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RESEARCH ARTICLE

Factors and Design Features Influencing the Continued Use of Wearable Devices

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Abstract
The initial healthy uptake of wearable devices is not necessarily accompanied by sustained or continued use. Accordingly, this study investigates the factors influencing the continuous use of wearable devices with a particular emphasis on design features. We complemented the expectation-confirmation model (ECM) theoretical foundation with various design features such as trust, readability, dialogue support, personalization, device battery, appeal, and social support. The study employs a simultaneous mixed method research design denoted as QUANT + qual. The quantitative analysis leverages partial least squares structural equation modeling (PLS-SEM) using survey data collected from wearable device users. The qualitative analysis complements the quantitative focus of the research by providing insights into the results obtained from the quantitative analysis. We found that subjects tend to use wearables daily (60%) or several times a week (33%), and 91% plan to use them even more. Subjects indicated multiple usages for wearables. Most subjects were using wearables for healthcare and wellness (61%) or sports and fitness (54%) and had smartwatches wearable type (74%). The model explains 24.1% ($p < 0.01$) of the variance of continued intention to use. As a theoretical contribution, the findings support using the ECM as a theoretical foundation for explaining the continued use of wearables. Partial least squares (PLS) and qualitative data analysis highlight the relative importance that wearable users place on perceived usefulness. Most notable are tracking functions and design features such as device battery, integration with other apps/devices, dialogue support, and appeal.

Keywords Wearables · Continued use · Expectation-confirmation model (ECM) · Design

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1 Introduction

Wearable devices refer to computers or electronic devices that are attached to or worn on the body. Some of the most popular wearable devices are smartwatches. Other examples include eyewear (glasses), jewelry, and headbands [1]. The global wearable technology market is estimated at around USD 116.2 [2] and 121.7 billion [3] in 2021. The estimated compound growth rate range from 18% for 2021–2026 [2] and 13.89% for 2023–2030 [3]. Wearable devices are being used in various domains including entertainment and healthcare [4]. Wearables demonstrate the largest potential in the areas of health, medicine, and fitness [1] and growing research focuses on the design of wearables as persuasive and behavioral change support systems (BCSS) [5] where wearables are designed and presented to users to encourage them to adopt healthy approaches through quantifying and monitoring their lifestyles in a systematic manner. The increased awareness among users of wearable devices regarding their health motivates them to adopt healthier lifestyle [6]. Although wearable devices are receiving considerable attention and the number of users adopting wearables is increasing, the sustained usage and the continuous intention to use wearables are questionable [7]. Continued use is necessary for the potential for wearables to impact behavior and ultimately improve health and wellness.

Theoretical models such as the expectation-confirmation model (ECM) can provide insights into factors influencing the continued use of wearables. Various design features may also drive such factors. For example, wearable designers need to take into consideration various aspects, including dynamic change of the user's external environment (e.g., deaf-blindness), steep learning curve, small screen size, short battery lifetime, and input/output modalities (e.g., utilizing gestures) [8]. Furthermore, El-Gayar et al. [9] highlighted a number of design guidelines and recommendations derived from mining social media posts related to wearables. These included user concerns related to dialogue support, device battery, personalization, appeal, readability, trust, and social support. Despite the proliferation of research related to the adoption of wearables [10], fewer focused on the sustained usage of wearable devices through continuous intention to use [11–13] whereas device characteristics that may drive adoption, e.g., novelty [14], may not necessarily drive continued use [12]. Furthermore, while the research into the abandonment of wearable devices [15–18] provide valuable insights regarding device features and user characteristics that may drive abandonment, such research often does not explicitly account for an underlying theoretical model.

Accordingly, this study aims to complement prior research by exploring the antecedents of the continuance use intentions with a particular focus on design considerations. The underlying theoretical model is informed by the expectation-confirmation model (ECM) to emphasize continued intention to use wearables [19, 20]. The research utilizes a mixed methods approach to add rigor and relevance through the notion of triangulation [21, 22]. From a theoretical perspective, this study contributes to the understanding of the factors influencing the continuance of use with a particular focus on design features. The proposed theoretical model represents an expansive perspective on the continuance of use of information technology (IT) innovations that incorporates conceptual elements from the ECM. The implication to practice includes insights into user experience with a better understanding of the different users' needs that might lead to future design improvements for wearables and hence increase continued use.

The remainder of the paper is organized as follows: the next section presents a synopsis of recent developments regarding the adoption and continued use intentions of wearables followed by a depiction of the underlying theoretical model and associated hypotheses. Next, we describe the research methodology followed by the results from the quantitative and qualitative analysis. Insights and implications are presented in the discussion section. The last section concludes the paper with a summary of key findings, contributions, implications, limitations, and directions for future research.

2 Literature Review

Over the years, technological developments resulted in design improvements of wearables changing from being bulky and heavy and with limited functionality to more portable, comfortable, and lightweight design with an ever expanded list of functions [23, 24]. Accordingly, research pertaining to user acceptance and the adoption of wearable devices has garnered significant attention. For example, Kalantari [10] performed a literature review that covered a wide range of studies that explored the use of technology acceptance theories and models such as the theory of planned behavior (TPB), the technology acceptance model (TAM), the unified theory for acceptance and use of technology (UTAUT) and its variant UTAUT2, the uses and gratifications theory (U&GT), and the innovation diffusion theory (IDT) to explain the adoption of wearables. The models and theories identified factors categorized into five different groups: perceived benefits, technology features, social influences, individual characteristics, and perceived risks. Among these articles, Chau et al. [25] used the TAM and the health belief model (HBM) to investigate the perceived convenience and perceived usefulness as antecedents to adoption intention. Using the same models, Cheung et al. [26] explored perceived usefulness, consumer innovativeness, and social influence as antecedents to the adoption of wearables and highlighted privacy protection as an antecedent to the perceived usefulness of wearables. Dai et al. [27] extended the UTAUT model to study the influence of social influence, effort expectancy, facilitating conditions on users' behavior, and acceptance of using wearable devices by caregivers of dementia patients. In another context, Niknejad et al. [23] studied the adoption of smart wellness wearable devices in Malaysia. The study extended the UTAUT and value-based adoption model (VAM) and identified the effect of perceived trust and perceived health increase on the adoption of wearables.

In a qualitative study, Shih et al. [28] identified adoption patterns of wearable devices and provided insights into the adoption and usage patterns of wearable activity trackers. The research highlighted a set of design considerations and a variety of issues with design implications, including physical design, aesthetics, data management integration and sharing, and concerns with data accuracy. In another qualitative study, Adapa et al. [29] relied on TAM, IDT, and UTAUT as an underlying theoretical foundation to investigate a set of design recommendations to meet users' expectations to adopt wearable devices, specifically smart glasses and smartwatches. Adapa et al. [29] identified design considerations for two groups of users:

working professionals and college students. Among the design consideration highlighted were affordability (price), perceived risk (lack of knowledge, information privacy, and technological novelty), perceived usefulness (form factor and battery life), comfortability (battery heat and weight), and perceived image (look and feel).

While adoption studies explored a diverse set of constructs, these studies aimed to explain the intention to use as opposed to continued use or abandonment. Specifically, some users may abandon the use of wearable devices as some feel that the device does not fit their conception of themselves and others find the data collection not useful, or the extra work associated too large [30]. As Niknejad et al. [23] note that while the adoption of smart wellness wearables is on the rise, users do not utilize the full potential of smart wellness wearables due to abandonment after a few weeks from adoption.

2.1 Wearable Continuous Use Intention

Beyond adoption research, research into continued use and abandonment of wearables aims to explore factors influencing wearable users' decision to continue or abandon the use of a particular wearable. To explore factors influencing continuous intention, Nascimento et al. [13] extended the expectation-confirmation theory (ECT) to study the influence of habit, perceived usability, and perceived enjoyment on continuous intention to use wearables using a quantitative approach. Focusing on smartwatches, Pal et al. [31] investigated various factors associated with continuous usage across four Asian countries using a research model based on the ECM. Also focusing on smartwatches, Dehghani [32] employed qualitative analysis to explore motivational factors on continuous usage intention. Furthermore, Ahmad et al. [11] extended the TAM model and studied the impact of perceived usefulness, perceived ease of use, perceived credibility, compatibility, and social influence on continuous intention to use wearables by elderly patients.

Emphasizing design features driving continued use of wearables, Canhoto and Arp [12] interviewed users of wearable devices and noted that increasing perceived enjoyment and improving design features such as appeal and improving battery lifetime could favor sustained use and decrease the likelihood of wearable abandonment. In a mixed method study, Epstein et al. [16] identified six reasons why people stop tracking and five perspectives of life after tracking. While the focus of the study is on life beyond abandonment, the findings reveal a number of reasons for abandonment with potential design implications, including the cost for collecting, integrating, and sharing data, the quality of the data, and the continued usefulness and relevance of tracking. In the context of smartwatches, Jeong et al. [17] studied multiple factors affecting wearing smartwatches including micro-interaction needs in daily routines, smartwatch charging, aesthetic concerns, and activity/exercise tracking accuracy for improving wearability of smartwatches and leveraging smartwatches for delivering behavioral intervention. Also, Dehghani et al. [33] studied the influence of user's motivations and device features such as aesthetic appeal and operational imperfection on the continuous intention to use smartwatches. From a social media analytics perspective, El-Gayar et al. [9] derived design guidelines from users' concerns related to wearable devices on Twitter, while Clawson et al. [15] analyzed the sale of personal health-tracking technologies on Craigslist to identify the health motivations and rationale for abandonment and implications for wearable design.

The findings indicate that not all abandonments were the result of failure in design. However, over a quarter of the devices were abandoned due to a mismatch between users' expectations and device capabilities. This is echoed in [18], where research participants tended to abandon devices as the data collected was no longer perceived to be useful or the device maintenance became unmanageable.

Despite the rich literature that studied wearable adoption, only a subset focused on the sustained usage of wearable devices through continuous intention to use. Factors that may influence adoption may not necessarily support sustained use [12]. In that regard, research emphasizing a theoretical foundation did not necessarily emphasize design concerns as antecedents for continued use, while studies that explored the wearable abandonment often did not include an account for an underlying theoretical model with the focus of capturing the influence of design antecedents on the continuous use intention of wearables. Furthermore, compared to mining messy social media or relying exclusively on quantitative methods, a mixed method approach provides rigor and relevance through the notion of triangulation [17, 18]. Accordingly, this study aims to complement prior research emphasizing theories explaining continuous use intentions by explicitly accounting for several antecedents of the continuance of use with a particular focus on design considerations while complementing research into wearable device abandonment by including an underlying theoretical model.

3 Theoretical Model

In marketing research, the expectation-confirmation theory (ECT), or expectation-disconfirmation theory (EDT), is used to explain the satisfaction feeling of consumers and the influence on the repurchase intention. The ECT postulates that consumers intend to buy a product or continue to use a service if they are satisfied with their prior purchase of the product or service as shown in Fig. 1 [34–36]. In the context of information systems, Bhattacherjee [19] adapts the ECT and integrates it with theoretical and empirical findings from prior IS usage research to propose the expectation-confirmation model (ECM) as a model of information systems continuance of use. ECM has been adapted and applied to a variety of information technologies, including e-commerce [37], mobile applications [38–40], mobile internet services [20], mobile instant messaging [41], smartphone banking services [42], and wearables [13, 43]. The following subsections describe ECM constructs, design features, and associated hypotheses purported in the proposed model.

3.1 ECM Constructs

Confirmation Confirmation is defined as "the congruence between expectation and actual performance." Users' perceived confirmation represents the consumers' subjective post-only rating at the product or service level or at an individual attribute level [19]. Confirmation captures the pre-consumption expectations and confirms those after system use [38].

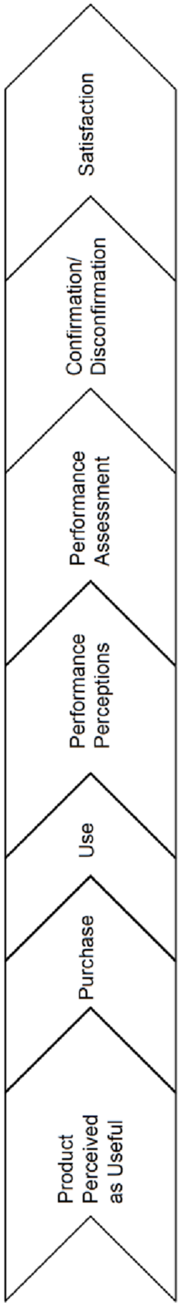

Fig. 1 Expectation-confirmation theory process [13]

Perceived Usefulness The word usefulness is defined as "capable of being used advantageously." Perceived usefulness is the degree to which a person believes that using a particular system would improve his or her performance [44]. Contrary to pre-usage perceived usefulness, the expectation-confirmation theory (ECT) refers to the post-usage perceived usefulness that is acquired after an accumulated experience of using [19, 45].

Hedonic Motivation Unlike perceived usefulness, hedonic motivation refers to the level of users' enjoyment, fun, and pleasure that is acquired while using a system. Hedonic motivation is shown to impact the technology acceptance and use [46]. Hew et al. [47] found that hedonic motivation is a significant construct that influences the intention to use mobile apps, while Kim et al. [48] observed that if users find fun using mobile apps, they are more inclined to adopt using them. Feelings such as pleasure and playfulness can be experienced while utilizing wearable technology with unique and well-thought-out design factors.

Satisfaction In marketing, satisfaction is identified as a critical factor when considering customer loyalty [13]. In the context of information systems, satisfaction is an important determinant in post-acceptance behavior after using the system [19]. Satisfaction tends to reinforce a user's intention to continue using the system [49]. This is represented as ex-post perceived usefulness and confirmation of expectation following actual use.

3.2 Design Features

Vodanovich et al. [50] highlighted that traditional information systems design has focused on functionality at the expense of five usability design characteristics, namely, personalization, attractiveness (appeal), intuitiveness, interaction, and social support. The research further highlights the importance of the five usability design characteristics in ubiquitous information systems (UIS). In this research, we are extending the design-related constructs derived from concerns of wearables' users on social media El-Gayar et al. [9] to study: device battery, dialogue support, personalization, appeal, readability, trust, and social support as design antecedents impacting the continuous intention following the ECT in the context of using wearable devices as shown in Fig. 2. The following describes the constructs:

Dialogue Support Dialogue support design focuses on how users provide and capture information during a specific task in an information system. For example, human-computer dialogues are analogous to a conversation between two people [51]. The dialogue support of human-computer interaction, where the computer praises and rewards the usage progress and provides feedback to the user, adds a level of desired interactivity [52]. This is typically accomplished via verbal information or textual summaries and helps users keep moving toward their goal or target behavior.

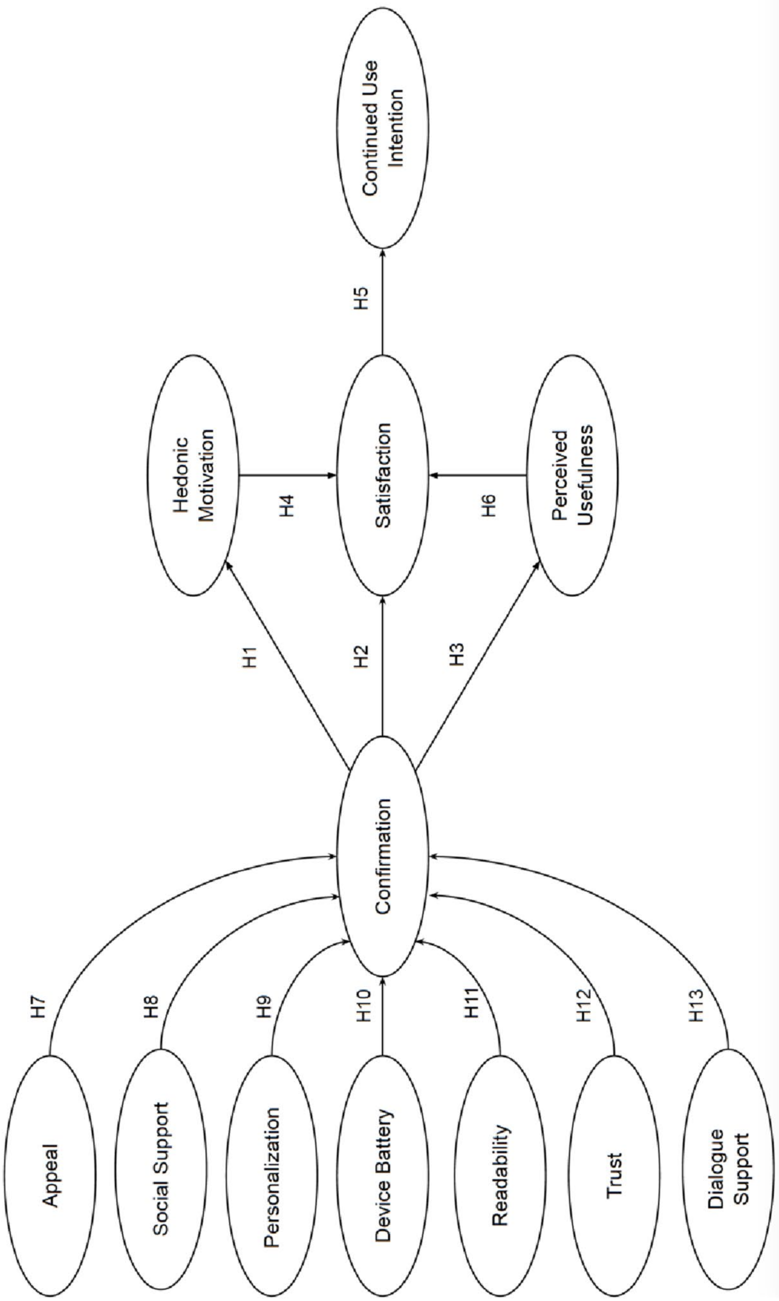

Fig. 2 Conceptual model

Device Battery Devices have the ability to hold charge over time, and users of wearable devices have to deal with limited battery life through a reciprocal process called human-battery interaction (HBI) [53]. From a user perspective, the level of inconvenience increases as wearable devices require to be charged more frequently to avoid running out of battery. Wearables should include mechanisms to reduce the need to be regularly charged [9].

Personalization Personalization is the automatic adaption to user's behavior and being adaptable through explicit configuration according to the user's preferences [50]. Personalization gives the ability to adjust the interface according to the user's preference, e.g., enables more complex functions like offering an "expert mode" with more details. Also, personalization enables users to create their own goals without any restrictions; users can utilize the wearable device to set personalized goals and a more custom-tailored experience.

Appeal Appeal or attractiveness relates to the design being up-to-date, fashionable, and "cool." It is difficult to generalize an appealing design; that is why systems need to empower users to give them a chance to configure their preferred attractive design [50]. The appeal is an aspect that captures the means of visual communication where users can choose the aesthetics like color, texture, design, and form that meets or exceeds their expectations [54–57]. Kalantari [10] stated that appeal is an effective aspect that captures users' attention and emotions and is influential in decision-making. Jeong et al. [56] studied that aesthetics influence the continuous intention to use smartwatches. In China, Gan and Li [58] found that appeal positively affects the continued intention to use the social media platform WeChat.

Readability Readability or legibility is related to the characteristics, clarity, and quality of the information being displayed to be clear enough to read with a good level of comfort. Interface element design, such as font type, font size, icons, character spacing, and line spacing which Liu and Yu [59] found, has a significant influence on the usage behavior of smartphones. Rodriguez et al. [24] noted the role of high color contrast between text and background in improving readability and aesthetic features.

Trust Trust is studied in different disciplines and contexts and could have various interpretations [60]. A widely referenced definition of trust in information systems is perceptions of uncertainty and risk when using an unfamiliar system or device [61]. Users of information systems have specific beliefs related to the level of security of the information system, the integrity of the information displayed, and benevolence. Several researches in information systems studied trust; among those are Oinas-Kukkonen and Harjumaa [52], who studied the verifiability of results in information systems and credibility support, which are also echoed in other work highlighting trustworthiness and verifiability as important design principles influencing continued use of persuasive systems [9, 62, 63].

Social Support The social aspect captures the ability of the system to show which social relation contributed to what and to allow users to express their own virtual identities [50]. Social relations are either formal support groups or informal relationships [64, 65]. Social support feature is deemed important for wearables as it provides users with social motivation to have a positive impact on physical activity and achieve health goals [66, 67]. In the context of wearables, examples of social support include the ability of users to connect with their peers.

3.3 Hypotheses

Bhattacherjee and Barfar [68] mentioned that it is likely that confirmation also influences the post-acceptance perceived usefulness and perceived enjoyment, which in turn motivates users to use continuously. Furthermore, the research of Bhattacherjee [19] and Limayem et al. [49] has shown that the level of users' satisfaction is positively affected by conformation. Confirmation precedes satisfaction; i.e., users typically confirm their beliefs which influence the satisfaction [13, 38]. Oghuma et al. [41] found that confirmation had a positive influence on hedonic motivation and enjoyment when studying continued use of mobile instant messaging. Accordingly, the following hypotheses are proposed.

H1. Users' confirmation of expectations is positively related to their hedonic motivation for wearable devices.
H2. Users' confirmation of expectations is positively related to their satisfaction with wearable devices.
H3. Users' confirmation of expectations is positively related to their perceived usefulness of wearable devices.

Thong et al. [20] studied the effects of post-adoption beliefs on the expectation-confirmation model for continued information technology use and found that hedonic motivation positively influences satisfaction. Lee and Kim [69] also demonstrated the impact of hedonic values on the satisfaction and loyalty of Airbnb users.

H4. Users' hedonic motivation with wearable technology is positively related to their satisfaction with wearable devices.

User satisfaction is determined by users' expectation of the IS, which is represented as ex-post perceived usefulness and confirmation of expectation following actual use. This construct will influence IS continuance intention. Chen et al. [70], Chen et al. [38], and Nascimento et al. [13] studied the positive impact of perceived usefulness on users' satisfaction and then the impact of satisfaction on the continuous intention to use self-service technologies, mobile applications, and wearables. Accordingly, the following hypotheses are proposed.

H5. Users' satisfaction with wearable technology is positively related to their continued wearable use intention.

H6. Users' perceived usefulness with wearable technology is positively related to their satisfaction with wearable technology.

Kim and Shin [71] analyzed the main determinants of smartwatch adoption, and they included subcultural appeal that was adapted from the model of Sundar et al. [72] and hypothesized that smartwatches are viewed both as utilitarian products and fashion products that have aesthetic attributes that can help users express their characteristics and values. They found a significant effect of subcultural appeal on user's attitude [10]. Hwang et al. [73] analyzed the aesthetic attributes of solar-powered clothing and observed a significant effect of these attributes on consumer's attitude toward this technology. Jeong et al. [56] also found a significant effect of aesthetic attributes on consumers' perceived confirmation leading to the attitude toward satisfaction and then the intention to continue to use smartwatches.

H7. The aesthetic appeal of the device has a positive effect on confirmation.

Social support is defined as the information that leads a person to believe that they are cared for, loved, and respected as a member of a network of people that is built on mutual obligation [65]. In the wearable context, social support is defined as the ability of users to connect with their peers. The social support feature is deemed important for wearables; it provides users with social motivation to have a positive impact on physical activity and achieve health goals and positively influences the perceived confirmation leading to the attitude toward hedonic motivation and satisfaction [67].

H8. Social support has a positive effect on confirmation.

Personalization is considered among system quality features (SQ) that measure the system's quality, including items such as localization, personalization, flexibility, interaction, and overall quality of the service. In studying the continuance intention of mobile application use, system quality positively influences the perceived confirmation and then satisfaction [38]. Cobos [74] found that personalization in the cognitive phase positively influences the perceived confirmation that then impacts hedonic motivation in the affective phase.

H9. Users' device personalization has a positive effect on confirmation.

The wearable devices' battery devices have the ability to hold a charge over time. This construct measures if the user feels their device battery lasts long enough in a day. Wearables should include mechanisms to reduce (if not eliminate) the burden of having to regularly charge these devices [9]. The need for more frequent charging would provide less flexibility and availability for the user when running out of battery.

H10. Users' device battery has a positive effect on confirmation.

Output quality (demonstrability) in the technology acceptance model (TAM2) refers to how well the information is displayed [75]. Output quality is also referred to as readability, clarity, information importance, or completeness [76]. Readability was reported to positively affect the perceived confirmation [38].

H11. Users' device readability has a positive effect on confirmation.

Gefen et al. [62] and Gu et al. [63] reference trust as a supporting variable to the perceived confirmation leading to the perceived usefulness and then satisfaction to impact a positive attitude toward continuous intention to use. Chen et al. [38] studied trust as a system quality that influences perceived confirmation.

H12. Users' trust in the device has a positive effect on confirmation.

Interaction support belonging as a dimension of system quality was studied to positively influence perceived confirmation in mobile applications and websites in the flight industry [38, 77]. Furthermore, interactivity had a positive influence on the perceived confirmation leading to the perceived usefulness in the learning management systems [78].

H13. Users' dialogue support within the device has a positive effect on confirmation.

4 Research Methodology

Mingers [22] highlighted that a research study is not a single piece of work but a series of phases seeking to validate data and results by combining a range of data sources, methods, or observers to add rigor and relevance through the notion of triangulation. This research employed a simultaneous mixed method research design where the quantitative method is emphasized [79, 80]. According to Morse [80], such design is denoted as QUANT + qual and is driven by an a priori theoretical framework. The qualitative analysis complements the quantitative focus of the research by providing insights into the results obtained from the quantitative analysis.

4.1 Survey Instrument

The survey instrument starts with demographic information followed by questions regarding usage patterns and the specific types and brands of wearables. The survey instrument relies on measurement items that were adapted from the literature. The measurement items were written in the form of statements, and survey participants were asked to indicate to what extent they agreed or disagreed with the statement (5-point Likert scale). Also, the last item measures the frequency of using wearables on (5-point Likert scale: daily, several times a week, every few weeks, once in a few months or more rarely, never). The appendix list the items included in the final questionnaire. A pilot survey was administered to a focus group comprised of six subjects. After revising the survey instrument, we tested it on another focus group of ten subjects. The instrument was written in English and administered using Qualtrics.

4.2 Data Collection

Upon obtaining authorization from the Institutional Review Board (IRB), the survey link was sent to online discussion boards and social networks. The survey was open to all respondents regardless of geographic location. Participation was limited to those 18 years of age and older. We found that there is a strong correlation between incomplete responses and responses that took less than 3 min. We removed all incomplete responses and responses that appear to have been rushed. Rushed responses were responses that took less than 3 min for the subject to complete. Qualitative data was collected using the same survey instrument. Respondents were asked to answer the following open-ended question:

What are the key factors that drive you to continue/abandon using your favorite wearable?

4.3 Quantitative Data Analysis

We used the R library, partial least squares path modeling PLS-PM model version (0.4.9), for the quantitative analysis of the data. PLS allows researchers to analyze the relationships simultaneously, does not rely on distributional assumptions, and makes fewer demands regarding sample size than other methods [81] and can be applied to complex structural equation models with a large number of constructs [82]. The minimum sample recommendations as per [83] (based on [84]) are necessary to detect minimum R^2 values of 0.10 and 0.25 for a significance level of 10% and to achieve a statistical power of 80% for the designated model complexity that are 112 and 42, respectively. Furthermore, the 10 times rule method (a common rule of thumb) for determining the minimum sample size for PLS analysis [83] implies a minimum sample of 70. For the measurement model, internal consistency was tested using the composite reliability and Cronbach's alpha with values of 0.60–0.70 deemed acceptable [13, 83]. Measurement loads with a significant t-value on its latent construct demonstrate convergent validity. Bootstrapping with 200 iterations was used to obtain the necessary t-values [85]. Correlations of the latent variables scores show appropriate patterns of loading, and appropriate average variance extracted (AVE) was used to confirm the discriminant validity [85]. The loadings should exceed 0.7, and every item with loading less than 0.4 should be excluded [13, 83, 86]. AVE should exceed 0.5 to explain more than half of the variance of its indicators [13, 86–88]. Furthermore, the loading of each indicator should be greater than all cross-loadings [81, 89, 90].

4.4 Qualitative Data Analysis

The objective of the qualitative analysis was to elicit concepts related to drivers or challenges for the continuous use of wearables from the responses to the corresponding open-ended question. This was obtained through the coding of the responses. Coding is the process of assigning labels to the responses and is comprised of two steps: initial (open) coding and focused (axial) coding [91, 92]. During the initial coding, the objective is to "learn" from the data, i.e., grounded in the data. Open coding moves quickly through the data and attempts to remain as close to the data as possible [91]. In focused coding, the emphasis is to abstract away from the initial codes obtained to infer any underlying concepts and relations [91, 92]. One author served as the primary coder, while the second author served as a secondary coder/reviewer. Issues raised by the secondary coder were discussed and resolved. All coding was performed using the Atlas.Ti software version 8 for Mac.

5 Results

We collected 372 responses. Filtering incomplete and rushed responses resulted in a total of 116 valid responses. Seventy-one percent of the subjects were males, and 38% fell in the 35–39 age group. As shown in Table 1, most subjects (86%) are still using wearables. Subjects tend to use wearables daily (60%) or several times a week (33%), and 91% plan to use them even more. Subjects indicated multiple usages for wearables. Most subjects were using wearables for healthcare and wellness (61%) or sports and fitness (54%) and had smartwatches wearable type (74%). Garmin and Apple watches were the most commonly used brands accounting for almost 52% of the wearables used (Table 1).

5.1 PLS Measurement Model

The assessments of the reliability and validity of the constructs are satisfactory. Outer model loading (measurement model) *t*-values exceeded 1.96 corresponding to a 5% significance level, thereby confirming convergent validity. Discriminant validity is also supported as all item loadings exceed 0.7, and the AVE for all constructs exceeds 0.5. All cross-loadings are below the loadings for their respective constructs. Accordingly, the constructs can be used to test the structural model.

5.2 PLS Structural Model

As shown in Fig. 3, the R^2 of the dependent variables are 0.24, 0.46, 0.11, 0.14, and 0.32 for continued use intention, satisfaction, hedonic motivation, perceived usefulness, and confirmation, respectively. The model explains that 24.1% of the variance of continued intention to use is explained through a single variable of satisfaction which is significant at $p < 0.01$ supporting hypothesis 5. In turn, the model explains the variation in satisfaction at 45.6%. All antecedents to satisfaction (confirmation, perceived usefulness, and hedonic motivation) are statistically significant at $p < 0.01$ denoting support for hypotheses 2, 4, and 6.

The model explains 10.8% of the variation in hedonic motivation where its antecedent confirmation is also statistically significant at $p < 0.01$ supporting hypothesis 1. The model explains 13.5% of the variation in perceived usefulness where its antecedent confirmation is statistically significant at $p < 0.01$ supporting hypothesis 3. Last but not least, the model explains 31.6% of the variation in confirmation, and three of the seven variables are statistically significant. Dialogue support and device battery are significant at $p < 0.01$. Appeal is significant at $p < 0.10$. Trust, social support, personalization, and readability are not significant.

Table 1 Analytics on subjects of the survey

Category	Count
Usage pattern	
Used and still using	100
Used before but abandoned using	16
Future intention to use expectation pattern	
Will use the device more in the future	106
Will use the device less in the future	8
Will not use device in the future	2
Usage frequencies	
Daily	70
Several times a week	38
Every few weeks	5
Once every few months or more rarely	3
Usage purposes (multipurpose)	
Health and wellness	71
Sports and fitness	63
Security and prevention	11
Lifestyle and fashion	11
Interface and novelty	6
Gaming	4
Wearable medical device	2
Device types	
Smartwatch	86
Others	14
Fitness tracker	13
Wearable medical device	2
Smart eyewear	1
Brands	
Apple	31
Garmin	29
Others	23
Samsung	17
Fitbit	15
Microsoft	1

Therefore, hypotheses 7, 10, and 13 are supported, while hypotheses 8, 9, 11, and 12 are not supported. In total, of the thirteen hypotheses, four were disconfirmed.

5.3 Qualitative Data Analysis (QDA)

Of the 116 subjects, 104 provided responses to the question “What are the key factors that drive to continue/abandon using your favorite wearable?”. Open and focused

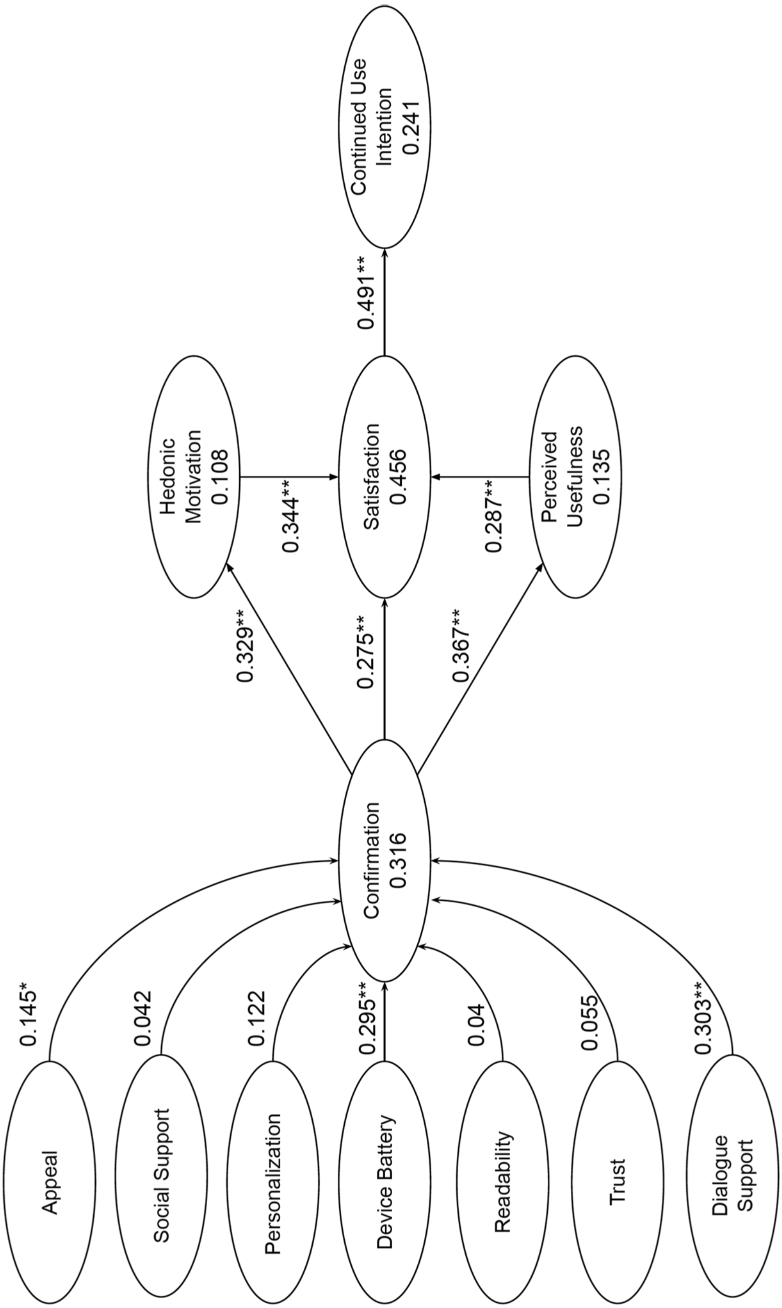

Fig. 3 Structural model results

coding of the responses resulted in a total of 41 codes pertaining to various drivers or challenges noted for continued use. Codes corresponded to six categories pertaining to drivers for continued use. These categories are appeal, design features, hedonic motivation, perceived usefulness, perceived ease of use, and price value, as shown in Table 2. Of the six categories, design features, perceived usefulness, and perceived ease of use were also associated with challenges to continued use (Table 3).

With respect to design features, device accuracy, battery life, overall perception of quality, and integration with other apps/devices were the most frequently mentioned features associated with drivers for continued use. Of these features, the device battery was also frequently mentioned as a challenge for continued use. Other challenges noted included distractions due to notifications and device integration.

Perceived usefulness driving continued use was overwhelmingly associated with tracking functions including tracking exercise/workout, activities/steps, sleep, and tracking vitals, e.g., calories burnt and heart rate. Getting fit and motivating to stay active as well as communication (call/text/email/misc. notifications) were also frequently noted. There were several responses referencing the perceived benefit/usefulness of wearables without providing specifics regarding the nature of such benefit. There was some reference to the lack of perceived benefits as a challenge for continued use. However, such reference did not specify the nature of the benefit expected.

Generally, subjects found the ease of use of wearables a driver for continued use. Reference to ease of use was relatively generic, e.g., “easy to use” and “handy.” There was no specific mention of interface issues such as dialogue support and readability. There was one reference to perceived ease of use as a challenge for continued use. The comment specifically mentioned the difficulty in logging health data.

6 Discussion

The study reflects the significance of satisfaction as an antecedent for continued use intention. This could also be inferred, albeit indirectly from the qualitative responses referencing antecedents to satisfaction, namely, perceived benefits and hedonic motivation. The role of satisfaction as an antecedent to continued use intention is consistent with prior research utilizing the ECM in the context of smartwatches [13, 31, 43] and other information technologies [20, 38, 40–42]. The results also support that users’ perceptions of perceived benefits, their enjoyment, and confirmation are significant antecedents for satisfaction. Qualitative responses further confirm the role of perceived benefits and hedonic motivation. The findings are consistent with [13, 31] for smartwatches as well as other information technologies [20, 41]. The qualitative analysis provides additional insights into the nature of perceived usefulness. Specifically, most references to usefulness are in the context of tracking activities, exercise, and vitals in the context of maintaining and improving health and well-being. This is related to the notion of health technology (Healthology) signifying the degree to which health is integrated into a person’s daily activities that were shown to drive continuous intention to use wearables [32]. In essence, for manufacturers, health and wellness continue to be a key market segment for wearable technologies.

Table 2 Codes associated with drivers to continuance use intention

Code	Count
Hedonic motivation	1
Appeal	5
Design features	
Accuracy	11
Battery life	10
Comfortlessness	2
Dialogue	3
General design	3
Integration with other apps	6
Lightweight	3
Quality	8
Perceived usefulness	
Collect data	7
Communicate (call/text/email)	5
Efficiency	2
Encourage me to stay active	7
Get fit	9
Get notifications	8
Navigation while driving	1
Provide information	1
Track activities	18
Tracking	
Track calories burnt	12
Track exercise/workout	18
Track heart rate	7
Track other vitals	3
Track sleep	9
Track steps	9
Useful	14
Visualizing data	2
Perceived ease of use (PEOU)/usability	
Convenient	8
Easy to use	13
Handy	2
Price value	1

Overall, the findings support that the expectation-confirmation model is suitable as a model for information systems (IS) continued use intention in the context of personal devices such as wearables. Users' continuance intention to use wearables is contingent on their satisfaction with the technology. Satisfaction, in turn, depends on the extent of benefits/usefulness received, the pleasure and enjoyment experienced, and the confirmation or pre-consumption expectation from using the wearables. Accordingly, and

Table 3 Codes associated with challenges to continuance use intention

Code	Count
Design features	
Battery life	7
Continued notifications	2
Cumbersome to wear	1
Device integration	1
Independent operation	1
Lack of app functionality	2
Perceived benefits	
No perceived benefit	6
Tracking long-term health data	1
Perceived ease of use (PEOU)/usability	
General PEOU	1
Remembering to wear	2

as demonstrated elsewhere in [13, 38], in order to retain users, manufacturers must focus on the users' satisfaction with their devices. This can be accomplished by further emphasizing a user-centric approach in identifying design features critical to adoption and sustained use.

With respect to design features as antecedents for continued use, PLS analysis reveals that design features such as device battery, dialogue support, and appeal support users' confirmation of expectations. This is consistent with the finding obtained from mining social media for users' preferences and expectations [9]. However, there is a lack of support for readability, personalization, social support, and trust. This could complement the findings by Canhoto and Arp [12] where device characteristics that may drive adoption may not necessarily drive continued use. As post-adoption beliefs play a role in determining continued intention to use, such beliefs are affected by their level of confirmation. Users' initial expectations of design features are either confirmed or unconfirmed after adoption. The user has initial expectations of the design features and will then modify or hold their beliefs if the design features meet their expectations or continue to be relevant to their expectations. The qualitative analysis supports the prevalence of device battery as a driver and a potential challenge to continued use. However, such analysis also alludes to the importance of device accuracy (and trust in the device measurements), perception of quality, and integration with other apps/devices and thus echoes design principles found in [9].

Few studies have focused on design features informing the ECM. These models focused on the theoretical constructs underlying continuance intention, while our research aimed to provide explanatory power in the form of design features using a mixed method approach. While Canhoto and Arp [12] focus on determining qualitative design features and El-Gayar et al. [9] focus on mining social media to infer design principles, in this study, we quantitatively and qualitatively explored design features reported in the literature as antecedents for continued use. Collectively, the findings support all the design recommendations reported in [9], with the exception of social support and data security.

There are a few limitations that can serve as a basis for future research. One limitation pertains to the scope of the research, namely, the emphasis on device features. Individuals' abandonment of self-monitoring technologies is a rich, complex, and dynamic phenomenon, and not all device abandonment is associated with failure in design [15]. For example, beyond device novelty that may drive initial adoption, Shin et al. [14] highlight the importance of the user's context and existing intrinsic and extrinsic motivations as drivers for continued use. While these findings align with the ECT, future research may aim to further unpack ECT constructs and how particular design considerations may pertain to these constructs. The model may also be extended to account for users' experiences, such as the need fulfillment [93] as a potential driver for continued use. Another limitation with respect to this study pertains to the characteristics of the respondents and the devices and the potential for a selection bias. Most notable is the increased emphasis on health, wellness, and sport, males, and a younger user group in the sample. Future research may explore the extension of the findings to other user populations, e.g., elderly users and patients with chronic health conditions. Further research is also warranted to explore design features that were not supported by the research. This can be in the form of a follow-up qualitative study involving interviews and focus groups.

7 Conclusion

Wearable devices have garnered significant attention over the last few years as an emerging technology with significant potential for positive societal impact. Such attention is echoed by an exponential uptake of these technologies by users. However, such uptake is not necessarily coupled with sustained use. While there is research addressing the adoption and acceptance of wearable devices, fewer have investigated the design features related to continued intention to use. Unfortunately, the anticipated benefits of wearable adoption and use will not come to fruition if users abandon the technology. Grounded in the expectation-confirmation model as an underlying theoretical model and using a simultaneous mixed method QUANT + qual approach, this research investigated various design features as antecedents to factors influencing continued intention to use wearables. Overall, the findings support the notion that certain design features such as device battery, accuracy, dialogue support, appeal, and perception of quality are drivers for continued use intentions. The findings also highlight the significance of perceived benefits, hedonic motivation, and confirmation.

From a theoretical perspective, this research demonstrates that the expectation-confirmation model is suitable as a model for information systems' continued use intention. It extends the understanding of the continued intention to use models by evaluating various design features that could drive sustained use. From a practical perspective, the findings suggest that there is a need to focus on design features that not only drive adoption, e.g., perceived readability, but also features that are critical to sustained use. A notable example is the quality of the device battery. Well-thought-out design features will result in a higher confirmation level which in turn enhances how satisfied a user is with the device resulting in sustained use.

Appendix

Table 4 Survey items

Constructs		Measurement items
Hedonic motivation (HM)	I1	Using wearables is fun
	I2	Using wearables is boring
	I3	Using wearables is exciting
Social support (SS)	I4	The wearable device enables me to share my physical activities on social media
	I5	The wearable device does not share any physical activity progress to anyone
Appeal (AP)	I6	The design of the wearable device is visually appealing and marketable
	I7	Can be used efficiently and comfortably and with a minimum of fatigue
Dialogue support (DS)	I8	The design of the wearable device helps to keep me moving toward my goal or target through verbal praise and/or rewards (points, badges, trophies, etc.)
	I9	The design of the wearable device gives suggestions and recommendations (healthier eating habits, tips to improve your physical health, etc.)
	I10	The design of the wearable device provides a pleasant and well-timed (not obtrusive) notifications
Readability (R)	I11	The information displayed on the wearable screen is clear and can be read comfortably
	I12	The information displayed on the wearable screen is presented in a convenient font size and nice color contrast
Personalization (P)	I13	The wearable device easily accommodates my preferences
	I14	The wearable device not adaptable to any needs
Trust (TS)	I15	I believe that the design of the wearable device is reliable for data recording
	I16	I believe that the design of the wearable device protects my personal information
	I17	I believe that the design of the wearable device is safe or reliable

Table 4 (continued)

Constructs		Measurement items
Perceived usefulness (PU)	I18	Using the wearable device helps me monitor my physical health
	I19	Using the wearable device provides features that are useful
	I20	I wanted to use a wearable device regardless of who suggested it
Device battery (BT)	I21	The battery charge of the wearable device I currently use or have used is sufficient for my purposes
	I22	The wearable device I currently use or have used needs to be charged very often to keep it going
Confirmation (CONF)	I23	Overall, my experience with using the wearable is better than what I expected
	I24	My experience with using the applications installed on the wearable device was better than what I expected
	I25	The customer service provided by the vendor of the wearable device was better than what I expected
Satisfaction (SA)	I26	Overall, I am satisfied with the wearable device
	I27	I feel frustrated with the wearable device
	I28	I am pleased with my overall experience of using the wearable device
Continuous intention to use (CIU)	I29	In the future, I intend to use wearables
	I30	How often have you used or currently use a wearable device?

Declarations

Competing Interests The authors declare no competing interests.

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