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PAPER

Towards A Wearable Technology Model 2: The Paradox of Wearable Technology Adoption

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ABSTRACT

This study presents an updated version of the original wearable technology model (WTM) proposed by Alduaij, referred to as the Wearable Technology Model 2 (WTM2). The new model adopts a more user-centered approach by incorporating experiential constructs, such as user satisfaction and user enjoyment, to better capture the affective dimensions of wearable technology (WT) adoption. Wearable technologies represent a paradigm shift in user interaction with digital systems, transitioning from handheld devices to seamlessly integrated wearable technology. These technologies offer valuable benefits in health monitoring, fitness tracking, productivity enhancement, and ubiquitous communication, making them increasingly central to daily life. The proposed WTM 2 extends the original WTM by incorporating two additional constructs (user satisfaction and user enjoyment) alongside the core technology acceptance model (TAM) constructs of perceived usefulness (PU) and perceived ease of use (PEOU) and the WTM constructs of privacy (PRV) and design. A quantitative methodology was employed, utilizing an online, randomly distributed questionnaire that targeted diverse demographic segments of the population. Data were analyzed using multiple regression and chi-square tests to examine the relationships between constructs. This study makes both theoretical and practical contributions by refining our understanding of adoption drivers and barriers while providing actionable insights for high-tech companies seeking to enhance the wearable user experience and increase market uptake.

KEYWORDS

wearable technology model (WTM), user satisfaction, user enjoyment, technology adoption, perceived usefulness (PU), perceived ease of use (PEOU), technology acceptance model (TAM)

1 INTRODUCTION

Wearable technology (WT) refers to electronic devices that can be worn as accessories, embedded in clothing, implanted, or tattooed onto the skin. These devices are hands-free gadgets with practical applications, driven by microprocessors, and capable of sending and receiving data over the Internet. WTs include smartwatches,

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wristbands, smart eyewear, inventive jewelry, and electronic clothes [1]. WT can sense, collect, and upload physiological data around the clock, providing the potential to improve the quality of life that smartphones alone cannot match. Wearables can also help users execute a variety of useful microtasks, such as viewing urgent information and checking incoming text messages [3].

Wearable technologies have grown in popularity and usage in recent years, and experts expect this trend to continue in the education sector [4]. However, the widespread adoption of this technology necessitates a more thorough understanding of its benefits and applications. Most consumers are still unaware of the unique purpose of wearable devices, often referred to as innovative technologies. The WT market is expanding rapidly, especially in the entertainment industry, where wearable gadgets improve user experience. According to the findings, smart glasses are becoming increasingly popular in the entertainment industry, providing consumers with AR experiences that combine digital information with the physical environment. Data on fitness and wellness devices demonstrate a surge in interactive fitness games and virtual sports, offering consumers compelling methods to remain active [5]. Even if smartphone use is at an all-time high, the mobile device market is experiencing a new trend. Users are increasingly interested in wearing mobile devices that promise to improve their quality of life in ways that smartphones cannot [1]. Despite these advancements, difficulties remain in the form of privacy (PRV) concerns originating from data collection methods and battery endurance limitations, which are the primary causes inhibiting widespread adoption among customers worldwide. Research is being conducted to discover and address these challenges, ultimately improving user experience.

1.1 Research aim and objectives

This study sought to create and empirically validate an updated version of the WT model (WTM) [1], known as Wearable Technology Model 2 (WTM 2), which is more user-oriented and focuses on the user's experience and satisfaction with wearable devices. The proposed WTM 2 builds on the original WTM by adding two new constructs (user satisfaction and user enjoyment) to the fundamental technology acceptance model (TAM) [2] elements of perceived utility and perceived ease of use (PEOU), as well as the WTM constructs of PRV and design. The study has four particular goals: (a) to investigate the impact of perceived usefulness (PU), PEOU, PRV concerns, and design and enjoyment on user satisfaction with wearable devices; (b) to determine the extent to which these constructs, along with user satisfaction, predict users' intention to continue using wearable devices; (c) to identify key demographic correlates of continued intention, particularly the frequency of use; and (d) to validate WTM 2 as an integrative framework for explaining WT adoption among smartwatch, fitness bracelet, and smart headphone users.

2 LITERATURE REVIEW

2.1 Theoretical foundations of technology adoption

WT adoption is based on well-known information system theories, including the TAM and its extensions. According to TAM, PU and PEOU are key drivers of consumer acceptance [2]. This approach has been extensively validated in various technical contexts, including mobile applications, e-learning systems, and social media platforms. Building on this foundation, Alduaij [7] demonstrated that PU and PEOU have a considerable impact on user perceptions and behavioral intentions in social media adoption, highlighting TAM's robustness across digital contexts.

2.2 From functional adoption to experiential engagement

While early adoption models emphasized utility and usability, contemporary research has shifted to user experience and engagement. Jamalova [8] notes that adoption research is increasingly adding contextual and affective characteristics, such as trust, social impact, and behavioral intention, indicating a shift toward more user-centered frameworks. Similarly, Alduaij [6] investigated the paradox of technology adoption, demonstrating that growing usage can both increase dependence and raise worries, reflecting the complex emotional and behavioral dynamics of technology use. In the wearable arena, Chen [9] highlighted this change by presenting context-aware interaction models that prioritize an intuitive and seamless user experience. These studies show that adoption is no longer just cognitive but also intensely experiential, which supports the inclusion of user pleasure and enjoyment in WTM2.

2.3 Wearable technologies

Wearable technologies (WT) are becoming increasingly popular and appealing [10]. Wearables allow users to immerse themselves in unfamiliar environments, listen to their favorite music secretly, and track and analyze health data in real time. Wearables, as the name implies, are devices equipped with wearable smart sensors that transmit, record, and analyze data via the Internet. The current wearable market includes smartwatches, fitness trackers, headphones, extended reality (XR) devices, virtual reality (VR) headsets, and augmented reality (AR) glasses. The wearable market is estimated to ship almost 560 million devices by 2024, making it a promising part of the consumer electronics industry. These technologies, which include smartwatches, glasses, earphones, clothing, shoes, accessories, and jewelry, allow ordinary people to track and monitor private data on fitness, health, and chronic conditions, which was previously impossible [11], [12]. Owing to rapid technological breakthroughs, a comprehensive WT ecosystem has emerged. Small sensors with wireless communication and low independent computing power enable WT to track sensitive data while remaining mobile and user-wearable [11]. These technologies are intended to alter how people interact with their surroundings by providing health monitoring features through mobile applications and wireless connectivity capabilities. WTs continue to improve people's lives by developing a wide range of wearable, high-tech gadgets that can be used daily. WT exists in various forms. The first category of wearables includes accessories such as smartwatches and wristbands. Wearable gadgets with touchscreen interfaces are often referred to as smartwatches. Wristbands, on the other hand, are wearable gadgets that have additional functionalities, such as fitness tracking, but do not have touchscreens [13]. The second group comprises head-mounted gadgets, including earbuds, headsets, and smart glasses. Smart eyewear also includes contact lenses and spectacles with wireless networking, sensors, and other functionalities [3]. Bluetooth-enabled gadgets include headphones and ear buds.

This study examined popular WT devices such as fitness trackers, smartwatches, and headphones. Fitness trackers and smartwatches are popular consumer gadgets that integrate WT fitness and health tracking into daily life. The WT helps users manage their health by monitoring their heart rate, physical activity, sleep patterns, and other health parameters. First, there are fitness trackers or bracelets, such as the Fitbit Charge. These gadgets track sleep patterns, physical activity, and other health indicators. Second, smartwatches were the most used WT gadgets among the participants. Smartwatches provide connectivity, alerts, and a variety of wrist apps. The third type of WT equipment is Bluetooth headphones, which allow hands-free conversation and audio streaming. Jamalova [8] conducted a thorough literature evaluation of user behavior toward cellphones and wearable devices, focusing on technology adoption models such as TAM and UTAUT/UTAUT2. This study employs a two-stage methodology: first, it analyzes 213 publications from the Scopus database using citation and bibliographic coupling techniques and then examines the most influential studies. The data show that TAM remains the dominant framework, despite a considerable increase in UTAUT-based studies in recent years, indicating a trend towards user-centric and contextual elements such as trust, social influence, and behavioral intention. The study also reveals fragmentation in the research environment, as many studies are weakly integrated, and indicates deficiencies such as limited moderator integration and insufficient theoretical extension. Overall, this study adds to the literature by charting the evolution of adoption models and recommending pathways for more integrated and comprehensive future research.

2.4 Device design

Because WT is physical and personal, design is important for its adoption. Unlike traditional technology, wearables must be worn continually; therefore, user adoption is based on comfort, aesthetics, and usability. Previous research has shown that poor design can cause discomfort and eventual abandonment [14]. The user interface, which includes the technology's visual design and usability, is another important factor influencing adoption and experience. Because product aesthetics may create user connections and meet their needs, the "form follows function" design approach is critical. Although function is still the most important element, the design must also be practical and comfortable for daily use [14]. Consequently, design is a core construct, ensuring its inclusion in WTM2.

2.5 User satisfaction and system success

User satisfaction has long been considered an important outcome in information system success models (ISS) [15]. Previous studies have shown that satisfaction is influenced by system quality, information quality, and perceived value [16], [17], [18]. Alduaij and Alterkait's [19] empirical findings confirm that information quality has a major impact on user satisfaction in e-learning systems, with satisfaction mediating the relationship between system performance and continuous usage. Furthermore, Alduaij et al. [19] revealed that mobile application efficiency directly affects user satisfaction when accessing information, highlighting the role of system performance in shaping users' perceptions. A recent study employing the ISS model found that system and information quality have favorable effects on the UIoT [20]. In terms of user happiness and enjoyment, a study examined how individuals like to use smart home IoT devices and discovered that consumers who think the gadget is more valuable enjoy it more. In a previous study, [17] assessed user satisfaction with system and device information quality in terms of PU and PEOU. The data show that the information quality improves user pleasure. That is, the higher the quality of the information, the greater the satisfaction and utility. Furthermore, the study found that system quality had a positive influence on system satisfaction, with higher system quality resulting in higher user satisfaction with the system and, thus, higher PEOU. A study on smart home IoT devices revealed that users who perceive them as valuable tend to enjoy them more. Similarly, ease of use and usefulness influence user satisfaction and enjoyment of IoT devices [16], [15]. However, wearable technologies differ from traditional systems in that satisfaction is not derived solely from efficiency but also from comfort, aesthetics, and emotional engagement. This distinction highlights a limitation of traditional IS success models and supports the extension proposed in WTM2's model.

2.6 User enjoyment

User enjoyment is critical for WT because it promotes good and engaging interactions. Familiarity with technology, ease of use, service quality, and perceived value all affect how much people love IoT devices. An enhanced user experience can stimulate the uptake and continuous use of WT devices, thereby increasing their market potential. From an experiential perspective, enjoyment increases user engagement and encourages continuous use. Gamification, intuitive interfaces, and individualized interactions contribute to increased satisfaction [21]. Gamification, which includes game mechanics such as challenges, rewards, and competition, can increase user engagement and enjoyment. By combining these factors, devices deliver a more engaging experience, resulting in increased levels of enjoyment. Devices can be designed to increase enjoyment by improving their usability, usefulness, perceived value, context awareness, and gamification. Additionally, user feedback is critical for the advancement of WT devices to satisfy user wants and preferences and assure long-term acceptance and satisfaction [21]. This is consistent with the findings of Alduaij [22], who found perceived benefits and experiential value to be significant drivers differentiating actual users from non-users in mobile commerce adoption. The study found that people are more likely to accept and stick with technologies that deliver meaningful and engaging experiences rather than utilitarian benefits. As a result, it is a central construct rather than a peripheral element, reinforcing its integration within WTM2.

2.7 PRV concerns and the adoption paradox

Device PRV is a significant challenge. One of the most significant impediments to the adoption of WT is PRV concerns. Wearable technologies capture sensitive personal data, such as health and behavioral information, raising concerns about data security and misuse [1], [14]. PRV concerns impede adoption because wearable gadgets collect sensitive personal data, prompting concerns about data breaches and misuse. Wearable technologies capture large amounts of personal data, such as health indicators and location information, which raises serious PRV concerns [1]. The potential for data breaches and illegal data sharing poses a significant challenge in this scenario. Similarly, Alduaij [18] found that perceived risks and contextual factors heavily influenced user adoption decisions in mobile commerce environments. For example, the 2018 MyFitnessPal data breach exposed more than 150 million user accounts to hackers. The adoption of WT involves the installation of effective technological solutions for storing and processing massive amounts of user data, creating personalized services, and developing decision-making algorithms using machine learning [14]. Another way to encourage WT use while also resolving data PRV concerns is to include users as an intrinsic part of the security and PRV standards, thereby giving them authority over the acquired data. Allowing users to control their information may encourage consumers to adopt WT and increase adoption rates. These findings indicate a continuous paradox: users adopt technologies despite being aware of the risks involved. This paradox is important for wearable technologies, in which the advantages are immediate and profound, but the risks are abstract and delayed. WTM2 immediately addresses this contradiction by treating PRV as both a barrier and a contextual factor influencing continued activity.

Recent empirical evidence from Kuwait enhances the need for including both functional and experiential components in technology adoption models. A mixed-methods study of 310 students and instructors discovered that AI tools are commonly regarded as beneficial in improving learning outcomes, particularly through automation, customization, and increased engagement. Despite these favorable opinions, major worries persist about ethical issues, data PRV, expense, and the complexity of AI systems. Importantly, the study indicates that consumers see AI as a supplement rather than a replacement for human contact in education, highlighting the ongoing necessity of human-centered design. These findings strongly support the reasoning for WTM2, which goes beyond solely utilitarian notions by including experience elements like user happiness and enjoyment, as well as recognizing contextual constraints like PRV and trust. The juxtaposition of positive sentiments and persistent fears parallels the broader "adoption paradox," in which users embrace technology despite being aware of its risks, highlighting the importance of integrative models that capture both the behavioral and emotional elements of technology use [23].

2.8 Continuance intention

Continuance intention is an important step in technology adoption, representing users' decisions to continue or quit use over time. Unlike initial adoption, which is frequently motivated by PU and simplicity of use, continued behavior is influenced by a variety of experiential, contextual, and post-adoption factors. Wearable devices prioritize comfort because of their proximity to the user. Awolusi et al. [24] discovered that workplace wearables commonly experience utilization declines when continuous use causes discomfort. Similarly, Dehghani et al. [25] discovered that even technologically capable users quit using devices when gadgets fail to satisfy comfort expectations, implying that comfort is a barrier to long-term engagement and habit building. Recent research has shown that, in addition to physical variables, a broader set of behavioral and psychological characteristics impacts continuation intention. Pal et al. [26] found that trust is essential for maintaining user engagement with wearable devices, especially when personal data are involved. Ahmad et al. [27] found that traditional constructs like PU and ease of use are insufficient to explain continuance behavior in health-related wearable contexts, where user experience and perceived value are equally important. Guo et al. [28] found that motivation, user experience, and perceived advantages strongly impact wearable users' intention to continue using them, emphasizing the significance of experiential engagement. Naz et al. [29] suggested that user behavior is influenced by both pre-adoption expectations and post-adoption experiences, emphasizing its dynamic nature over time. Demographic variables also influenced this decision. Pobiruchin et al. [30] and Jacobs et al. [31] proposed that age and gender influence comfort perceptions, with older and female users being more likely to reject gadgets viewed as obtrusive, heavy, or visually unpleasant. Taken together, these data show that the desire to continue using WT is determined by a combination of comfort, trust, user experience, and context. In conclusion, continuation intention goes beyond initial adoption to reflect a more sophisticated evaluation process in which experiential quality, bodily comfort, and perceived risk influence continued usage behavior. This multifaceted perspective emphasizes the importance of integrative models, such as WTM2, which consider both the functional and experiential aspects of long-term technology use.

2.9 Theoretical grounding

The analysis is based on two major models: the WTM [1] and TAM [32], [2]. The WTM structures are PRV [33] and design (weight, size, and shape) [34]. The PRV concept investigated the degree of perceived security associated with wearing the device. Safety investigates the user's impression of the level of safety, sensation of the device on the body, and proximity of the gadget to the user in terms of potential injury while wearing it. The design considered the dimensions of the WT, including its size, weight, form, material, and individuality. The TAM is a prominent model that has been historically used in many research fields [35], [36]. TAM consists of three main components: PU, PEOU, and intention to continue using the technology. According to Davis [32], [2], PU and PEOU are strong predictors of a user's decision to accept or reject a technology. The TAM defines perceived utility as the extent to which the user perceives the device to be advantageous, PEOU as the extent to which the device is simple to use, and intention to continue usage as the user's desire to use the device [2], [33].

2.10 Research hypotheses

The following hypotheses were developed and tested based on the theoretical foundations of TAM [2] and WTM [1], as well as empirical evidence linking technology acceptance constructs to user satisfaction and continuance intention [16], [15], [17]. Hypotheses H1–H4 address the determinants of user satisfaction with wearable devices, while H5–H9 address the determinants of users' intention to continue using the wearable device.

Determinants of User Satisfaction

H1: PU positively influences user satisfaction with the wearable device.
H2: PEOU positively influences user satisfaction with the wearable device.
H3: PRV concerns negatively influence user satisfaction with wearable devices.

H4: Design and enjoyment positively influence user satisfaction with the wearable device.

Determinants of Intention to Continue Use

H5: User satisfaction positively influences the intention to continue using the wearable device.
H6: PU positively influences the intention to continue using the wearable device.
H7: PEOU positively influences the intention to continue using wearable devices.
H8: PRV concerns negatively influence the intention to continue using the wearable device.
H9: Design and enjoyment positively influence the intention to continue using the wearable device.

2.11 Toward an integrated WTM2

The original WTM [1] established a core framework for understanding WT adoption by incorporating concepts such as design, PRV, safety, and mobility. However, as wearable technologies advance, there is a growing need to consider their affective and sensory components. The current study addresses this gap by extending WTM to WTM2, incorporating user satisfaction and enjoyment alongside TAM components (PU and PEOU), and contextual aspects (design and PRV). This integration aligns with broader research trends emphasizing user-centered design, experience engagement, and behavioral complexity in technology adoption processes. Importantly, past research by Alduaij [22], [1], [19] on e-commerce, mobile applications, and digital systems repeatedly shows that user behavior is shaped by a combination of functional, experiential, and contextual elements rather than independent variables. The WTM2 expands on existing evidence to provide a more comprehensive and realistic model of WT adoption.

3 RESEARCH METHODOLOGY

This study used a quantitative approach to test and validate the WTM2, an expansion of the original WTM [1]. The proposed WTM 2 builds on the original WTM by adding two new constructs (user satisfaction and user enjoyment) to the fundamental TAM [2] elements of perceived utility and PEOU, as well as the WTM constructs of PRV and design. The theory was evaluated using a stimulus that included three smart devices: a smartwatch, fitness bracelet, and smart headphones.

3.1 Framework structure

- Foundational Theories: WTM [1] and TAM [2].
- Key Outcomes: This study aimed to assess users' intentions to continue using wearable gadgets.
- Device Types Investigated: Three wearable devices were selected as stimuli for testing and validating WTM2: smartwatches, fitness bracelets, and revolutionary headsets. They were chosen because of their high user adoption rates [37].

3.2 Sample size

Non-probability sampling was used to recruit respondents using social media sites, regardless of their background, age, or educational level. The final sample size comprised 271 completed replies. The data gathering period lasted six months, and the study's geographic scope was Kuwait.

3.3 Questionnaire design

Data were gathered using an electronically generated and randomly distributed questionnaire created using the SurveyMonkey software. The data collection cycle lasted for six months. Finally, the geographic scope of the study was limited to Kuwait. This study used a survey instrument developed by Gliem and Gliem [38], which has been validated in previous research and tailored to the context of wearable technology. All items were rated on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The questionnaire consisted of five sections. The first section contained demographic information, such as gender, age, education, occupation, and previous technology use. Second, device usage habits, including the type of WT, frequency, and purpose of use, should be considered. The WTM constructs, including PU and PEOU, were developed based on Davis [2]. Design, PRV, and safety constructions were drawn from the WTM [1], [14], [39], [40]. Wixom and Todd [17] and DeLone and McLean [15] identified user happiness as a new WTM2 construct. The gamification literature and Thomas et al. [21] highlight the importance of user enjoyment.

3.4 Data analysis

All statistical analyses were performed using IBM SPSS Statistics [41]. Missing data were addressed using listwise deletion, and the final analytical sample comprised 271 respondents. Statistical significance was evaluated at α = .05 (two-tailed).

3.5 Preliminary and descriptive analyses

Descriptive statistics were first computed to characterize the sample and response distributions of the individual scale items. Frequencies and percentages were reported for categorical variables (sex, age group, qualification, device type, frequency of use, and continuance intention), while item means (M) and standard deviations (SD) were computed for the Likert-scale items measuring each WTM 2 construct. The response options ranged from 1 (*strongly disagree*) to 5 (*strongly agree*) [38].

3.6 Reliability analysis

The internal consistency of the five multi-item measurement scales (Design and Enjoyment, PRV, PEOU, PU, and User Satisfaction) was assessed using Cronbach's α.

A threshold of $\alpha \geq .70$ [42] was adopted as the criterion for acceptable reliability. Item-level diagnostics (item means, item standard deviations, corrected item–rest correlations, and "α if item dropped") were examined to determine whether the exclusion of any item would meaningfully improve scale reliability [43]. Once reliability was established, composite scores for each construct were computed as the unweighted mean of the constituent items and used as predictors in the regression models described below.

3.7 Multiple linear regression

To test hypotheses H1–H4, a multiple linear regression was conducted with the composite User Satisfaction score as the dependent variable and PU, PEOU, PRV, and Design and Enjoyment entered simultaneously as predictors. The overall model fit was evaluated using the multiple correlation coefficient (R) and the coefficient of determination (R^2). For each predictor, the unstandardized regression coefficient (B), standard error (SE), t-statistic, and two-tailed p-value were reported. Ninety-five percent confidence intervals around each coefficient were computed as $B \pm 1.96 \times SE$ and are visualized in the accompanying coefficient plot.

3.8 Binomial Logistic Regression

To test hypotheses H5–H9 and evaluate the contribution of demographic factors, a binomial logistic regression model was estimated with intention to continue use *(intend/no intend)* as the dichotomous outcome. Sex, frequency of use, User Satisfaction, PU, PEOU, PRV, and Design and Enjoyment were entered simultaneously as predictors. Females were set as the reference category for sex, and the lowest level of use frequency served as the reference category for frequency comparison. For each predictor, the unstandardized logit coefficient (B), SE, z-statistic, and two-tailed p-value were reported. The overall model fit was assessed using the residual deviance, Akaike's Information Criterion (AIC), and McFadden's pseudo-R^2 [44]. As with the linear regression, 95% confidence intervals on the log-odds scale ($B \pm 1.96 \times SE$) are visualized in the corresponding coefficient plot to facilitate the interpretation of the magnitude and direction of each effect.

4 RESULTS

This study contributes to the literature by developing the WTM2. This study tests the TAM and extends the WTM to develop an updated model called the WTM 2. These findings provide vital insights for the WT industry and propose recommendations to support WT companies and designers in future product development [45], [46]. Data were collected from a sample of 271 respondents using an online questionnaire distributed across different segments of society. The sample composition is summarized in Table 1, and the internal consistency of the measurement scales is presented in Table 2. Tables 3 and 4 present the linear regression predicting user satisfaction and the binomial logistic regression predicting the intention to continue using the wearable device. The coefficient plots for both models are presented in Figures 1 and 2.

4.1 Tables

Table 1. Demographic characteristics of the sample (N = 271)

Characteristic	*N*	%
Sex		
Female	221	81.5
Male	50	18.5
Age (years)		
13–17	7	2.6
18–25	209	77.1
26–35	23	8.5
36–45	16	5.9
46+	16	5.9
Qualification		
High school and below	21	7.7
College	209	77.1
University	36	13.3
Master's	3	1.1
PhD	2	0.7
Device type		
Smart headphones	160	59.0
Smart watch	102	37.6
Fitness bracelet	9	3.3
Frequency of use (1 = rarely, 5 = very frequently)		
1	5	1.8
2	12	4.4
3	46	17.0
4	97	35.8
5	111	41.0
Intention to continue use		
Intend	230	84.9
No intend	41	15.1

Note: The table summarizes the demographic profiles of the respondents who completed the online questionnaire regarding WT adoption. n = frequency; % = percentage of the total sample size. N = 271.

The sample was predominantly female (81.5%) and composed mainly of young adults aged 18–25 years (77.1%), with college-level education being the most common qualification (77.1%). Smart headphones were the most frequently owned wearable devices (59.0%), followed by smartwatches (37.6%), whereas fitness bracelets were comparatively rare (3.3%). Most respondents reported frequent use of their devices (ratings of 4 or 5 together accounted for 76.8% of the sample) and expressed their intention to continue using the device (84.9%). This demographic profile indicates that the findings generalize most directly to young, educated users of wearable audio and smartwatch technologies, which is consistent with the target population envisaged for the revised WTM 2.

Table 2. Scale and item reliability statistics for the WTM 2 measurement scales

Scale/Item	*M*	*SD*	Item-rest *r*	*α* if item dropped
Design and Enjoyment (*α* = .810)				
DES1	4.43	0.70	.47	.80
DES2	4.33	0.79	.39	.81
DES3	3.61	1.18	.66	.77
DES4	4.04	0.86	.59	.78
DES5	4.24	0.86	.50	.79
DES6	4.35	0.69	.60	.78
DES7	3.76	1.11	.67	.76
PRV (*α* = .778)				
PRV1	3.25	1.19	.60	.71
PRV2	3.34	1.20	.68	.63
PRV3	3.59	1.09	.57	.75
PEOU (*α* = .832)				
PEOU1	4.42	0.68	.61	.80
PEOU2	4.41	0.75	.60	.81
PEOU3	4.45	0.74	.69	.78
PEOU4	4.40	0.84	.56	.82
PEOU5	4.49	0.68	.72	.78
PU (*α* = .778)				
PU1	4.11	0.89	.57	.73
PU2	4.09	0.85	.65	.69
PU3	4.38	0.75	.57	.74
PU4	4.22	0.91	.56	.74
User Satisfaction (*α* = .781)				
SysQual	4.39	0.71	.58	.74
InfoQual	4.32	0.73	.59	.73
DevSat	4.34	0.74	.53	.75
InfoSat	4.27	0.76	.55	.74
Portability	4.36	0.85	.43	.78
Comfort	4.18	0.75	.51	.75

Notes: The table reports item-level descriptive statistics and reliability indicators for the five measurement scales of the revised WTM 2. The overall scale Cronbach's *α* is shown next to each scale name, and the item statistics below each scale refer to what would occur if the given item were dropped. *M* = mean; *SD* = standard deviation; Item-rest *r* = corrected item–rest correlation. DES = Design and Enjoyment; PRV = Privacy; PEOU = Perceived Ease of Use; PU = Perceived Usefulness. User satisfaction items: SysQual = system quality; InfoQual = information quality; DevSat = device satisfaction; InfoSat = information satisfaction. *N* = 271.

All five scales met the conventional reliability threshold of $\alpha \geq .70$ [42], with Cronbach's *α* values ranging from .778 (PRV and PU) to .832 (PEOU), indicating good internal consistency across the measurement models. Item M was generally high for the technology-acceptance constructs: PEOU (*M*s = 4.40–4.49), PU (*M*s = 4.09–4.38), and User Satisfaction (*M*s = 4.18–4.39), suggesting favorable overall evaluations of the wearable devices. PRV items showed lower M (*M*s = 3.25–3.59) and larger standard deviations, indicating more dispersed and somewhat more critical responses in this dimension. The corrected item–rest correlations for all 25 items exceeded the .30 cutoff [43], and no item removal would have produced a meaningful increase in scale α beyond the observed values; therefore, all items were retained for subsequent regression analyses.

Table 3. Linear regression predicting user satisfaction from technology acceptance constructs

Predictor	*B*	SE	*T*	*P*
(Intercept)	1.29	0.20	6.35	< .001
PU	0.24	0.04	5.37	< .001
PEOU	0.13	0.05	2.66	.008
PRV	0.01	0.02	0.43	.665
Design and Enjoyment (DES)	0.34	0.05	7.29	< .001

Notes: Unstandardized ordinary least-squares regression coefficients predicting the composite User Satisfaction score from four technology-acceptance predictors. Model fit: $R = .728$, $R^2 = .530$. B = unstandardized regression coefficient; SE = standard error of the mean. PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PRV = Privacy; DES = Design and Enjoyment. $N = 271$.

The regression model explained a substantial proportion of the variance in User Satisfaction ($R^2 = .530$), indicating that the four predictors jointly accounted for approximately 53% of the variation in satisfaction scores. Design and Enjoyment emerged as the strongest predictors ($B = 0.34$, $SE = 0.05$, $t = 7.29$, $p < .001$), followed by PU ($B = 0.24$, $p < .001$) and PEOU ($B = 0.13$, $p = .008$). All three effects were positive, indicating that higher scores on these constructs corresponded to higher user satisfaction. PRV did not reach statistical significance ($B = 0.01$, $p = .665$), suggesting that PRV perceptions were not meaningfully associated with satisfaction in this sample once the other constructs were controlled. These findings support the theoretical claim that affective and utility-based evaluations of a device, particularly its design and enjoyable qualities, drive user satisfaction more than PRV-related concerns do.

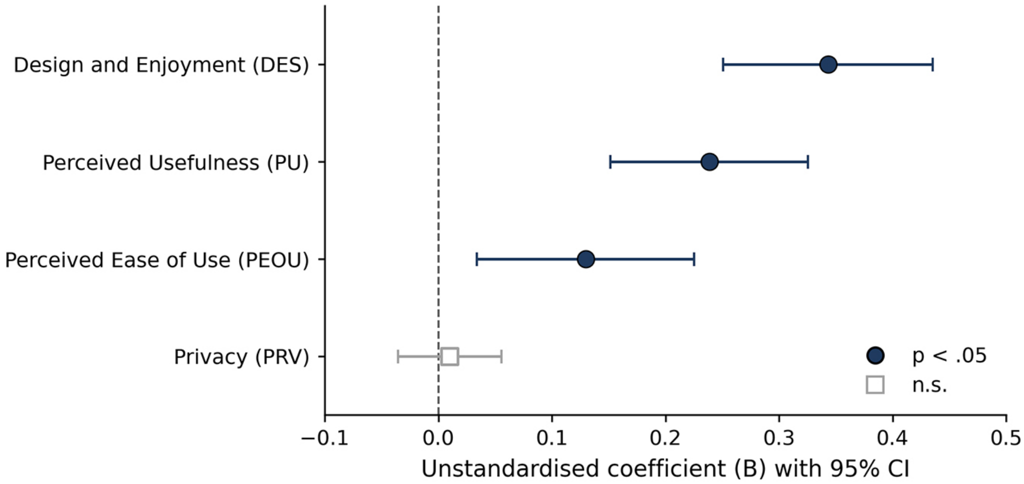

Fig. 1. Unstandardized regression coefficients predicting user satisfaction, with 95% confidence intervals

Notes: Filled circles indicate statistically significant predictors ($p < .05$); hollow squares indicate non-significant predictors. Error bars represent 95% confidence intervals (computed as $B \pm 1.96 \times SE$). The vertical dashed line at 0 represents the null value; coefficients whose confidence intervals cross 0 are not statistically distinguishable from zero. PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PRV = Privacy; DES = Design and Enjoyment. $N = 271$.

Table 4. Binomial logistic regression predicting intention to continue using the wearable device

Predictor	*B*	SE	*Z*	*P*
(Intercept)	6.71	2.56	2.62	.009
Sex				
Male vs. Female	–0.56	0.55	–1.03	.303
Frequency of use				
2 vs. 1	–2.88	1.55	–1.86	.062
3 vs. 1	–2.99	1.38	–2.17	.030
4 vs. 1	–2.91	1.34	–2.17	.030
5 vs. 1	–4.51	1.42	–3.16	.002
User Satisfaction	–0.94	0.56	–1.70	.089
PU	–0.20	0.45	–0.45	.653
PEOU	0.78	0.48	1.63	.104
PRV	1.04	0.33	3.14	.002
Design and Enjoyment (DES)	–1.90	0.50	–3.83	< .001

Notes: The coefficients represent the log-odds of "Intention = No intend" relative to "Intention = Intend"; therefore, negative coefficients indicate a lower probability of reporting no intention. Model fit: deviance = 155, AIC = 177, McFadden R^2 = .326. *B* = unstandardized logit coefficient; *SE* = standard error of the estimate. Reference categories: Sex = Female, Frequency of use = 1. PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PRV = Privacy; DES = Design and Enjoyment. *N* = 271.

The binomial logistic regression model provided an acceptable account of the intention to continue using the wearable device (McFadden's R^2 = .326). Frequency of use emerged as the most consistent demographic predictor: relative to the lowest use group, users reporting frequencies of 3, 4, and 5 were significantly less likely to indicate no intention to continue (all *ps* ≤ .030), with the strongest effect observed for the most frequent users ($B = –4.51$, $p = .002$). Among the psychological predictors, Design and Enjoyment were negatively associated with non-intention ($B = –1.90$, $p < .001$), indicating that higher design and enjoyment ratings predicted a greater probability of intending to continue use, whereas PRV showed the opposite pattern ($B = 1.04$, $p = .002$): respondents scoring higher on PRV concerns were more likely to report no intention to continue use. Sex, User Satisfaction, PU, and PEOU did not reach statistical significance (all *ps* > .05). Taken together, the results suggest that continued use is driven primarily by established usage habits and the experiential qualities of the device (design and enjoyment), while PRV-related concerns deter sustained adoption.

Some key findings indicate the following:

- The user satisfaction model accounted for a significant amount of variance, with design and delight, perceived utility, and PEOU all having significantly positive effects on satisfaction. However, PRV was not a concern.
- The strongest predictors of user happiness were design and enjoyment, implying that experiential and aesthetic elements influence satisfaction more than PRV concerns.
- Continued usage was primarily connected with the frequency of use and the experiential factors of design and enjoyment, implying that habitual use and a positive user experience were critical to continued intention.

- PRV significantly predicted continued use intention, but in the opposite direction: higher PRV concerns were associated with a lower intention to continue using the device.
- PU, PEOU, gender, and user satisfaction were not significant predictors of continuance intention in the logistic model, implying that contentment may not directly translate into continued use in this sample population.

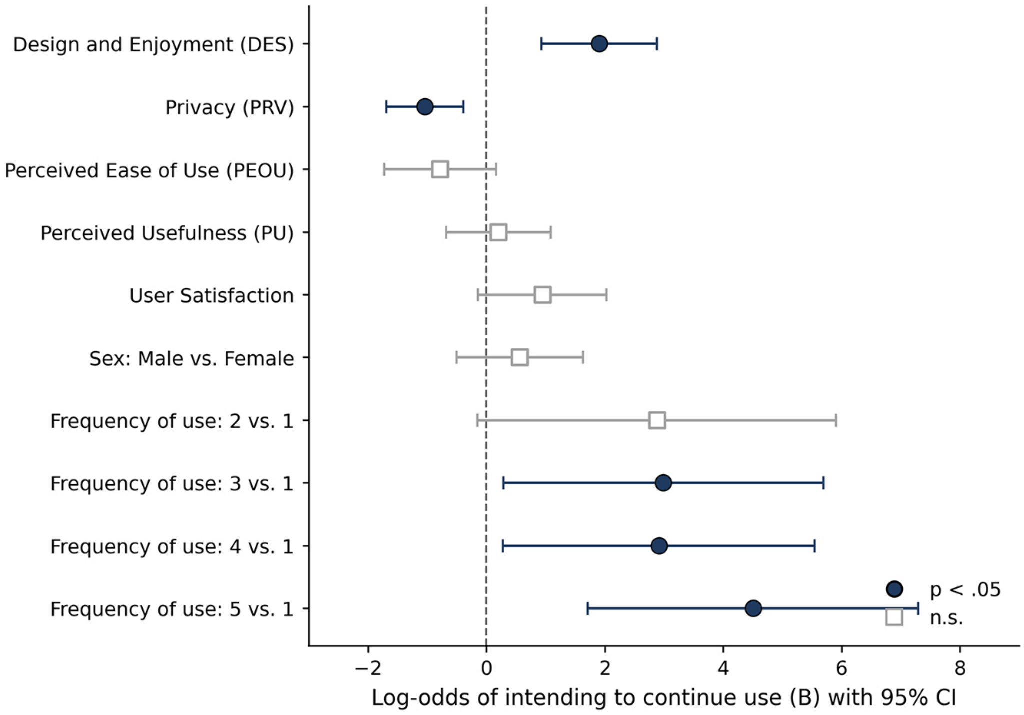

Fig. 2. Logistic regression coefficients predicting intention to continue using the wearable device, with 95% confidence intervals

Notes: The coefficients are plotted as the log-odds of "intending to continue use" (i.e., the sign of each coefficient has been inverted relative to Table 4 so that positive values indicate a higher probability of intending to continue use). Filled circles indicate statistically significant predictors ($p < .05$); hollow squares indicate non-significant predictors. Error bars represent 95% confidence intervals (computed as $B \pm 1.96 \times SE$). The vertical dashed line at zero represents a null value. Reference categories: Sex = Female, Frequency of use = 1. PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PRV = Privacy; DES = Design and Enjoyment. $N = 271$.

The findings indicate that WT adoption in this study was influenced more by experiential and design aspects than by utilitarian concerns. In the user satisfaction model, design and enjoyment were the biggest predictors, followed by PU and PEOU, indicating that consumers preferred devices that were appealing, engaging, and easy to incorporate into their daily lives. In contrast, PRV did not significantly impact satisfaction, implying that concerns about data security may be less important at the satisfaction stage than the device's immediate functional and sensory benefits. These findings are broadly consistent with previous research, which shows that user experience, utility, and usability are critical to technology acceptance and pleasure. The favorable effects of PU and PEOU are consistent with the TAM research, which has long shown that users are more inclined to rate technologies positively when they assist them in executing activities successfully and with low effort. The relevance of design and enjoyment also complements previous research emphasizing the impact of comfort, aesthetics, and engagement on wearable adoption, as well as studies claiming that adoption is increased when wearables are pleasurable and intuitive rather than merely practical. The findings of the continuance intention study contribute to the literature by demonstrating that prolonged use is dependent not only on satisfaction but also on habitual involvement and PRV concerns. The frequency of use was the most consistent behavioral predictor, implying that regular engagement may strengthen commitment to the device and reduce the likelihood of withdrawal. Design and enjoyment were again important considerations, emphasizing the notion that wearables must provide a positive everyday experience if users are to continue wearing them over time. PRV concerns reduce continued intention, demonstrating that sensitive data gathering remains a significant obstacle to long-term use, even when the devices are desirable.

5 DISCUSSION

This study sought to evaluate the WTM2 and investigate the relative impact of functional, experiential, and contextual aspects on user satisfaction and intention to continue using wearable devices. The findings provide a clear and, in some cases, uncomfortable interpretation: WT adoption is predominantly motivated by experience rather than utility or ease of use. Design and enjoyment were the most powerful indicators of user happiness, followed by PU and simplicity of use. PRV had no major impact on satisfaction. In contrast, continuance intention was influenced less by satisfaction and more by habitual use (frequency) and experience characteristics, with PRV serving as a strong disincentive to continue use. This presents a paradox: people may be satisfied with wearable gadgets despite PRV concerns, yet the same problems arise when considering whether to continue using them.

These findings are consistent with and question those of previous studies. The favorable effects of perceived utility and PEOU are consistent with the TAM [2], indicating that it is still relevant in explaining the first appraisals of technology. Similarly, the importance of design and enjoyment validates previous research that has focused on user experience and affective engagement in wearable adoption [9]. However, the findings deviate from standard adoption models by revealing that satisfaction may not always convert into continued intention, which contradicts the assumptions in previous IS success models [15]. Furthermore, whereas Jamalova [8] emphasized the increasing importance of social influence and trust in adoption research, our study implies that experiential aspects may outweigh these constructs. The negative impact of PRV on continued intention is consistent with earlier concerns about data security in wearable ecosystems; however, its lack of influence on satisfaction suggests a mismatch between what users worry about and what they prioritize in everyday use. This conflict is rarely addressed openly in the literature and is an important contribution of this study.

The findings of the current study both support and question existing knowledge. First, previous research using the TAM has shown that PU and PEOU have considerable beneficial effects on user satisfaction. According to the research, TAM has consistently shown that people value technologies higher when they believe they are useful and simple to use [2]. Similarly, other studies referenced in the literature review [16], [15], [17] demonstrate that system quality, usefulness, and simplicity of use are significant predictors of user satisfaction. The current study reinforces these findings by demonstrating that both PU and PEOU significantly predict happiness, highlighting TAM's continuous significance in the context of wearable technology.

However, the findings go beyond the standard TAM perspective, indicating that design and enjoyment are the best indicators of user happiness. This finding is consistent with previous research, emphasizing the relevance of the user experience, comfort, and engagement in the adoption of wearable technology. For example, the literature emphasizes that wearable devices must be useful, comfortable, and aesthetically appealing to maintain user engagement [14] and that enjoyment plays an important role in improving user experience and retention [21]. Furthermore, [9] advocated a transition from technology-driven to experience-driven design, focusing on context-aware and intuitive interactions. The current study clearly supports this viewpoint, as design and enjoyment surpass all other variables in predicting satisfaction, implying that experiential characteristics are essential for the user evaluation.

In contrast, the importance of PRV presents a complex and sometimes contradictory picture. The literature regularly highlights PRV as a major obstacle to WT adoption, citing concerns about data security and misuse [1], [14]. The current study partially confirms this claim: PRV strongly predicts continued intention, with more PRV concerns decreasing the likelihood of continued use. However, the data contradict previous ideas by demonstrating that PRV has no substantial effect on user pleasure. This disparity shows that while consumers are aware of PRV hazards, these worries may not immediately impair their enjoyment of the device but become more important when considering whether to continue using it. In other words, this study improves the literature by distinguishing short-term appraisal (satisfaction) from long-term behavioral intention (continuance), which is frequently overlooked.

Another key point of comparison is the intention to continue working. Previous research has assumed that user satisfaction is an important predictor of continued use [15]. However, the results of this study question this assumption, as user satisfaction did not significantly predict continuing intention in the logistic regression model. Instead, frequency of usage (habit), design and enjoyment, and PRV concerns significantly impacted continued intention. This contradicts established IS success models, implying that satisfaction alone cannot explain long-term involvement in wearable technologies. These findings are consistent with research identifying behavioral habits and experience engagement as key determinants of ongoing usage [45]. The finding that satisfaction does not directly drive continuance intention is consistent with previous research focusing on post-adoption dynamics. For example, Pal et al. [26] and Guo et al. [28] demonstrated that trust and user experience are more important for persistent use than initial satisfaction alone. Similarly, Naz et al. [29] believe that continuance behavior is determined by the interaction of pre- and post-adoption factors, which helps explain the observed discrepancy between satisfaction and maintained usage in the findings of this study. Furthermore, this study confirms Jamalova's [8] bibliometric findings, which show a change in the literature toward more user-centered and contextual characteristics, such as trust, social impact, and behavioral intention. Although the current study does not specifically assess all these variables, its findings support the larger point that adoption cannot be explained exclusively by the functional dimensions. Instead, experiential and environmental elements play a significant role, underscoring the need for more integrative models, as proposed in previous research.

In conclusion, while this study substantially confirms previous research on the importance of utility, simplicity of use, and user experience, it also questions fundamental assumptions, particularly the impact of satisfaction and PRV. This study builds on previous research by revealing that WT adoption is influenced more by sensory and behavioral aspects than by merely functional concerns, highlighting the need for more comprehensive models such as WTM2.

6 CONCLUSION

The goal of this study was to create and empirically evaluate the WTM2 by including experience characteristics such as user happiness and enjoyment in established adoption frameworks. The findings suggest that WT adoption is mostly influenced by sensory and design aspects rather than strictly functional characteristics of the device. Although PU and simplicity of use had a substantial impact on user happiness, design and enjoyment were the strongest predictors. In contrast, the intention to continue using was influenced more by habitual usage and experiential quality, with PRV concerns acting as a significant barrier to prolonged use. Notably, user happiness did not immediately correlate with sustained use, defying the traditional assumptions in technology adoption research.

6.1 Theoretical implications

From a theoretical perspective, the findings support the extension proposed in WTM2 by demonstrating that affective dimensions, particularly user enjoyment and satisfaction, are not optional extras but rather key predictors of WT adoption. The findings indicate that standard models, such as the TAM, are inadequate when applied to wearable environments because they underestimate the importance of experiential and emotional aspects. Practically speaking, the ramifications of this are more direct. Designers and producers should not assume that enhancing functionality alone will result in increased adoption. Instead, the focus should be placed on aesthetics, comfort, and engagement, as these variables have a greater impact on satisfaction and retention. Simultaneously, the negative impact of PRV on continued intention serves as a clear warning to the industry and policymakers: consumers may initially tolerate PRV issues, but they are unlikely to disregard them continuously. This emphasizes the importance of transparent data practices, user control over personal data, and tighter regulatory frameworks for building long-term trust.

One important practical implication is that developers and businesses should prioritize user experience and engaging design over incremental functional improvements to increase user satisfaction while addressing PRV concerns to ensure long-term user retention. Despite these contributions, the limitations of this study must be addressed. First, the sample consisted mostly of female respondents, limiting the applicability of the findings to other demographic and cultural contexts. Second, reliance on self-reported survey data raises the likelihood of response bias, which limits causal inference.

6.2 Future studies

Future studies should test the WTM2 model in more diverse demographic and cultural settings to increase external validity. Longitudinal studies are especially important for investigating how satisfaction, PRV concerns, and usage habits interact over time, especially given the differences found between contentment and sustained intention. Future models should include characteristics such as trust, perceived risk, and social impact to properly reflect the complexities of wearable adoption. Comparative studies across device types could also reveal whether the dominance of experience elements is consistent across settings or limited to certain device categories. Finally, combining behavioral data with self-reported measures would provide a more complete insight into actual usage patterns, moving beyond stated intentions and toward observed behaviors. In short, this study not only extends an existing paradigm but also reveals a structural mismatch in how WT adoption has been interpreted. Users do not behave as models expect, and any framework that overlooks this tension risks becoming obsolete. Overall, this study adds to the literature by revealing that WT adoption involves a complex interplay of experience, behavior, and trust, emphasizing the importance of more holistic and user-centered models in future studies.

7 ACKNOWLEDGEMENTS

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