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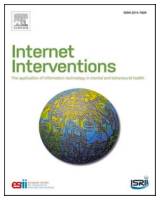

Acceptability and concerns about innovative wearable health sensors in persons with and without chronic disease diagnosis

Frank T. Materia [a,*], Joshua M. Smyth [b]

[a] Departments of Otolaryngology and Population Health, University of Kansas Medical Center, Kansas City, KS, United States of America
[b] Department of Psychology, The Ohio State University, Columbus, OH, United States of America

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ABSTRACT

Advances in biomedical engineering continue to produce innovative wearable health sensors capable of real-time ambulatory assessments (e.g., of physiology, the environment), holding great potential for advancing precision monitoring and interventions through the integration of such devices and data into eHealth systems. As with any novel device, however, user views on acceptability and concerns about the technology must be evaluated to facilitate widespread implementation and user adoption of such devices. One factor that may strongly influence user views is the potential relevance to, and need for, self-care for chronic disease management. We examined if acceptability and concerns regarding innovative wearable devices differed between individuals living with or without chronic disease. A U.S. adult sample ($N = 448$; 20-70 yrs.; 34 % Female; 60 % White, 35 % Hispanic) completed a web-based survey regarding their thoughts/opinions related to innovative wearable sensors. Two-thirds (67 %, $N = 298$) reported at least one chronic disease; one-third (33 %, $N = 150$) reported no chronic health conditions. Participants viewed learning modules about two innovative devices: a watch to detect environmental gases for respiratory health, and a chest-patch monitoring real-time ECG. For each device, participants rated acceptability across multiple dimensions, and then rated potential concerns (including general concerns and specific worries about negative health impacts). Respondents with and without chronic disease differed in education, race, and ethnicity. Controlling for these differences, individuals with chronic disease reported significantly higher acceptability for the watch and for the chest-patch. Healthy participants reported significantly higher general concerns about technology. However, when concern questions were asked specifically about the potential negative impacts of the two study devices on physical health and well-being, participants with chronic disease reported significantly higher concerns. Overall, results show that living with chronic disease influences acceptability and concerns associated with adoption of innovative sensors. These findings suggest it is essential to take potential users' health status into account when studying the design and implementation of innovative wearable sensors. Dissemination strategies may benefit from emphasizing the beneficial features of these devices, addressing hesitations, and customizing implementation approaches by user group.

1. Introduction

1.1. Background

Scientists have long utilized technologies to monitor individuals' physiological and environmental data (Einthoven, 1957), and advancements in device accessibility, usability, and reliability have facilitated continued integration of these devices into health research and treatment approaches. Historically, such systems have been largely confined to use within the controlled environments of laboratory or clinical settings (Fotiadis et al., 2006). The American College of Medical Informatics (ACMI), as well as the European Commission's (EC) Information Society Technologies (IST) initiative, were primary forces that spurred interest around large-scale implementation of new medical technologies beyond the confines of laboratory bench and hospital bedside. In 1998, ACMI published their official vision for advancing the future of healthcare into the new millennium, asserting that enhancing and extending research into portable technologies was necessary for advancing modern biomedical science and healthcare (Greenes and Lorenzi, 1998). Between 1999 and 2006, the EC's *Research and*

* Corresponding author at: University of Kansas Medical Center, 2106 Olathe Blvd., MS 3010, Kansas City, KS 66160, United States of America.
E-mail address: fmateria@kumc.edu (F.T. Materia).

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Development Framework Programs (i.e., FP5 and FP6) also prescribed investment and advancement in research related to smart, wearable health products (Lmberis and Dittmar, 2007). In the years that followed, research and development of innovative wearable sensors began to proliferate.

A wide variety of wearable devices capable of passively collecting real-time physiological, behavioral, and environmental data during individuals' everyday lives (i.e., ambulatory monitoring) have been developed. These innovative wearable sensors hold tremendous promise to collect these data in real-time throughout a person's normal daily routines and activities and can remotely monitor patients over lengthy periods of time (Cornet and Holden, 2018). Such devices can also support the direct delivery of behavioral and clinical intervention components to patients (e.g., through notifications, smartphone syncing, and/or telehealth system integration), in turn advancing treatment for chronic diseases that require ongoing monitoring and adherence (Arigo et al., 2019; Kubiak and Smyth, 2019). Emerging wearable health sensors are not only available to individuals at high-risk for, or diagnosed with, chronic disease. In recent years, off-the-shelf consumer-grade device ownership has also increased dramatically. Over 21 % of Americans own a fitness tracker or smartwatch (Vogels, 2020), as well as 19 % of 16–74 year olds in the European Union (Eurostat, 2020). Generally healthy consumers, without major health issues, continue to express interest in the utilization of medical-grade devices for personal health monitoring (Choe et al., 2017; Holko et al., 2022).

Before these emergent technologies can be effectively implemented as reliable tools for chronic disease patients and health-conscious consumers, however, it is important to address broad questions related to whether individuals will likely adopt or abandon innovative devices with unfamiliar features and functions. Assessing and evaluating various design and implementation factors early on is crucial to inform later product development, marketing, and support widescale adoption (Sekhon et al., 2017; Zhao et al., 2018). Ultimately, even if a perfect sensor exists for use in the laboratory or clinic, it will not be adopted beyond the boundaries of these spaces or reach its potential efficacy out in the real-world if it is unacceptable or presents concerns to potential end users.

Previous work has shown that designing these technologies to support initial acceptability (i.e., an individual's willingness to engage with a digital technology) can enhance users' intended adoption with wearables within a research study or during medical treatment (e.g., Schnall et al., 2016; Materia and Smyth, 2021). Additionally, an emerging body of literature has documented potential users' concerns and worries regarding the technological components and data sharing requirements (e.g., wireless power, Wi-Fi) inherent to new-age devices – underscoring the potential for these concerns to hinder uptake and successful marketing of these technologies at scale (Materia et al., 2020).

Assessing end user endorsements and hesitations during product development provides researchers with evidence-informed design and marketing strategies that can address subsequent adoption; this may in turn increase the likelihood of effective engagement with these devices out in the real-world during daily life (Materia et al., 2020). However, research in this space to date (as it specifically relates to acceptance of innovative digital health tools) has been conducted using disparate methodologies, uneven attention to theory, and has yielded mixed results (Perski and Short, 2021; Short et al., 2018; Stoumpos et al., 2023), making it difficult to draw conclusions across studies regarding how aspects of specific devices affect adoption. In addition, most of this research uses readily available commercial wearables as the focal device of interest (e.g., FitBit, Apple Watch); this, in turn, does not account for newly emerging functions and features found in novel wearables that are not yet available at market and are unfamiliar to potential user groups. It is imperative to further explore the breadth of potential users' baseline acceptance, concerns, and potential worries regarding advanced wearable health sensors, and if these characteristics are different between diverse types of likely user groups.

1.2. Aims and objectives

This study was conducted as part of a multi-institutional collaborative grant examining acceptance and concerns around novel wearable sensors. The specific sensors of interest were recently developed by biomedical engineers in the laboratory and utilize advanced capabilities (e.g., multi-sensor arrays, new wireless charging methods) that are not yet available to the public. In the near future, devices such as these (i.e., that are not produced by existing companies that dominate the current market share) may likely emerge at scale on the market and become more common for remote health monitoring in patients diagnosed with difficult-to-manage chronic conditions.

The current study focused on comparatively evaluating baseline perceptions of these advanced wearable health sensors in two user groups: patients with at least one chronic disease diagnosis, and healthy individuals with no chronic disease diagnosis. The broad goal of this work was to investigate baseline perceptions around potential users' adoption of these types of innovative wearable sensors. Specifically, the study aimed to characterize potential differences between these two groups in their baseline acceptability and concerns regarding these technologies. User perceptions were measured using online theory-based surveys and focused on two exemplar prototypes of real-life innovative wearable devices recently developed: 1) a smartwatch with the ability to detect movement and other environmental factors (e.g., ozone) related to acute respiratory outcomes; and 2) a low-powered real-time precision chest-mounted ECG monitor.

2. Methods

2.1. Study design and recruitment

The study was approved by the Institutional Review Board of The Pennsylvania State University. Participants were recruited for an online survey study through the Amazon Mechanical Turk (MTurk) crowdsourcing service. Only verified US citizens who were Master-Qualified and had completed previous tasks and surveys with high data quality and reliability were invited to participate through MTurk. Before being enrolled in the study and advancing to the main survey, potential participants were required to first pass eligibility screening. Eligibility criteria included being at least eighteen years of age, fluent in English, and requiring a completed response to the question, "Do you, or have you ever, suffered from any chronic diseases (e.g., heart disease, asthma) [Yes]/[No]?" Potential participants who refused to answer an eligibility question were excluded. In order to ensure participants with a wide range of chronic disease diagnoses were captured in the sample, a stratified recruitment method was utilized such that participants diagnosed with any chronic disease and those never being diagnosed with a chronic disease were recruited in a 2:1 ratio, respectively.

2.2. Device learning modules

To evaluate differences in wearable device evaluations, we presented two novel devices to all participants (i.e., to equate the target device across respondents). As part of this process, we created a systematic introductory paradigm to acquaint participants with the two study devices so they were similarly familiar with the purpose, capability, and technological requirements of the target devices. At the beginning of the survey participants were presented with two learning modules, the first regarding the smartwatch with the ability to detect movement and environmental factors related to respiratory outcomes and the second focused on the low-powered real-time precision chest-mounted ECG monitor related to cardiovascular outcomes. Each of the two learning modules took ~2 min to view and featured a written paragraph describing each devices' look, feel and function. To enhance ecological validity of participant perception of the devices (in their current state) and associated responses, we obtained these devices directly from the

development engineers and included pictures of each within the device learning modules. Content from the two learning modules is presented in Fig. 1.

2.3. Survey measures

2.3.1. Demographics

Participants completed a demographic questionnaire that included items regarding gender, age, ethnicity, race, and income. Participants who answered "YES" to having a chronic disease during eligibility screening were also presented a list of common chronic diseases and asked to select all that apply to them (i.e., "Which of the chronic health conditions below do you have? Select all that apply: [AIDS] [Arthritis] [Asthma] [Diabetes] [Emphysema/COPD] …"). Additional assessments, including health-related quality of life and health behavior (i.e., current levels of physical activity) were also collected at baseline for exploratory analysis.

2.3.2. Acceptability

Previous acceptability measures (Materia et al., 2018; Materia and Smyth, 2021) grounded in theory from behavioral science (i.e., The Technology Acceptance Model [Davis, 1989] and The Theory of Planned Behavior [Ajzen, 1991]) were utilized and items ($n = 8$) assessed various dimensions of acceptability: interest, enjoyment, difficulty, utility, benefit, appeal, confidence, recommendation of device to others. After viewing each of the two innovative sensor learning modules, participants utilized a 5-point Likert-type slider scale ranging from 1 (not at all) to 5 (very) to rate each acceptability dimension (e.g., "How INTERESTING would it be to use this smartwatch? NOT AT ALL [1] [2] [3] [4] [5] VERY") at baseline.

2.3.3. Concerns

Two sets of items assessing concern were developed based on a previous review of population-level concerns about emerging digital health technologies (Materia et al., 2020). Theory from implementation science (Bauer et al., 2015; Mummah et al., 2016; Sekhon et al., 2017), as well as previous literature focused on the effects of intervention marketing and worry (Faasse and Martin, 2018), also informed measure development. All concern items in both sets were presented to participants in a random order to reduce any item ordering effect bias in responses.

The first set of items ($n = 7$) assessed broad concerns about technological components inherent to the general function of wearable sensors. After completing the acceptability measures for each of the two device learning modules, participants utilized a 5-point Likert-type scale ranging from 1 (No Concern) to 5 (Extreme Concern) across the following technology components: Bluetooth, Wi-Fi, magnetic fields, wireless power, radio wave, cell phones, and microwaves (e.g., "Overall, do any of these technologies concern you? 'Bluetooth': NO CONCERN [1] [2] [3] [4] [5] EXTREME CONCERN").

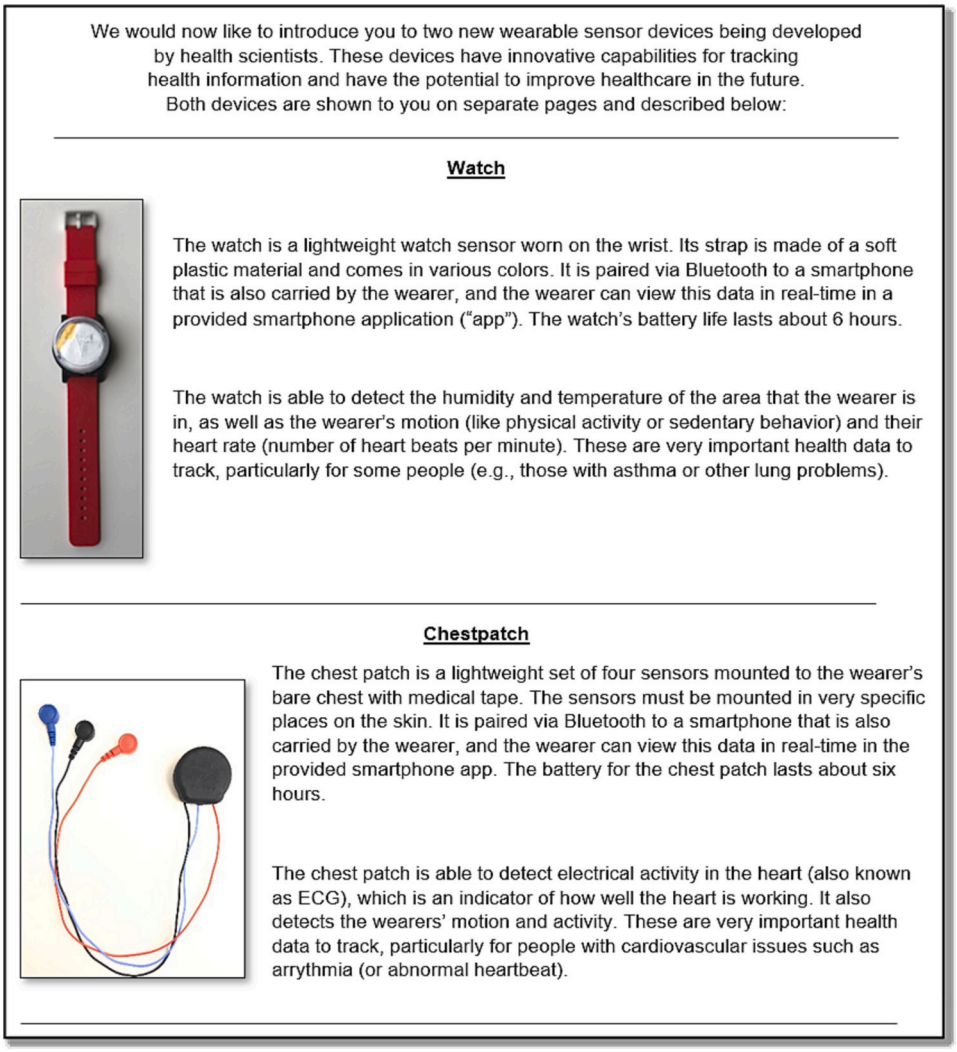

Fig. 1. Content of watch and chest-patch learning modules.

The second set of items (n = 12) assessed participants' concerns regarding how the particular components and characteristics of the two study devices may affect their physical health and well-being. Participants were reminded to think specifically about the watch and chest-patch's functions, respectively, and then rated their health concerns on the same 5-point Likert scale ranging from 1 (No Concern) to 5 (Extreme Concern) for each component: Bluetooth, Wi-Fi, magnets, electricity, lithium-ion batteries, Apple© devices, Android© devices, data privacy, "self-powering", "energy storage", "low power", and "energy harvesting" (e.g., "The two devices use Bluetooth. My level of concern with this 'Bluetooth' technology affecting my health and well-being is: NO CONCERN [1] [2] [3] [4] [5] EXTREME CONCERN"). The 1–5 response choices for both sets of concern items were utilized to capture broad initial concerns about the devices' specific features and functionalities that may affect adoption (as opposed to evaluating participant issues with the more specific nuances involved in the devices' daily upkeep and usage).

2.3.4. Data quality verifications

To ensure the quality and accuracy of the data, attention checks were administered to assess careless responding. Five careless responder questions were presented at different points in the survey and required participants to identify information they should have read if they were paying attention (as opposed to quickly clicking through items and providing superficial responses; e.g., "Which of the following is in the same category as an 'apple'?: [1] ship, [2] ring, [3] banana, [4] motorcycle"). The use of careless responder items has been shown to be a reliable and effective method for helping to confirm respondent data quality (Schneider et al., 2018).

2.4. Data analysis

Descriptive statistics were used to characterize sample demographics and data quality verification items. SPSS version 29 (English) software was used to conduct all analyses. The sample was coded into two separate disease diagnosis groups (i.e., living with a chronic disease diagnosis vs. no diagnosis). SPSS' GLM procedure was used to conduct ANCOVA analyses to evaluate the between group effects of disease diagnosis on the mean acceptability rating of both devices, as well as between group effects of diagnosis on the mean general concern and the mean device-specific health-related concern ratings. Initial Chi square tests identified statistically significant demographic differences between the two groups in education, race, and ethnicity; accordingly, these three factors were included in all ANCOVA models as covariates and controlled for in all between group analyses. There were no statistically significant demographic differences in gender or income between the groups. In addition, an independent samples t-test found no significant difference between the two groups in age. In an exploratory fashion, we investigated the possibility of differences in other health-related quality of life (i.e., Patient Reported Outcomes Measurement Information System [PROMIS] Global Health measure version 1.2; Rose et al., 2014) and health behavior (i.e., moderate physical activity throughout the week via the International Physical Activity Questionnaire [IPAQ]; Hagströmer et al., 2006) factors that were collected in the survey. No statistically significant differences in reported quality of life or physical activity behavior were found (i.e., p = .078, and p = .189, respectively).

3. Results

Online data collection was completed within 19 days. Examining careless responder questions, 87.9 % of respondents (N = 394) answered all questions correctly, supporting the likelihood of good data quality.

3.1. Participants

A diverse U.S. English-speaking adult sample (N = 448; M age = 37.19; age range: 20-70 yrs.; 34 % Female; 60 % White, 35 % Hispanic) was recruited. Two-thirds (67 %; N = 298) reported at least one chronic disease diagnosis, and one-third (33 %; N = 150) reported no chronic disease diagnoses (Table 1).

Table 1
Participant characteristics.

Characteristic	Entire sample (N = 448)	Chronic disease dx group (n = 298)	No chronic disease dx group (n = 150)	Difference between groups
Gender				
Male	294 (65.6 %)	198 (66.4 %)	96 (64.0 %)	p = .607
Female	154 (34.4 %)	100 (33.6 %)	54 (36.0 %)	
Mean age (years)	*37.19*	37.71	36.14	p = .071
Education				
≤High school	20 (4.5 %)	9 (3 %)	11 (7.3 %)	*p ≤0.001
Some college	50 (11.2 %)	22 (7.2 %)	28 (18.6 %)	
College graduate	216 (48.2 %)	148 (50.5)	68 (45.3 %)	
Graduate degree	156 (34.8 %)	113 (38.5 %)	43 (28.8 %)	
Prefer not to answer	6 (1.3 %)	6 (0.8 %)		
Race				
White	268 (59.8 %)	163 (54.7 %)	105 (70.0 %)	*p = .001
Black	156 (34.8 %)	121 (40.6)	35 (23.4 %)	
Other	21 (4.7 %)	11 (3.7 %)	10 (6.6 %)	
Prefer not to answer	3 (0.7 %)	3 (1.0 %)		
Ethnicity				
Hispanic/ Latinx	156 (34.8 %)	115 (38.6 %)	41 (27.3 %)	*p = .017
Not Hispanic/ Latinx	291 (65.0 %)	182 (61.1 %)	109 (72.7 %)	
Prefer not to answer	1 (0.2 %)	1 (0.3 %)		
Income				
Low (≤ 25 k)	42 (9.4 %)	25 (8.4 %)	17 (11.3 %)	p = .706
Lower-Middle (25-75 k)	256 (57.1 %)	170 (57.0 %)	86 (57.3 %)	
Middle (75-125 k)	124 (27.7 %)	83 (27.9 %)	41 (27.3 %)	
Middle-high (125-175 k)	17 (3.8 %)	13 (4.4 %)	4 (2.8 %)	
High (175 k+)	7 (1.6 %)	5 (1.7 %)	2 (1.3 %)	
Prefer not to answer	2 (0.4 %)	2 (0.6 %)		

Note: N = entire sample size; n = group sample size; "Difference between groups" column presents initial Chi square and independent samples t-test results indicating any statistically significant between group differences for each demographic factor; * indicates $p < .05$.

3.2. Association of chronic disease diagnosis with dimensions of acceptability of each device

Table 2 provides the between group effects results of disease diagnosis on acceptability of each device. Table 3 provides means ratings of acceptability dimensions for each device by group.

3.2.1. Watch

There were significant associations between chronic disease diagnosis on reports of acceptability of the watch. Having ever been diagnosed with at least one chronic disease was associated with significantly higher average acceptability of the watch ($p \leq 0.001$) (see Table 2). Overall, for all dimensions of acceptability of the watch, both groups' mean ratings were above the midpoint (i.e., >3.00) of the 1–5 scale, indicating moderate to high acceptability overall for all positive dimensions of the watch; chronic disease patients were more accepting overall but perceived the watch to be more difficult to use (see Table 3).

3.2.2. Chest-patch

There were significant associations between reported health diagnosis and acceptability of the chest-patch. Diagnosis of a chronic disease was associated with significantly higher average acceptability of the chest-patch ($p \leq 0.001$). Regarding acceptability ratings of the chest-patch, both groups' mean ratings were generally high (i.e., above the midpoint of the scale); chronic disease patients reporting higher acceptability across dimensions overall (see Table 3).

Table 4 provides the between group associations of disease diagnosis with general technology concerns and study device-specific health-related technology concerns. Table 5 provides means ratings of acceptability dimensions for each device by group.

3.3. General and device-specific health concerns

3.3.1. General concerns about technology

There were significant associations between chronic disease diagnosis and reports of general concerns about technologies inherent to innovative health sensors. Having ever been diagnosed with at least one chronic disease was associated with a significantly lower average general concern about innovative health technologies ($p < .001$). Overall, for all general technology concerns, both groups' mean ratings of each concern dimension were below the midpoint (i.e., <3.00) of the 1–5 scale suggesting generally modest levels of worry/concern; chronic disease patients were lower on all general technology concern dimensions (see Table 4).

Table 2
Between group effects results of chronic disease diagnosis on mean acceptability for both devices.

Device and Group	Mean acceptability rating (SD)	Effect of chronic disease dx on acceptability		
		Mean square	*F*	*P value*
Watch				
Chronic disease dx	3.95 (0.657)	6.795	14.312	* < 0.001
No chronic disease dx	3.61 (0.803)			
Total	3.84 (0.727)			
Chest-patch				
Chronic disease dx	3.79 (0.760)	19.733	35.961	* < 0.001
No chronic disease dx	3.21 (0.877)			
Total	3.59 (0.847)			

Note: All mean ratings are on a 1–5 scale; dx = diagnosis; SD = standard deviation; * indicates $p < .05$.

Table 3
Mean ratings of acceptability for both groups for the watch and chest-patch.

Acceptability dimension/devices	Chronic disease dx group rating mean (SD)	No Chronic disease dx group rating mean (SD)
Interest		
Watch	3.98 (1.01)	3.62 (1.09)
Chest-patch	3.82 (1.12)	3.25 (1.35)
Enjoyment		
Watch	4.00 (1.04)	3.44 (1.22)
Chest-patch	3.52 (1.26)	2.51 (1.45)
Difficulty		
Watch	3.43 (1.30)	2.80 (1.51)
Chest-patch	3.87 (1.08)	3.93 (1.08)
Utility		
Watch	4.06 (0.92)	3.99 (1.00)
Chest-patch	4.01 (0.91)	3.85 (1.08)
Benefit		
Watch	4.06 (0.89)	3.97 (1.01)
Chest-patch	4.00 (0.96)	3.74 (1.12)
Appeal		
Watch	3.93 (1.01)	3.52 (1.18)
Chest-patch	3.66 (1.24)	2.69 (1.51)
Confidence		
Watch	4.10 (0.93)	3.99 (1.08)
Chest-patch	3.76 (1.14)	2.95 (1.41)
Recommend to others		
Watch	4.05 (0.99)	3.55 (1.26)
Chest-patch	3.72 (1.23)	2.80 (1.50)

Note: All mean ratings are on a 1–5 scale; dx = diagnosis; SD = standard deviation.

Table 4
Between group effects results of disease diagnosis on mean general technology concern and mean study device-specific health-related technology concern.

Concern category and group	Mean concern rating (SD)	Effect of chronic disease dx on concern		
		Mean square	*F*	*P value*
General technology concern				
Chronic disease dx	2.49 (1.079)	21.287	20.122	<0.001
No chronic disease dx	2.76 (1.259)			
Total	2.58 (1.149)			
Device-specific health-related technology concern				
Chronic disease dx	3.41 (1.105)	19.513	18.376	<0.001
No chronic disease dx	2.72 (1.295)			
Total	3.17 (1.216)			

Note: * indicates $P < .05$; dx = diagnosis.

3.3.2. Health concerns regarding the devices' specific technology characteristics and components

In sharp contrast, there were significant associations in the opposite direction of chronic disease diagnosis with concerns regarding how the two specific devices presented in the study may affect user physical health and well-being. Having ever been diagnosed with at least one chronic disease was associated with a significantly higher average rating of study device-specific concern about their use of the proposed devices affecting personal health ($p < .001$). Across all concern dimensions specific to how the study devices' technology characteristics and components may affect personal physical health and well-being, mean ratings were significantly higher and above the midpoint of the scale for individuals ever diagnosed with a chronic disease; all mean ratings for individuals without chronic disease were below the midpoint for all device-specific health concern dimensions (see Table 4)

4. Discussion

Modern wearable health sensors, with all their multifaceted

Table 5
Means ratings of acceptability for both groups for general technology concerns and study device-specific health-related technology concerns.

Concern items	Chronic disease dx group rating mean (SD)	No Chronic disease dx group rating mean (SD)
General technology concern items		
Bluetooth	2.33 (1.37)	2.56 (1.49)
Wi-Fi	2.50 (1.38)	2.52 (1.43)
Magnetic fields	2.47 (1.21)	2.87 (1.41)
Wireless power	2.48 (1.29)	2.77 (1.48)
Radio waves	2.51 (1.26)	2.81 (1.44)
Cell phones	2.57 (1.29)	2.83 (1.44)
Microwaves	2.55 (1.26)	2.93 (1.35)
Device-specific health-related technology concern items		
Bluetooth	3.42 (1.33)	2.64 (1.49)
Wi-Fi	3.37 (1.30)	2.64 (1.46)
Magnets	3.46 (1.21)	2.93 (1.36)
Electricity	3.50 (1.27)	2.85 (1.52)
Lithium ion	3.39 (1.32)	2.76 (1.41)
Apple	3.41 (1.35)	2.64 (1.49)
Android	3.48 (1.28)	2.67 (1.51)
Data privacy	3.39 (1.24)	2.86 (1.47)
"Self-powering"	3.36 (1.27)	2.68 (1.51)
"Energy storage"	3.31 (1.30)	2.65 (1.42)
"Low power"	3.42 (1.22)	2.53 (1.43)
"Energy harvesting"	3.40 (1.31)	2.77 (1.45)

Note: All mean ratings are on a 1–5 scale; dx = diagnosis; SD = standard deviation.

capabilities, possess great potential for transforming clinical care and chronic disease management. More and more healthy individuals are also opting to purchase these devices for self-monitoring. Yet, as these devices become ever more looked to as healthcare supports, implementation research regarding different user groups' potential adoption behaviors and possible barriers to broad engagement is necessary. In this study, acceptability and concerns surrounding baseline perceptions of two real-world, innovative, wearable health sensors were examined. Results indicated that, in general, the two sensors were broadly acceptable, with the watch sensor being slightly more acceptable than the chest-patch – a finding favorable overall to support the feasibility of largescale implementation of these kinds of innovative sensor technologies.

These findings are consistent in some aspects with, and extend in other ways, other studies that have sought to broadly understand individuals' baseline perceptions of emerging wearable technologies. For example, prior studies have examined acceptability of wearable devices and results generally indicate that overall acceptability is moderate to high, and that perceived utility and personal value can vary depending on device type (e.g., standard fitness trackers vs. clinical blood pressure monitors) and user group (e.g., fitness-minded healthy adults vs. patients with severe illnesses) (Gao et al., 2015; Zhao et al., 2018). Other research has documented perceived barriers to successful implementation of innovative sensors into healthcare, including patient worries about receiving real-time technical support and a lack of physician familiarity with device features (Materia et al., 2020; Smuck et al., 2021). Additional research has further noted concerns about data security, privacy and equity in device accessibility (Canali et al., 2022). Many researchers believe that wearable devices, despite the great potential to improve individual and collective health outcomes, cannot effectively proliferate without better addressing individual factors (e.g., acceptability, concerns) during commercial marketing or clinical prescription (Chandrasekaran et al., 2020; Smuck et al., 2021).

Our study, however, also highlighted several potentially informative and important between-group differences by addressing some existing gaps in current understanding of these issues. Most notably, this study examined these differences between individuals living with a chronic disease against those never having been diagnosed with one. Our study was also innovative in that it systematically and consistently introduced participants to real-world (not hypothetical) examples of new devices that have been recently developed and are intended to advance to FDA-approval and scalability at market.

Individuals with chronic diseases reported higher acceptability of the devices across all dimensions. They were also less concerned about technology in general than their healthy counterparts. What was most striking, however, was that individuals reporting chronic illness also reported substantially higher levels of concern about how new technologies may directly affect their physical health and well-being. It is possible that individuals with chronic disease may be more accepting of wearable sensors due to high salience and need for daily monitoring of physiology and environment (Tran et al., 2019). They may be less worried generally about technology during their day-to-day lives, expending their mental energy on broader concerns about health-focused processes within their control.

However, when a real-life novel sensor is described in detail to these individuals, across the board these same individuals report higher hesitancies and concerns at baseline about the potential impact of these technologies on their physical health and well-being. It may be the case that some individuals with chronic conditions may already be concerned about integrating new clinical supports into their care (Greiwe and Nyenhuis, 2020). It could also be that case that, compared to healthy individuals, people with chronic disease exhibit higher fragility overall and therefore hesitate to introduce sensors into their monitoring before the devices have been used widely and successfully by others. There may also be a "white coat" effect for some chronic disease patients – these sensors have the potential to detect major health issues in real-time which could potentiate high anxiety for specific disease processes. Depending on the severity of disease, it is possible individuals with long-term illnesses feel more concerned about the physical consequences of an unfamiliar technology because they are exhausted from trying numerous previous therapeutic supports.

Some previous research has explored the unintended consequences associated with integrating innovative clinical approaches into care, such as inducing worry and stress among patients (Azodo et al., 2020). These psychological processes can be particularly detrimental to individuals with chronic disease, sometimes even manifesting as physical illness due to exacerbated concern (i.e., the "nocebo" effect; Faasse and Petrie, 2013). It is therefore critical to consider how innovative sensors are designed (e.g., look, feel, and function), initially described, and delivered to users to mitigate unfavorable outcomes, limit avoidance, and support adoption.

Although interesting, we view these initial findings as preliminary and additional work will be needed to better evaluate the pragmatic implications (e.g., influence on potential dissemination and uptake of devices). The differences in ratings between groups for both acceptance and concerns, although statistically significant, were of modest magnitude (with the possible exception of those concerns associated with health effects, which seemed somewhat more robust in importance). Nonetheless, the findings do give us some insight into how health scientists, medical providers, and healthcare entities might attend carefully to individuals' perceptions, acceptance, and concerns about using novel health sensor devices, like smartwatches and body-worn patches. For all potential users, but especially for those with chronic disease, providing individuals with evidence of device safety and extensive information about how the devices' technologies are trustworthy and can seamlessly integrate into daily routines is imperative to support initial implementation.

To effectively implement these devices at scale in the commercial market or in healthcare, it may be important to mitigate potential user concerns during baseline introduction to the sensor. The amount of time spent describing a device, its capabilities, and inherent technological components may need to be tailored to the individual or group's salience of need for healthcare support (e.g., more time may need to be spent

upfront describing the technology to an individual with complex chronic disease monitoring needs versus to a healthy individual who is simply tracking their daily steps). Along with previous recommendations from the literature (Canali et al., 2022; Smuck et al., 2021), we suggest that these conversations may be best conducted with a trusted healthcare provider who reassures the user of device safety and efficacy. Providing accessible technical support and assistance after initial adoption of a new wearable sensor, particularly if prepared to help manage health and/or general concerns and worries, may also improve acceptance. Our results also suggest that word choice may also be important in patient-provider discussions and marketing materials. To limit user hesitations, it is likely prudent to stay away from using scary or unfamiliar terminologies when describing novel device functions (e.g., the term "energy harvesting" may be less desirable than "self-powered"). Finally, the physical look and feel and bodily placement of devices may also be related to user adoption and concerns (Adapa et al., 2018), although this issue was not one we could carefully address in this study.

This study was mainly focused on examining differences in potential user groups' initial perceptions likely related to eventual adoption of unfamiliar, advanced health sensor devices. It is still unclear, from the literature, how initial perceptions and avenues of adoption (e.g., provider prescription vs. individual purchase for self-monitoring) may be associated with duration of use of digital health products and, furthermore, meaningful biobehavioral outcomes (Kupfer et al., 2016; Wang and Qi, 2021). We propose that adoption is the first step towards long-term engagement with new health technologies. Future research can extend this early work by attending to questions related to device design and marketing decisions, and how differences in these strategies may also influence adoption and sustained usage. Facilitating meaningful engagement, past initial adoption, will also depend on research that addresses a number of user-centered factors, such as options for tailoring sensor systems to end users' own behavioral, lifestyle, and proximal health needs.

This study has several notable strengths and limitations. The overall sample was diverse across multiple demographic factors (e.g., race, ethnicity, income, education, gender) and any differences in these factors between the two study groups were statistically controlled for in analyses. In addition, the data verification items integrated within the survey indicated high data quality and reliability, with 87.9 % of respondents answering all questions correctly. Given the remaining 12.1 % of respondents answered only two questions or less incorrectly during attention verifications, their data quality was considered good and as such these participants were included in the final sample.

One limitation of the study was that (due to being conducted online via Amazon's MTurk crowdsourcing platform) disease diagnosis data were self-report and could not be verified with actual clinical records. In addition, we found no significant differences in the groups on age, health-related quality of life, and health behavior. It is possible that the entire potential MTurk sample pool, regardless of chronic disease status, is mostly made up of younger adults with fair quality of life and mobility. Future research utilizing other sampling methods (e.g., community convenience sampling) may find more diversity on these factors between groups (and would subsequently need to then control for these factors in additional analyses).

Another limitation is that there may have been overlap in how participants perceived device-specific requirements that are similar in function, such as discerning Bluetooth from WiFi. Given the average age of the sample was 37 years, it is likely most respondents grew up with and were familiar with most of the device requirements in the survey. In future work, to ensure all participants are equally familiar, descriptions of each device requirement can be made available within the survey.

Finally, it is important to consider how the descriptions of both devices may have influenced participant perceptions. For example, the descriptions noted that the devices track "very important" health data. We would like to reinforce that all participants received the same information. If there were any priming effects resulting from our descriptions, they would have likely influenced all participants equally and not biased any major differences in perception between the groups.

There is wide-ranging variety in how innovative wearable sensors may be described to potential users. It will be beneficial to further investigate how the level of detail attached to descriptions of such devices affects adoption between different groups. Future work is needed to parse out the reasons for differences in acceptability and concerns between chronic disease patients and those without a diagnosis. There may be subgroups of different disease diagnoses (e.g., cancer vs. HIV vs. asthma), or different types of devices (e.g., location on body, look and feel) which were not explored in this report that may be driving some aspects of acceptability perceptions and potential uptake.

In conclusion, this research shows people are sensitive to how innovative wearable sensors are presented and function, and differences in their initial perceptions may affect adoption and scalability of these novel technologies. As this study suggests, effective implementation of innovative sensors and devices to improve health can be facilitated by considering potential users' acceptability and concerns with these devices as a function of important user characteristics (e.g., health status). Future dissemination approaches should highlight acceptable capabilities, alleviate concerns, and tailor implementation strategies to user groups.

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Declaration of competing interest

Both authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as potential conflicts of interest.

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