, and 114 tracking after 320 days (Hermsen et al., 2017). One study compared the characteristics of current and former users and found that former users had a lower body mass index, reported fewer medical conditions, shared data from their device less often, and received the device as a gift more frequently (Friel et al., 2020).

Engagement Strategy (n = 24)

Studies on engagement strategies investigated user-centered designs based on psychosocial factors to foster acceptance and adherence of wearable-based health interventions. We identified four types of engagement strategies: (a) social incentives (*n* = 11) leveraged the influence of social networks involving experts, friends, family, and so on; (b) information feedback (*n* = 10) included content provided to users about their health status, goal achievements, or performance benchmarking; (c) financial incentives (*n* = 4) were monetary rewards used in the combination of wearable health interventions; (d) and gamification (*n* = 3) was the incorporation of game elements such as competition, points, and virtual gifts to improve participation, loyalty, and fun.

Social incentives (*n* = 11) were informed by social support or social comparison theories. Social support included emotional, informational, instrumental, or companionship resources mediated by technology that one could get from peers, family members, experts, and other people in their social network. Studies suggest that social support, in the form of motivational interviewing (Aschbrenner et al., 2016), habit education (Ellingson et al., 2019), and consultations (Lyons et al., 2017), have the potential to enhance the effect of wearables for increasing physical activity. Social comparison theory suggests that such benchmarking may provide an inspiration to improve; for example, participants who received messages that compared their calorie-burning exercise with that of a friend were more willing to perform preventive healthcare measures (D.-H. Shin & Biocca, 2017).

In general, wearable interventions, in combination with social incentives, helped to improve self-efficacy (Colón-Semenza et al., 2018), enhance motivation (Rönkkö, 2018), and reinforce habit formation (Ellingson et al., 2019). The additional benefits of social incentives were examined in only one study, which found no significant differences (a small increase of ~48 steps/day) between groups that used Fitbit individually or in combination with health coaching (Ellingson et al., 2019).

Information feedback (*n* = 10) as an engagement strategy is informed by conceptualization from human–computer interaction theories to support self-monitoring for achieving health goals. Various formats of information feedback were designed, and their effects were compared. In one study, intelligent auditory cues performed better than verbal feedback in improving gait (Ginis et al., 2017). In another, messages using egocentric statements and contextual goal-setting were more useful than allocentric and fixed-goal messages for health behavior change (Jang & Kim, 2019). Researchers found that text walking distance was more effective than image walking routes in encouraging physical activity participation (D.-H. Shin & Biocca, 2017). Participants with bite-count feedback combined with a bite-count goal consumed less food (Jasper et al., 2016), while motion feedback encouraged participants to stretch more (S. Kim et al., 2018). Idle alerts (Lyons et al., 2017) and activity reminders (Wang et al., 2015) based on wearables were useful for increasing physical activity.

Information feedback helped support self-monitoring, goal-setting, prompts, and cues, and therefore encouraged individuals to participate in healthy behaviors. One study indicated that when wearable-based interventions were combined with short message service (SMS) to prompt physical activity, the intervention group increased their activity by 1,266 steps/week, compared to the control group, which solely used wearables, although the SMS effect lasted for only a week (Wang et al., 2015).

Financial incentives (*n* = 4) are designed based on various psychological principles to enhance the motivation of individuals. Regarding physical activity, studies suggested that a loss-framed financial incentive was effective (Chokshi et al., 2018). Alternatively, a tiered incentive design was more effective compared with a fixed amount (Norman et al., 2016), while rewards in cash were more effective than in the form of a charity donation in the name of participants (Finkelstein et al., 2016). The addition of financial incentives to wearable-based interventions, with total possible incentive of US$268, induced an additional 2-kilogram weight loss in a 12-week intervention (D. W. Shin et al., 2017).

Financial incentives were reported as effective in all four studies, but it was unclear whether the effect could be sustained after the incentives were removed. Among the four studies, two did not investigate the follow-up period, one found that activity levels fell back to baseline values, and another claimed the effects were sustained.

Gamification (*n* = 3) was applied to promote healthy behavior through game-based persuasion. Studies awarded virtual medals (S. Kim et al., 2018) and trophies (Ratz et al., 2019) as rewards for exercise goal attainment. An online game (Clans of Oulu) based on interaction between users allowed players to use earned points to claim area for their clan (Leinonen et al., 2017).

In terms of the effectiveness of gamification, Kim et al. (2018) indicated that the simple design of virtual medal rewards did not show effectiveness, whereas Clans of Oulu, which included enriched game elements such as competition, conflict, collaboration, and scoring or rewards, was effective in promoting moderate-to-vigorous activity (Leinonen et al., 2017).

Mechanisms: Theoretical Explanations About Related Behaviors

Mechanisms were the least studied in the existing literature on wearables. Only 38 studies (14% of the total of 275 papers) covered this by providing theoretical explanations about users' behaviors in using wearables. First, we noted that studies on adoption (*n* = 22) aimed to understand determinants of adoption of wearables and offered theory-based explanations such as the technology acceptance model (TAM). Second, postadoption usage (*n* = 10) studies proposed theoretical models to explain user behaviors after the adoption phase, such as continuous use, selective use, and intermittent discontinuance. Third, studies of health behavior change (*n* = 7) explored the underlying psychosocial mechanisms of users' health-related behavior change, such as increased physical activity induced by the use of wearables.

Adoption (n = 22)

In studies on adoption, the TAM (*n* = 9) and the unified theory of acceptance and use of technology (UTAUT/UTAUT2; *n* = 8) were the most commonly used models to understand the adoption of wearables.

Perceived usefulness and perceived ease of use are the two main underlying constructs in TAM (Davis, 1989). Studies confirmed that perceived usefulness has a significant impact on consumer intention to adopt wearables, while the reported path coefficient varied broadly, from r = 0.21 (Choi et al., 2017) to r = 0.69 (J. Li et al., 2019). Perceived ease of use appeared less important in explaining the adoption of wearables. Some studies showed that the path coefficient was either insignificant (J. Li et al., 2019) or relatively small (the largest path coefficient reported was r = 0.15; Choi et al., 2017).

The UTAUT unified several previous models, including TAM, and identified four determinants—that is, performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). UTAUT2 extended the model by integrating hedonic motivation, price, and habit (Venkatesh et al., 2012). Existing studies reported mixed findings about the determinants of users' intentions to adopt wearables. Some studies reported that performance expectancy and effort expectancy positively affected adoption intention (Wang et al., 2020). However, one study found the two path correlations significant for the adoption of wearable medical devices, but insignificant for the adoption of wearable fitness devices (Gao et al., 2015).

Across the adoption studies, factors concerning the unique characteristics of wearable technologies that directly or indirectly influenced adoption were compatibility (J. Li et al., 2019), usability (Rupp et al., 2018), reliability (J. Kim, 2014), functional congruence (Gao et al., 2015), interactivity (Park et al., 2016), perceived informativeness (H. Li et al., 2016), perceived irreplaceability (Zhang et al., 2017), and perceived credibility (Zhang et al., 2017). At the same time, the influence of incomplete data (Hardy et al., 2018) was not supported. A comparison of the effect size of those factors was not possible since these rarely appeared in studies with high heterogeneity.

Individual differences also explained adoption. Studies revealed that age (Rupp et al., 2018) and self-reported health conditions (J. Li et al., 2019) have negative effects on adoption intention. Self-efficacy, physical activity level, personality (Rupp et al., 2018), innovativeness (Macdonald et al., 2019), and health interest (S. Y. Lee & Lee, 2018) have positive impacts on adoption intention. However, the effect of experience with the technology was not supported (Choi et al., 2017).

Theory-based adoption models provide understanding of the underlying psychosocial mechanisms of how technical features, individuals' internal psychological factors, and external environmental factors impact adoption. Self-determination theory (SDT) and privacy calculus theory (PCT) were applied in the development of adoption models. In line with SDT, consumers tended to adopt wearables with greater affordances to support self-determination needs—namely, autonomy, competence, and relatedness (Rupp et al., 2018). In line with PCT, people's decisions to adopt wearables are determined by risk-benefit analysis. If perceived benefits are higher than perceived risk, then they are more likely to adopt the wearable device (H. Li et al., 2016).

Research models based on technical-centered theories (i.e., TAM, UTAUT/UTAUT2) showed strong power in explaining individual adoption intention toward wearable products, with reported R^2 values ranging from 32% (Zhang et al., 2017) to 69% (J. Li et al., 2019). Models based on PCT offered low explanation power, with one reported R^2 = 15% (H. Li et al., 2016). A model integrating factors from TAM, PCT, and the health belief model showed the strongest explanatory power, with R^2 = 75% (Cheung et al., 2019).

Postadoption Use (n = 10)

Existing studies explored three types of postadoption use behaviors: (a) continued use (n = 6), which refers to long-term adherence after the initial adoption of wearables; (b) selective use of wearable technology features (n = 3), which indicates exploration and selection of different functions of wearables following adoption; and (c) intermittent discontinuance (n = 1), pointing to an in-between state where people neither continuously used the wearable device nor entirely abandoned it.

Researchers explored the determinants of successful adoption, indicated by continued use (n = 6). Determinants identified were users' characteristics, such as self-efficacy (Windasari et al., 2021) and health motivations (Deranek et al., 2021; Peng et al., 2021), and technological features such as accuracy, perceived usefulness, and ease of use (Canhoto & Arp, 2017; Lunney et al., 2016; Shin et al., 2017).

Studies also found that users applied selective use (n = 3) postadoption. This line of research generally highlights a need for fit between the motivation and needs of users and the features of wearables to support achieving health-related goals.

Marakhimov and Joo (2017) used coping theory to develop a theoretical model for predicting the extended use of wearables, including exploring and applying more of the available functions of wearables at hand. The model suggested that concerns about privacy and health initiate a coping process, and coping with problems (r = 0.52) and emotions (r = 0.22) significantly predicted extended use (R^2 = 0.36). Using affordance theory, Jarrahi et al. (2018) identified five groups of users (i.e., aspiring starters, motivation seekers, quantified selfers, curious immobiles, and persistent roamers) and found that the former two types of users interact with both information and motivation aspects of the activity trackers, whereas the latter three only interact with its information affordances. Applying goal content theory, James, Deane et al. (2019) identified three types of exercise goals: intrinsic goals, body-focused extrinsic goals, and social extrinsic goals, and examined how these impact the way users selectively use features of wearable fitness technology. They found that exercisers who had intrinsic goals preferred data features, those who had body-focused goals used data features and social features, and those who had social goals used social features and exercise control features such as goal-setting.

Identifying mechanisms of intermittent discontinuance (n = 1), Shen (2018) found a status in which the adequate expectations on information system use are fulfilled but the desired expectations remain unfulfilled. This is conceptualized as a neutral expectation-disconfirmation based on the expectation-disconfirmation model. It exerts positive effects on neutral satisfaction and attitudinal ambivalence, both of which further have positive effects on intermittent discontinuance.

Health Behavior Change (n = 7)

Studies investigated the psychosocial mechanisms of wearable technologies in promoting health behavior change. Social-cognitive predictors (i.e., self-efficacy, intention, and action planning) partially mediated the relationship between technology interventions, including wearables, and physical activity change (Ratz et al., 2019; Rieder et al., 2021). Health empowerment from self-observation and goal-setting played a mediating role between features of wearables (such as information feedback) and health commitment, which refers to people's psychological attachment to health goals (Nelson et al., 2016). In addition, perceived companionship fully mediated the relationship between feedback types of wearables (allocentric vs. egocentric, fixed-goal vs. contextual-goal) and health behavior change (Jang & Kim, 2019).

James, Deane et al. (2019) suggested that users' specific exercise motivations shape the feature sets of wearable fitness technologies used and that the ramifications of effects occurred due to the interaction between motivation types and feature set use. The results suggest that exercisers who are more self-determined (i.e., with intrinsic regulation) have a positive relationship with subjective vitality and that the use of social interaction features and data management features positively moderated this relationship.

Despite the positive role of wearables for promoting health behavior, one study indicated that the use of wearable activity trackers could create a dependency that can harm motivation (Attig & Franke, 2019). Findings suggest that the dependency effect was stronger for participants with high extrinsic motivation for physical activity, a high need for cognitive closure, and low hope of success.

In conclusion, the mediating mechanisms of wearable-based health behavior change are increasing self-efficacy (Ratz et al., 2019; Rieder et al., 2021), empowerment (Nelson et al., 2016), and perceived companionship (Jang & Kim, 2019). Preexisting motivations and individual characteristics have a moderate effect on the relationship between wearable-based intervention and health behavior change (Attig & Franke, 2019; James, Wallace, et al., 2019). In addition, wearable use patterns of following, ignoring, combining, and self-leading bring about different behavioral outcomes (Lehrer et al., 2021).

Output: Evidence of Effectiveness

Studies in the output stage ($n = 64$) provided evidence of the effectiveness of wearables. First, studies on individual outcomes ($n = 61$) provided evidence of the effectiveness of wearables at the individual level, including improving health behavior and biometric parameters. Second, studies covering organizational outcomes ($n = 3$) applied the use of wearables in hospital settings, examining their effectiveness on improving healthcare quality and efficiency.

Evidence of health-related outcomes in individuals ($n = 61$) dominated, while the effectiveness of wearables in organizations was demonstrated in only three studies. The difference in proportion suggests that organizational outcomes were rarely examined as compared to individual outcomes.

Individual Outcomes (n = 61)

Studies on individual outcomes looked at behavioral or health outcomes related with individual use of wearables. These were either objectively measured (*n* = 41) or self-reported (*n* = 20). Since studies on wearables mostly involved actual use of a wearable device, it made sense that objective measures were more frequently reported.

Studies indicated that the use of wearables is positively associated with self-reported outcomes (*n* = 20) such as health literacy (Sobko & Brown, 2019), health consciousness (Stiglbauer et al., 2019), and general health status (Ratz et al., 2019). More convincing evidence in the form of objectively measured outcomes (*n* = 41) was also provided, which indicates that the use of wearable technology could improve physical activity (Pope et al., 2018), sitting posture (Kuo et al., 2019), gait (Ginis et al., 2017), and food consumption (Jasper et al., 2016).

Among these individual-focused outcomes, the amount of objectively measured physical activity was examined most frequently (*n* = 30), while other outcomes were scarce. Evidence regarding physical activities can be divided into two groups: interventions solely using wearables (*n* = 14), and multifaceted interventions including various engagement strategies in addition to wearables (*n* = 16). Multifaceted interventions appeared to be more effective than those that included just the use of wearables, as we found that approximately 80% (*n* = 13) of the former reported significant improvements in physical activity, whereas only 50% of the latter (*n* = 7) noted improvements.

In the overall literature on individual outcomes, numerous studies showed mixed results of the effectiveness of wearables for intermediate health outcomes (i.e., health behavior change). However, there is a scarcity of evidence regarding endpoint effectiveness (*n* = 2). One study showed that the use of wearables could help lower blood pressure, hemoglobin A1c, and low-density lipoprotein cholesterol in patients with uncontrolled hypertension and type 2 diabetes (Frias et al., 2017). Another study showed that a health program based on wearables did not have significant impact on cholesterol or blood pressure (Yu et al., 2017).

Organizational Outcomes (n = 3)

Studies examined wearables for improvements in healthcare organizations from two aspects: healthcare quality (*n* = 2) and efficiency (*n* = 1). With regard to healthcare quality (*n* = 2), one study suggested that using a wearable patient sensor in an intensive care unit significantly helped to reduce the odds of pressure injuries (intervention group = 0.7% vs. control group = 2.3%) through the provision of optimal turning reminders aided by wearable sensors (Pickham et al., 2018). The other demonstrated that the use of wearable cardioverter defibrillators improved clinician adherence with the guideline-directed medical therapy for patients with heart failure (Mirro et al., 2018). For healthcare efficiency (*n* = 1), one study showed that use of a wearable system (HAIL-CAT [Human Alerting and Interruption Logistics–Clinical Alarm Triage]) for meta-cognitive attention reduced nurses' response time to important alarms in care delivery from 8.12 to 3.27 minutes (McFarlane et al., 2018).

Leveraging wearable technologies in healthcare organizations showed potential for empowering clinicians to take care of patients with high quality and efficiency. Yet, the evidence of the effectiveness of wearables in the clinical setting is scarce, and further investigations are needed.

Discussion

Using the input-mechanism-output (I-M-O) framework, findings from 275 studies on health wearables across technical, social scientific, and health disciplines were summarized. Thereby, an in-depth understanding concerning the development, use, and effectiveness of wearables technology was obtained. For a review of the broader trends across stages, refer to C. Li et al. (2020). Differently, the research status in each of the stages of the I-M-O framework—namely, the input factors, mechanisms, and output factors—was discussed in detail.

The distribution of research across the categories in each stage reflects the emphasis that researchers place on different types of studies within each stage of the I-M-O framework. The emphasis on some categories and the neglect of others reflect the gaps in research and highlight areas for researchers to advance the science on wearable technology.

The distribution of input studies across the categories suggests that the scientific trajectory for new technologies starts from overcoming technical obstacles with studies on technology design, progresses to user acceptance studies that gauge application barriers, and finally arrives at engagement strategy studies for driving effective use. Although the bulk of the input studies (n = 206) focused on technology development (n = 121) and user acceptance (n = 61), an emerging area of research was user engagement (n = 24). Input studies are moving beyond technology design, and there is increasing research for solving problems about users' acceptance and engagement. However, compared to studies on technology design, user-centered studies are largely scattered. The success of wearables for health promotion cannot rely solely on technological factors, but also on psychosocial factors. The status of research on wearables has considerable space for social scientists to make contributions.

The distribution of mechanisms studies across the categories of adoption (n = 22), postadoption usage (n = 10), and health behavior change (n = 7) points to the scarcity of theoretical models that provide an understanding of the continued use of wearables and on health behavior change as compared to adoption mechanisms. It follows that continued use and health behavior change are both hard to achieve. Research studies applying social cognitive frameworks are needed to provide principles and mechanisms that can inform, guide, and motivate people through the continuance of wearables and, thereafter, behavior change.

The distribution of output studies reveals that research on wearables has mainly been focused on individuals and not on organizations. However, positive outcomes were noted in the three papers that covered the use of wearables at the organizational level, suggesting potential benefit of organizational implementation. More studies are advocated to test the efficacy of wearables at the organizational level. Admittedly, there may be more hoops to jump through in administering such interventions in hospital settings. Thus, the suggestion is to begin in smaller organizational settings such as nursing homes, before scaling up to larger-scale interventions at big hospitals.

More studies assess the technological development of wearables in well-controlled laboratory settings (n = 66) than in field settings (n = 55). In laboratory tests, researchers can control parameters, which may lead to less realistic conditions. In addition, laboratory-based wearables are usually expensive, time-consuming, and impractical for long-term use (de Zambotti et al., 2018). Therefore, more practical and suitable wearables for prolonged recordings in free-living settings are needed (Han & Wang, 2017). Additionally, researchers had conservative or negative attitudes toward using wearables in research and clinical settings because of the uncertainties of their performance. The mixed results from validation tests hinder the formal adoption of wearables in clinical settings for serious use. At the same time, with the integration trends of sensors and advancement of algorithms, wearable measurements are getting progressively more detailed and precise. Studies also suggested the feasibility of wearables for reflecting high-level constructs, such as physical and mental frailty and cognitive ability, through computing direct measures of physiological indicators. Therefore, laboratory-based wearables can be further tweaked for consumer use, and validation tests should be performed in real-world situations to verify the validity of these devices.

Studies that looked at user attitudes reported positive attitudes, indicating potential for higher adoption rates and more intervention studies. The most frequently mentioned concern was violation of privacy, which has been addressed in a previous review (C. Li et al., 2020). Nonetheless, both utilitarian and hedonic aspects of wearables were valued by users. Social scientists can derive more engagement strategies, adding to the current four that we noted (social, informational, financial, gamification), to further inform the development, adoption, and use of wearables. Further, the current bias of usage patterns suggest that wearable devices currently appeal to more technology-savvy and health-conscious people. This insight is valuable for researchers and public health professionals aiming to foster the use of wearables in specific population subgroups, such as older people and patients with chronic disease.

Technocentric theories, such as the technology acceptance model (TAM) and the unified theory of acceptance and use of technology, sufficiently explain adoption of wearables. However, the integration of more user-centric theories seems to yield greater explanatory power. Compared to factors that explain adoption, determinants of postadoption use tend to be experience-based assessments of wearables. The explanatory power of TAM for understanding continued use becomes less effective postadoption, but the underlying mechanism for continued use is still not fully addressed. This is a research gap that future studies can explore—namely, what determines continued use (or abandonment) of wearables postadoption.

Only seven studies explored the mechanisms of health behavior change. These were mainly driven by psychosocial theories that explain how people react to the components in wearables. Nonetheless, as Sullivan and Lachman (2017) note, it remains unclear how different behavior change techniques result in actual behavior outcomes. Therefore, more theory-driven studies are needed to understand how and why wearables are effective (or not).

References

Alley, S., Schoeppe, S., Guertler, D., Jennings, C., Duncan, M. J., & Vandelanotte, C. (2016). Interest and preferences for using advanced physical activity tracking devices: results of a national cross-sectional survey <https://doi.org/10.1136/bmjopen-2016-011243>. *BMJ Open*, *6*(7), Article e011243.

Amft, O. (2018). How wearable computing is shaping digital health <https://doi.org/10.1109/MPRV.2018.011591067>. *IEEE Pervasive Computing*, *17*(1), 92–98.

Aschbrenner, K. A., Naslund, J. A., Shevenell, M., Kinney, E., & Bartels, S. J. (2016). A pilot study of a peer-group lifestyle intervention enhanced with mHealth technology and social media for adults with serious mental illness <https://doi.org/10.1097/nmd.0000000000000530>. *Journal of Nervous and Mental Disease*, *204*(6), 483–486.

Aschbrenner, K. A., Naslund, J. A., Shevenell, M., Mueser, K. T., & Bartels, S. J. (2016). Feasibility of behavioral weight loss treatment enhanced with peer support and mobile health technology for individuals with serious mental illness <https://doi.org/10.1007/s11126-015-9395-x>. *Psychiatric quarterly*,*87*(3), 401–415.

Attig, C., & Franke, T. (2019). I track, therefore I walk - Exploring the motivational costs of wearing activity trackers in actual users <https://doi.org/10.1016/j.ijhcs.2018.04.007>. *International Journal of Human-Computer Studies*, *127*, 211–224.

Bellicha, A., Mace, S., & Oppert, J. M. (2017). Prescribing of Electronic Activity Monitors in Cardiometabolic Diseases: Qualitative Interview-Based Study [qualitative] <https://doi.org/10.2196/jmir.8107>. *Journal of Medical Internet Research*, *19*(9), Article e328.

Betti, S., Lova, R. M., Rovini, E., Acerbi, G., Santarelli, L., Cabiati, M., Del Ry, S., & Cavallo, F. (2018). Evaluation of an integrated system of wearable physiological sensors for stress monitoring in working environments by using biological markers <https://doi.org/10.1109/tbme.2017.2764507>. *IEEE Transactions on Biomedical Engineering*, *65*(8), 1748–1758.

Brew-Sam, N., & Chib, A. (2019). How do smart device apps for diabetes self-management correspond with theoretical indicators of empowerment? An analysis of app features <https://doi.org/10.1017/S0266462319000163>. *International Journal of Technology Assessment in Health Care*, *35*(2), 150–159.

Brickwood, K. J., Watson, G., O'Brien, J., & Williams, A. D. (2019). Consumer-based wearable activity trackers increase physical activity participation: Systematic review and meta-analysis <https://doi.org/10.2196/11819>. *JMIR mHealth and uHealth*, *7*(4), e11819.

Byun, W., Lau, E. Y., & Brusseau, T. A. (2018). Feasibility and effectiveness of a wearable technology-based physical activity intervention in preschoolers: A pilot study <https://doi.org/10.3390/ijerph15091821>. *International Journal of Environmental Research and Public Health*, *15*(9), Article 1821.

Canhoto, A. I., & Arp, S. (2017). Exploring the factors that support adoption and sustained use of health and fitness wearables <https://doi.org/10.1080/0267257x.2016.1234505>. *Journal of Marketing Management*, *33*(1–2), 32–60.

Cheung, M. L., Chau, K. Y., Lam, M. H. S., Tse, G., Ho, K. Y., Flint, S. W., Broom, D. R., Tso, E. K. H., & Lee, K. Y. (2019). Examining consumers' adoption of wearable healthcare technology: The role of health attributes <https://doi.org/10.3390/ijerph16132257>. *International Journal of Environmental Research and Public Health*, *16*(13), 2257.

Chib, A., & Lin, S. H. (2018). Theoretical advancements in mHealth: A systematic review of mobile apps <https://doi.org/10.1080/10810730.2018.1544676>. *Journal of Health Communication*, *23*(10–11), 909–955.

Chib, A., van Velthoven, M. H., & Car, J. (2015). mHealth adoption in low-resource environments: A review of the use of mobile healthcare in developing countries <https://doi.org/10.1080/10810730.2013.864735>. *Journal of Health Communication*, *20*(1), 4–34.

Choi, B., Hwang, S., & Lee, S. (2017). What drives construction workers' acceptance of wearable technologies in the workplace?: Indoor localization and wearable health devices for occupational safety and health <https://doi.org/10.1016/j.autcon.2017.08.005>. *Automation in Construction*, *84*, 31–41.

Chokshi, N. P., Adusumalli, S., Small, D. S., Morris, A., Feingold, J., Ha, Y. P., Lynch, M. D., Rareshide, C. A. L., Hilbert, V., & Patel, M. S. (2018). Loss-framed financial incentives and personalized goal-setting to increase physical activity among ischemic heart disease patients using wearable devices: The ACTIVE REWARD randomized trial <https://doi.org/10.1161/jaha.118.009173>. *Journal of the American Heart Association*, *7*(12), Article e009173.

Colón-Semenza, C., Latham, N. K., Quintiliani, L. M., & Ellis, T. D. (2018). Peer coaching through mHealth targeting physical activity in people with parkinson isease: Feasibility study <https://doi.org/10.2196/mhealth.8074>. *JMIR Mhealth and Uhealth*, *6*(2), Article e42.

Compagnat, M., Batcho, C. S., David, R., Vuillerme, N., Salle, J. Y., Daviet, J. C., & Mandigout, S. (2019). Validity of the walked distance estimated by wearable devices in stroke individuals <https://doi.org/10.3390/s19112497>. *Sensors*, *19*(11), Article 2497.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology <https://doi.org/10.2307/249008>. *MIS Quarterly*, *13*(3), 319–340.

Deranek, K., Hewitt, B., Gudi, A., & McLeod, A. (2021). The impact of exercise motives on adolescents' sustained use of wearabletechnology <https://doi.org/10.1080/0144929X.2020.1720295>. *Behaviour & Information Technology*, *40*(7), 691–705.

de Zambotti, M., Baker, F. C., Willoughby, A. R., Godino, J. G., Wing, D., Patrick, K., & Colrain, I. M. (2016). Measures of sleep andcardiac functioning during sleep using a multi-sensory commercially-available wristband in adolescents <https://doi.org/10.1016/j.physbeh.2016.03.006>. *Physiology & Behavior*, *158*, 143–149.

de Zambotti, M., Goldstone, A., Claudatos, S., Colrain, I. M., & Baker, F. C. (2018). A validation study of Fitbit Charge 2 (TM) compared with polysomnography in adults <https://doi.org/10.1080/07420528.2017.1413578>. *Chronobiology International*, *35*(4), 465–476.

Di Rosa, M., Hausdorff, J. M., Stara, V., Rossi, L., Glynn, L., Casey, M., Burkard, S., & Cherubini, A. (2017). Concurrent validation of an index to estimate fall risk in community dwelling seniors through a wireless sensor insole system: A pilot study <https://doi.org/10.1016/j.gaitpost.2017.03.037>. *Gait & Posture*, *55*, 6–11.

Ehn, M., Eriksson, L. C., Akerberg, N., & Johansson, A. C. (2018). Activity monitors as support for older persons' physical activity in daily life: Qualitative study of the users' experiences <https://doi.org/10.2196/mhealth.8345>. *JMIR Mhealth and Uhealth*, *6*(2), Article e34.

Elgendi, M., & Menon, C. (2019). Assessing anxiety disorders using wearable devices: Challenges and future directions <*https://doi.org/10.3390/brainsci9030050*>. *Brain Sciences*, *9*(3), 50.

Ellingson, L. D., Lansing, J. E., DeShaw, K. J., Peyer, K. L., Bai, Y., Perez, M., Phillips, L. A., & Welk, G. J. (2019). Evaluating motivational interviewing and habit formation to enhance the effect of activity trackers on healthy adults' activity levels: Randomized intervention <*https://doi.org/10.2196/10988*>. *JMIR Mhealth and Uhealth*, *7*(2), Article e10988.

Fang, Y. M., & Chang, C. C. (2016). Users' psychological perception and perceived readability of wearable devices for elderly people <*https://doi.org/10.1080/0144929x.2015.1114145*>. *Behaviour & Information Technology*, *35*(3), 225–232.

Farivar, S., Abouzahra, M., & Ghasemaghaei, M. (2020). Wearable device adoption among older adults: A mixed-methods study <*https://doi.org/10.1016/j.ijinfomgt.2020.102209*>. *International Journal of Information Management*, *55*, Article 102209.

Ferguson, T., Rowlands, A. V., Olds, T., & Maher, C. (2015). The validity of consumer-level, activity monitors in healthy adults worn in free-living conditions: a cross-sectional study <*https://doi.org/10.1186/s12966-015-0201-9*>. *International Journal of Behavioral Nutrition and Physical Activity*, *12*, Article 42.

Ferrari, M., Harrison, B., Rawashdeh, O., Hammond, R., Avery, Y., Rawashdeh, M., Sa'deh, W., & Maddens, M. (2012). Clinical feasibility trial of a motion detection system for fall prevention in hospitalized older adult patients <*https://doi.org/10.1016/j.gerinurse.2011.11.011*>. *Geriatric Nursing*, *33*(3), 177–183.

Finkelstein, E. A., Haaland, B. A., Bilger, M., Sahasranaman, A., Sloan, R. A., Nang, E. E. K., & Evenson, K. R. (2016). Effectiveness of activity trackers with and without incentives to increase physical activity (TRIPPA): A randomised controlled trial <*https://doi.org/10.1016/s2213-8587(16)30284-4*>. *Lancet Diabetes & Endocrinology*, *4*(12), 983–995.

Frias, J., Virdi, N., Raja, P., Kim, Y., Savage, G., & Osterberg, L. (2017). Effectiveness of digital medicines to improve clinical outcomes in patients with uncontrolled hypertension and type 2 diabetes: Prospective, open-label, cluster-randomized pilot clinical trial <*https://doi.org/10.2196/jmir.7833*>. *Journal of Medical Internet Research*, *19*(7), e246.

Friel, C. P., & Garber, C. E. (2020). Who uses wearable activity trackers and why? A comparison of former and current users in the United States <*https://doi.org/10.1177/0890117120919366*>. *American Journal of Health Promotion*, *34*(7), 762–769, Article 0890117120919366.

Fusca, M., Negrini, F., Perego, P., Magoni, L., Molteni, F., & Andreoni, G. (2018). Validation of a wearable IMU system for gait analysis: Protocol and application to a new system <*https://doi.org/10.3390/app8071167*>. *Applied Sciences-Basel*, *8*(7), Article 1167.

Gao, Y. W., Li, H., & Luo, Y. (2015). An empirical study of wearable technology acceptance in healthcare <*https://doi.org/10.1108/imds-03-2015-0087*>. *Industrial Management & Data Systems*, *115*(9), 1704–1723.

Ginis, P., Heremans, E., Ferrari, A., Dockx, K., Canning, C. G., & Nieuwboer, A. (2017). Prolonged walking with a wearable system providing intelligent auditory input in people with parkinson's disease <*https://doi.org/10.3389/fneur.2017.00128*>. *Frontiers in Neurology*, *8*, Article 128.

Greenfield, R., Busink, E., Wong, C. P., Riboli-Sasco, E., Greenfield, G., Majeed, A., Car, J., & Wark, P. A. (2016). Truck drivers' perceptions on wearable devices and health promotion: A qualitative study <*https://doi.org/10.1186/s12889-016-3323-3*>. *BMC Public Health*, *16*, Article 677.

Grym, K., Niela-Vilen, H., Ekholm, E., Hamari, L., Azimi, I., Rahmani, A., Liljeberg, P., Loyttyniemi, E., & Axelin, A. (2019). Feasibility of smart wristbands for continuous monitoring during pregnancy and one month after birth <https://doi.org/10.1186/s12884-019-2187-9>. *BMC Pregnancy and Childbirth*, *19*, Article 34.

Han, K.-T., & Wang, P.-C. (2017). Validity of research-grade actigraphy unit for measuring exercise intensity <https://doi.org/10.3390/ijerph14050511>. *International Journal of Environmental Research and Public Health*, *14*(5), 511.

Hardy, J., Veinot, T. C., Yan, X., Berrocal, V. J., Clarke, P., Goodspeed, R., Gomez-Lopez, I. N., Romero, D., & Vydiswaran, V. G. V. (2018). User acceptance of location-tracking technologies in health research: Implications for study design and data quality <https://doi.org/10.1016/j.jbi.2018.01.003>. *Journal of Biomedical Informatics*, *79*, 7–19.

Hermsen, S., Moons, J., Kerkhof, P., Wiekens, C., & De Groot, M. (2017). Determinants for sustained use of an activity tracker: Observational study <https://doi.org/10.2196/mhealth.7311>. *JMIR Mhealth and Uhealth*, *5*(10), Article e164.

Hernando, D., Roca, S., Sancho, J., Alesanco, A., & Bailon, R. (2018). Validation of the apple watch for heart rate variability measurements during relax and mental stress in healthy subjects <https://doi.org/10.3390/s18082619>. *Sensors*, *18*(8), Article 2619.

James, T. L., Deane, J. K., & Wallace, L. (2019). An application of goal content theory to examine how desired exercise outcomes impact fitness technology feature set selection <https://doi.org/10.1111/isj.12233>. *Information Systems Journal*, *29*(5), 1010–1039.

James, T. L., Wallace, L., & Deane, J. K. (2019). Using organismic integration theory to explore the associations between users' exercise motivations and fitness technology feature set use <https://doi.org/10.25300/misq/2019/14128>. *Mis Quarterly*, *43*(1), 287–312.

Jang, J., & Kim, J. (2019). Healthier life with digital companions: Effects of reflection-level and statement-type of messages on behavior change via a perceived companion <https://doi.org/10.1080/10447318.2019.1615722>. *International Journal of Human-Computer Interaction*, *36*(2), 172–189.

Jarrahi, M. H., Gafinowitz, N., & Shin, G. (2018). Activity trackers, prior motivation, and perceived informational and motivational affordances <https://doi.org/10.1007/s00779-017-1099-9>. *Personal and Ubiquitous Computing*, *22*(2), 433–448.

Jasper, P. W., James, M. T., Hoover, A. W., & Muth, E. R. (2016). Effects of bite count feedback from a wearable device and goal setting on consumption in young adults <https://doi.org/10.1016/j.jand.2016.05.004>. *Journal of the Academy of Nutrition and Dietetics*, *116*(11), 1785–1793.

Jiwani, R., Dennis, B., Bess, C., Monk, S., Meyer, K., Wang, J., & Espinoza, S. (2021). Assessing acceptability and patient experience of a behavioral lifestyle intervention using fitbit technology in older adults to manage type 2 diabetes amid COVID-19 pandemic: A focus group study <https://doi.org/10.1016/j.gerinurse.2020.11.007>. *Geriatric Nursing*, *42*(1), 57–64.

Khakurel, J., Melkas, H., & Porras, J. (2018). Tapping into the wearable device revolution in the work environment: A systematic review <https://doi.org/10.1108/ITP-03-2017-0076>. *Information Technology & People*, *31*(3), 791–818.

Kelly, P., Doherty, A., Berry, E., Hodges, S., Batterham, A. M., & Foster, C. (2011). Can we use digital life-log images to investigate active and sedentary travel behaviour? Results from a pilot study <https://doi.org/10.1186/1479-5868-8-44>. *International Journal of Behavioral Nutrition and Physical Activity*, *8*, Article 44.

Keshav, N. U., Salisbury, J. P., Vahabzadeh, A., & Sahin, N. T. (2017). Social communication coaching smartglasses: Well tolerated in a diverse sample of children and adults with Autism <https://doi.org/10.2196/mhealth.8534>. *JMIR Mhealth and Uhealth*, *5*(9), Article e140.

Kim, J. (2014). Analysis of health consumers' behavior using self-tracker for activity, sleep, and diet <https://doi.org/10.1089/tmj.2013.0282>. *Telemedicine and E-Health*, *20*(6), 552–558.

Kim, D. S., Lee, H. J., Lee, S. H., Chang, W. H., Jang, J., Choi, B. O., Ryu, G. H., & Kim, Y. H. (2018). A wearable hip-assist robot reduces the cardiopulmonary metabolic energy expenditure during stair ascent in elderly adults: A pilot cross-sectional study <https://doi.org/10.1186/s12877-018-0921-1>. *BMC Geriatrics*, *18*, Article 230.

Knowles, B., Smith-Renner, A., Poursabzi-Sangdeh, F., Lu, D., & Alabi, H. (2018). Uncertainty in current and future health wearables <https://doi.org/10.1145/3199201>. *Communications of the ACM*, *61*(12), 62–67.

Kooiman, T. J. M., de Groot, M., Hoogenberg, K., Krijnen, W. P., van der Schans, C. P., & Kooy, A. (2018). Self-tracking of physical activity in people with type 2 diabetes a randomized controlled trial <https://doi.org/10.1097/cin.0000000000000443>. *Cin-Computers Informatics Nursing*, *36*(7), 340–349.

Lee, J.-M., Byun, W., Keill, A., Dinkel, D., & Seo, Y. (2018). Comparison of wearable trackers' ability to estimate sleep <https://doi.org/10.3390/ijerph15061265>. *International Journal of Environmental Research and Public Health*, *15*(6), 1265.

Lee, S. Y., & Lee, K. (2018). Factors that influence an individual's intention to adopt a wearable healthcare device: The case of a wearable fitness tracker <https://doi.org/10.1016/j.techfore.2018.01.002>. *Technological Forecasting and Social Change*, *129*, 154–163.

Kuo, Y. L., Wang, P. S., Ko, P. Y., Huang, K. Y., & Tsai, Y. J. (2019). Immediate effects of real-time postural biofeedback on spinal posture, muscle activity, and perceived pain severity in adults with neck pain <https://doi.org/10.1016/j.gaitpost.2018.10.021>. *Gait & Posture*, *67*, 187–193.

Lehrer, C., Eseryel, U. Y., Rieder, A., & Jung, R. (2021). Behavior change through wearables: The interplay between self-leadership and IT-based leadership <https://doi.org/10.1007/s12525-021-00474-3>. *Electronic Markets*, *31*(4), 747–764.

Leinonen, A. M., Pyky, R., Ahola, R., Kangas, M., Siirtola, P., Luoto, T., Enwald, H., Iakheimo, T. M., Roning, J., Keinanen-Kiukaanniemi, S., Mantysaari, M., Korpelainen, R., & Jamsa, T. (2017). Feasibility of gamified mobile service aimed at physical activation in young men: Population-based randomized controlled study (MOPO) <https://doi.org/10.2196/mhealth.6675>. *JMIR Mhealth and Uhealth*, *5*(10), Article e146.

Leonard, N. R., Silverman, M., Sherpa, D. P., Naegle, M. A., Kim, H., Coffman, D. L., & Ferdschneider, M. (2017). Mobile health technology using a wearable sensorband for female college students with problem drinking: An acceptability and feasibility study <https://doi.org/10.2196/mhealth.7399>. *JMIR Mhealth and Uhealth*, *5*(7), Article e90.

Li, C., Chen, X., & Bi, X. (2021). Wearable activity trackers for promoting physical activity: A systematic meta-analytic review. *International Journal of Medical Informatics*, *152*(104), 487.

Li, C., Lin, S., & Chib, A. (2020). The state of wearable health technologies: A transdisciplinary literature review. *Mobile Media & Communication*, *9*(2), 353–376.

Li, H., Wu, J., Gao, Y., & Shi, Y. (2016). Examining individuals' adoption of healthcare wearable devices: An empirical study from privacy calculus perspective <https://doi.org/10.1016/j.ijmedinf.2015.12.010>. *International Journal of Medical Informatics*, *88*, 8–17.

Li, J., Ma, Q., Chan, A. H., & Man, S. S. (2019). Health monitoring through wearable technologies for older adults: Smart wearables acceptance model <https://doi.org/10.1016/j.apergo.2018.10.006>. *Applied Ergonomics*, *75*, 162–169.

Li, X., Dunn, J., Salins, D., Zhou, G., Zhou, W., Schüssler-Fiorenza Rose, S. M., Perelman, D., Colbert, E., Runge, R., Rego, S., Sonecha, R., Datta, S., McLaughlin, T., & Snyder, M. P. (2017). Digital health: Tracking physiomes and activity using wearable biosensors reveals useful health-related information <https://doi.org/10.1371/journal.pbio.2001402>. *PLoS Biology*, *15*(1), e2001402.

Liang, J., Xian, D. Q., Liu, X. Y., Fu, J., Zhang, X. T., Tang, B. Z., & Lei, J. B. (2018). Usability study of mainstream wearable fitness devices: Feature analysis and system usability scale evaluation <https://doi.org/10.2196/11066>. *JMIR Mhealth and Uhealth*, *6*(11), Article e11066.

Lui, J., & Menon, C. (2019). Would a thermal sensor improve arm motion classification accuracy of a single wrist-mounted inertial device? <https://doi.org/10.1186/s12938-019-0677-7>. *Biomedical Engineering Online*, *18*, Article 53.

Lunney, A., Cunningham, N. R., & Eastin, M. S. (2016). Wearable fitness technology: A structural investigation into acceptance and perceived fitness outcomes <https://doi.org/10.1016/j.chb.2016.08.007>. *Computers in Human Behavior*, *65*, 114–120.

Lyons, E. J., Swartz, M. C., Lewis, Z. H., Martinez, E., & Jennings, K. (2017). Feasibility and acceptability of a wearable technology physical activity intervention with telephone counseling for mid-aged and older adults: A randomized controlled pilot trial <https://doi.org/10.2196/mhealth.6967>. *JMIR Mhealth and Uhealth*, *5*(3), Article e28.

Macdonald, E. M., Perrin, B. M., Hyett, M., & Kingsley, M. I. C. (2019). Factors influencing behavioural intention to use a smart shoe insole in regionally based adults with diabetes: A mixed methods study <https://doi.org/10.1186/s13047-019-0340-3>. *Journal of Foot and Ankle Research*, *12*, Article 29.

Majumder, S., Mondal, T., & Deen, M. (2017). Wearable sensors for remote health monitoring <https://doi.org/10.3390/s17010130>. *Sensors*, *17*(12), 130.

Maman, Z. S., Yazdi, M. A. A., Cavuoto, L. A., & Megahed, F. M. (2017). A data-driven approach to modeling physical fatigue in the workplace using wearable sensors <https://doi.org/10.1016/j.apergo.2017.02.001>. *Applied Ergonomics*, *65*, 515–529.

Marakhimov, A., & Joo, J. (2017). Consumer adaptation and infusion of wearable devices for healthcare <https://doi.org/10.1016/j.chb.2017.07.016>. *Computers in Human Behavior*, *76*, 135–148.

Mardonova, M., & Choi, Y. (2018). Review of wearable device technology and its applications to the mining industry <https://doi.org/10.3390/en11030547>. *Energies*, *11*(3), 547.

Martínez-Rodrigo, A., Fernández-Aguilar, L., Zangróniz, R., Latorre, J. M., Pastor, J. M., & Fernández-Caballero, A. (2020). Film mood induction and emotion classification using physiological signals for health and wellness promotion in older adults living alone <https://doi.org/10.1111/exsy.12425>. *Expert Systems: International Journal of Knowledge Engineering and Neural Networks*, *37*(2), e12425.

McFarlane, D. C., Doig, A. K., Agutter, J. A., Brewer, L. M., Syroid, N. D., & Mittu, R. (2018). Faster clinical response to the onset of adverse events: A wearable metacognitive attention aid for nurse triage of clinical alarms <https://doi.org/10.1371/journal.pone.0197157>. *PLOS ONE*, *13*(5), Article e0197157.

Menghini, L., Gianfranchi, E., Cellini, N., Patron, E., Tagliabue, M., & Sarlo, M. (2019). Stressing the accuracy: Wrist-worn wearable sensor validation over different conditions <https://doi.org/10.1111/psyp.13441>. *Psychophysiology*, *56*(11), e13441.

Mettler, T., & Wulf, J. (2019). Physiolytics at the workplace: Affordances and constraints of wearables use from an employee's perspective <https://doi.org/10.1111/isj.12205>. *Information Systems Journal*, *29*(1), 245–273.

Mirro, M. J., Keltner, E. E., Roebuck, A. E., & Sears, S. F. (2018). Playing it close to the VEST and the clinical guidelines: Clinical guideline compliance in HFrEF patientsRole of WCD <https://doi.org/10.1111/pace.13472>. *Pace-Pacing and Clinical Electrophysiology*, *41*(10), 1314–1320.

Naslund, J. A., Aschbrenner, K. A., & Bartels, S. J. (2016). Wearable devices and smartphones for activity tracking among people with serious mental illness <https://doi.org/10.1016/j.mhpa.2016.02.001>. *Mental Health and Physical Activity*, *10*, 10–17.

Nelson, B. W., & Allen, N. B. (2019). Accuracy of consumer wearable heart rate measurement during an ecologically valid 24-Hour period: Intraindividual validation study <https://doi.org/10.2196/10828>. *JMIR Mhealth and Uhealth*, *7*(3), Article e10828.

Nelson, E. C., Verhagen, T., & Noordzij, M. L. (2016). Health empowerment through activity trackers: An empirical smart wristband study <https://doi.org/10.1016/j.chb.2016.03.065>. *Computers in Human Behavior*, *62*, 364–374.

Norman, G. J., Heltemes, K. J., Heck, D., & Osmick, M. J. (2016). Employee use of a wireless physical activity tracker within two incentive designs at one company <https://doi.org/10.1089/pop.2015.0030>. *Population Health Management*, *19*(2), 88–94.

Paré, G., Leaver, C., & Bourget, C. (2018). Diffusion of the digital health self-tracking movement in Canada: Results of a national survey [qualitative] <https://doi.org/10.2196/jmir.9388>. *Journal of Medical Internet Research*, *20*(5), Article e177.

Park, E., Kim, K. J., & Kwon, S. J. (2016). Understanding the emergence of wearable devices as next-generation tools for health communication <https://doi.org/10.1108/ITP-04-2015-0096>. *Information Technology & People*, *29*(4), 717–732.

Peng, W., Li, L., Kononova, A., Cotten, S., Kamp, K., & Bowen, M. (2021). Habit formation in wearable activity tracker use among older adults: Qualitative study <https://doi.org/10.2196/22488>. *JMIR Mhealth and Uhealth*, *9*(1), Article e22488.

Pickham, D., Berte, N., Pihulic, M., Valdez, A., Mayer, B., & Desai, M. (2018). Effect of a wearable patient sensor on care delivery for preventing pressure injuries in acutely ill adults: A pragmatic randomized clinical trial (LS-HAPI study) <https://doi.org/10.1016/j.ijnurstu.2017.12.012>. *International Journal of Nursing Studies*, *80*, 12–19.

Pope, Z. C., Zeng, N., Zhang, R., Lee, H. Y., & Gao, Z. (2018). Effectiveness of combined smartwatch and social media intervention on breast cancer survivor health outcomes: A 10-week pilot randomized trial <https://doi.org/10.3390/jcm7060140>. *Journal of Clinical Medicine*, *7*(6), Article 140.

Radder, B., Prange-Lasonder, G. B., Kottink, A. I. R., Melendez-Calderon, A., Buurke, J. H., & Rietman, J. S. (2018). Feasibility of a wearable soft-robotic glove to support impaired hand function in stroke patients <https://doi.org/10.2340/16501977-2357>. *Journal of Rehabilitation Medicine*, *50*(7), 598–606.

Ratz, T., Lippke, S., Muellmann, S., Peters, M., Pischke, C. R., Meyer, J., Bragina, I., & Voelcker-Rehage, C. (2019). Effects of two webbased interventions and mediating mechanisms on stage of change regarding physical activity in older adults <https://doi.org/10.1111/aphw.12174>. *Applied Psychology-Health and Well Being*, *12*(1), 77–100.

Reiss, A., & Stricker, D. (2014). Aerobic activity monitoring: towards a long-term approach <https://doi.org/10.1007/s10209-013-0292-5>. Universal Access in the Information Society, 13(1), 101–114.

Rieder, A., Eseryel, U. Y., Lehrer, C., & Jung, R. (2021). Why users comply with wearables: The role of contextual self-efficacy in behavioral change <https://doi.org/10.1080/10447318.2020.1819669>. *International Journal of Human-computer Interaction*, *37*(3), 281–294.

Rönkkö, K. (2018). An activity tracker and its accompanying app as a motivator for increased exercise and better sleeping habits for youths in need of social care: Field study <https://doi.org/10.2196/mhealth.9286>. *JMIR Mhealth and Uhealth*, *6*(12), Article e193.

Rupp, M. A., Michaelis, J. R., McConnell, D. S., & Smither, J. A. (2018). The role of individual differences on perceptions of wearable fitness device trust, usability, and motivational impact <https://doi.org/10.1016/j.apergo.2018.02.005>. *Applied Ergonomics*, *70*, 77–87.

Schwenk, M., Mohler, J., Wendel, C., D'Huyvetter, K., Fain, M., Taylor-Piliae, R., & Najafi, B. (2015). Wearable sensor-based in-home assessment of gait, balance, and physical activity for discrimination of frailty status: Baseline results of the Arizona Frailty Cohort Study <https://doi.org/10.1159/000369095>. *Gerontology*, *61*(3), 258–267.

Setz, C., Arnrich, B., Schumm, J., La Marca, R., Troster, G., & Ehlert, U. (2010). Discriminating stress from cognitive load using a Wearable EDA device <https://doi.org/10.1109/titb.2009.2036164>. *IEEE Transactions on Information Technology in Biomedicine*, *14*(2), 410–417.

Shen, X. L., Li, Y. J., & Sun, Y. Q. (2018). Wearable health information systems intermittent discontinuance: A revised expectationdisconfirmation model <https://doi.org/10.1108/imds-05-2017-0222>. *Industrial Management & Data Systems*, *118*(3), 506–523.

Shin, D. H., & Biocca, F. (2017). Health experience model of personal informatics: The case of a quantified self <https://doi.org/10.1016/j.chb.2016.12.019>. *Computers in Human Behavior*, *69*, 62–74.

Shin, D. W., Yun, J. M., Shin, J.-H., Kwon, H., Min, H. Y., Joh, H.-K., Chung, W. J., Park, J. H., Jung, K.-T., & Cho, B. (2017). Enhancing physical activity and reducing obesity through smartcare and financial incentives: A pilot randomized trial <https://doi.org/10.1002/oby.21731>. *Obesity*, *25*(2), 302–310.

Sobko, T., & Brown, G. (2019). Reflecting on personal data in a health course: Integrating wearable technology and ePortfolio for eHealth <https://doi.org/10.14742/ajet.4027>. *Australasian Journal of Educational Technology*, *35*(3), 55–70.

Sprogis, S. K., Currey, J., & Considine, J. (2019). Patient acceptability of wearable vital sign monitoring technologies in the acute care setting: A systematic review <https://doi.org/10.1111/jocn.14893>. *Journal of Clinical Nursing*, *28*(15–16), 2732–2744.

Statista. (2022). *Medical wearable devices market revenue worldwide 2021–2026, by region* <https://www.statista.com/>.

Stiglbauer, B., Weber, S., & Batinic, B. (2019). Does your health really benefit from using a self-tracking device? Evidence from a longitudinal randomized control trial <https://doi.org/10.1016/j.chb.2019.01.018>. *Computers in Human Behavior*, *94*, 131–139.

Sullivan, A. N., & Lachman, M. E. (2017). Behavior change with fitness technology in sedentary adults: A review of the evidence for increasing physical activity <https://doi.org/10.3389/fpubh.2016.00289>. *Frontiers in Public Health*, *4*, 289.

Thorpe, J. R., Forchhammer, B. H., & Maier, A. M. (2019). Development of a sensor-based behavioral monitoring solution to support dementia care <https://doi.org/10.2196/12013>. *JMIR Mhealth and Uhealth*, *7*(6), Article e12013.

Ummels, D., Beekman, E., Theunissen, K., Braun, S., & Beurskens, A. J. (2018). Counting steps in activities of daily living in people with a chronic disease using nine commercially available fitness trackers: Cross-sectional validity study <https://doi.org/10.2196/mhealth.8524>. *JMIR Mhealth and Uhealth*, *6*(4), 25–38, Article e70.

Valenza, G., Nardelli, M., Lanata, A., Gentili, C., Bertschy, G., Paradiso, R., & Scilingo, E. P. (2014). Wearable monitoring for mood recognition in bipolar disorder based on history-dependent long-term heart rate variability analysis <https://doi.org/10.1109/jbhi.2013.2290382>. *IEEE Journal of Biomedical and Health Informatics*, *18*(5), 1625–1635.

Venkatesh, T., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology <https://doi.org/10.2307/41410412>. *MIS Quarterly*, *36*(1), 157.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view <https://doi.org/10.2307/30036540>. *MIS Quarterly*, *27*(3), 425–478.

Windasari, N. A., Lin, F.-r., & Kato-Lin, Y.-C. (2021). Continued use of wearable fitness technology: A value co-creation perspective <https://doi.org/10.1016/j.ijinfomgt.2020.102292>. *International Journal of Information Management*, *57*, 102292.

Xu, H., Yan, W., Lan, K., Ma, C., Wu, D., Wu, A., Yang, Z., Wang, J., Zang, Y., Yan, M., & Zhang, Z. (2021). Assessing electrocardiogram and respiratory signal quality of a wearable device (SensEcho): Semisupervised machine learning-based validation study <https://search.ebscohost.com/login.aspx?direct=true&db=psyh&AN=2021-82863-001&lang=zh-cn&site=ehost-live>. *JMIRmHealth and uHealth*, *2021*, 1–18.

Yang, L. Y., Lu, K., Diaz-Olivares, J. A., Seoane, F., Lindecrantz, K., Forsman, M., Abtahi, F., & Eklund, J. A. E. (2018). Towards smart work clothing for automatic risk assessment of physical workload <https://doi.org/10.1109/access.2018.2855719>. *IEEE Access*, *6*, 40059–40072.

Yu, J. N., Abraham, J. M., Dowd, B., Higuera, L. F., & Nyman, J. A. (2017). Impact of a workplace physical activity tracking program on biometric health outcomes <https://doi.org/10.1016/j.ypmed.2017.09.002>. *Preventive Medicine*, *105*, 135–141.

Wang, H. L., Tao, D., Yu, N., & Qu, X. D. (2020). Understanding consumer acceptance of healthcare wearable devices: An integrated model of UTAUT and TTF <https://doi.org/10.1016/j.ijmedinf.2020.104156>. *International Journal of Medical Informatics*, *139*, Article 104156.

Wang, J. B., Cadmus-Bertram, L. A., Natarajan, L., White, M. M., Madanat, H., Nichols, J. F., Ayala, G. X., & Pierce, J. P. (2015). Wearable sensor/device (fitbit one) and SMS text-messaging prompts to increase physical activity in overweight and obese adults: A randomized controlled trial <https://doi.org/10.1089/tmj.2014.0176>. *Telemedicine and e-Health*, *21*(10), 782–792.

Wong, C. K., Mentis, H. M., & Kuber, R. (2018). The bit doesn't fit: Evaluation of a commercial activity-tracker at slower walking speeds <https://doi.org/10.1016/j.gaitpost.2017.10.010>. *Gait & Posture*, *59*, 177–181.

Zhang, M., Luo, M. F., Nie, R., & Zhang, Y. (2017). Technical attributes, health attribute, consumer attributes and their roles in adoption intention of healthcare wearable technology <https://doi.org/10.1016/j.ijmedinf.2017.09.016>. *International Journal of Medical Informatics*, *108*, 97–109.

Related Articles

Digital Solutions to Public Health Issues