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Still on Track? An Investigation of the Factors Driving Continuance Intention in Wearable Fitness Technology

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Abstract: **Purpose** Despite the rapid growth of the Wearable Fitness Technology (WFT) market, high discontinuation rates persist. This study investigates the determinants of Satisfaction and Continuance Intention by extending the Expectation–Confirmation Model (ECM) (Perceived Usefulness, Confirmation) with device-specific (Personalization, Perceived Aesthetics) and contextual factors (Community Immersion, Social Influence, Perceived Security) to explain sustained WFT use.

Research Design and Methodology A quantitative survey of 213 WFT users was conducted. The extended ECM was empirically tested using Seemingly Unrelated Regression (SUR) to jointly estimate the determinants of Satisfaction and Continuance Intention while addressing correlated error terms between the outcomes. Additionally, post-hoc tests were conducted to better understand patterns within the data.

Findings The results validate the core ECM: Confirmation emerges as the dominant driver of Satisfaction, which subsequently predicts Continuance Intention. For contextual and device-specific factors, results varied: Contrary to prevailing assumptions, Community Immersion showed a marginally significant negative effect on Satisfaction, whereas Perceived Security is becoming increasingly important for users. Personalization showed a marginally significant positive effect on Satisfaction.

Practical implications The findings emphasize that managers should prioritize reliable functionality and expectation management over expanding feature sets, ensuring marketing claims align with actual performance. Additionally, security, personalization and community features emerge as factors that must be managed actively.

Originality/value This study integrates device-centric and contextual factors into a unified ECM framework for WFTs. It challenges the role of Perceived Security and provides novel evidence for the unexpected "dark side" of active Community Immersion on Satisfaction.

Keywords: Wearable Technology; Fitness Trackers; Expectation-Confirmation-Model; Continuance Intention; Smartwatch

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Table of Contents

List of Abbreviations

ANOVA	Analysis of Variance
CINT	Continuance Intention
CMI	Community Immersion
CON	Confirmation
ECM	Expectation-Confirmation Model
ECT	Expectation-Confirmation Theory
EHDS	European Health Data Space
EU	European Union
GPS	Global Positioning System
IoMT	Internet of Medical Things
IoT	Internet of Things
IS	Information System
JIF	Journal Impact Factor
n.s.	not significant
OS	Operating System
PA	Perceived Aesthetics
PE	Personalization
PU	Perceived Usefulness
ROI	Return on Investment
SAT	Satisfaction
SEM	Structural Equation Modeling
SI	Social Influence
SUR	Seemingly Unrelated Regression
TAM	Technology Acceptance Model
VIF	Variance Inflation Factor
WFT	Wearable Fitness Tracker

List of Tables

List of Figures

1. Introduction

The consumer market for wearable fitness trackers (e.g. Apple Watch, Garmin, Oura Ring, WHOOP) has expanded rapidly to a now $480 billion industry, with roughly half of all consumers having purchased a fitness wearable at some point in time (McKinsey, 2024). Moreover, the sector is continuously evolving. While smartwatches have been the dominant focus of prior academic research (Bölen, 2020), they no longer represent the full landscape of wearable technology. New modalities, such as fabric wristbands (e.g. WHOOP) and biometric rings (e.g. OURA), have become increasingly popular, alongside the emergence of advanced devices like continuous glucose monitors (McKinsey, 2024). Even while this study was being conducted, at least three new device types have entered the market: Apple's AirPods Pro 3, which enable heart rate tracking, Garmin's Blaze, a fitness tracker designed for horses and, indirectly, their riders and Lumia, a smart earring measuring heart rate and even blood flow to the head (Apple, n.d.; Garmin, n.d.; Lumia Health, n.d.). This rapid evolution highlights not only the continuous technological innovation in the wearable market but also the diversification of underlying business models. For instance, WHOOP relies on a subscription-based model (WHOOP, n.d.), Apple follows a one-time purchase model (Apple, n.d.), and hybrid models such as Garmin Connect Plus combine a one-time device payment with freemium software services (Garmin, n.d.).

Wearable Fitness Technology (WFT) has attracted growing academic attention due to its ability to monitor physical activity in real time and to engage individuals in tracking their performance with the aim of optimizing long-term health behaviors (Windasari et al., 2021). Beyond simple step-counting, these devices encourage individuals to take a more active role in managing their own health. However, the potential benefits of WFTs only materialize if consumers not only adopt but also continue to use them, rather than abandoning the devices shortly after purchase (Canhoto & Arp, 2017). Research indicates that use of WFTs often drops substantially after initial adoption, with approximately one-third (Windasari et al., 2021) to half (Shin et al., 2019) of consumers abandoning their device after the first six months. This underscores the importance of understanding the factors that drive continued use of WFT.

The dominant framework explaining *Continuance Intention* in Information Systems (IS) is Bhattacherjee´s (2001) Expectation-Confirmation Model (ECM), where the psychological constructs *Satisfaction, Perceived Usefulness* and *Confirmation* jointly determine *Continuance*

Intention. In WFT research, the ECM is frequently extended with various other factors to better explain the drivers of *Continuance Intention* in this specific context (e.g. Gupta et al., 2021; Nascimento et al., 2018; Siepmann & Kowalczuk, 2021). To the best of the authors' knowledge, no prior research has systematically consolidated the numerous extensions of the ECM and tested them with a single, integrated framework. This study develops an extended ECM-Model, holistically integrating device-centric (i.e. *Perceived Aesthetics* and *Personalization*) and contextual factors (i.e. *Community Immersion, Social Influence* and *Perceived Security*) alongside the aforementioned core ECM factors to provide a comprehensive understanding of what drives *Satisfaction,* and subsequently, *Continuance Intention* in WFTs.

The main research question guiding this study has thus been formulated as follows:

How do user, device, and contextual factors shape Satisfaction and Continuance Intention in the sustained use of Wearable Fitness Technology?

To address this gap and answer the research question, a survey was conducted, yielding 294 responses, of which 213 were retained after removing unsuitable responses. The resulting dataset was analyzed using a Seemingly Unrelated Regression (SUR) approach (Zellner, 1962) in R to test the proposed model.

The analysis strongly validates the core tenets of the ECM. Findings indicate that *Confirmation* of a user's expectations is the single most powerful determinant of *Satisfaction*, which, in turn, is the primary driver of *Continuance Intention*. While *Perceived Usefulness* was also a significant predictor of *Satisfaction*, the results for the extended device-centric and contextual factors were mixed. Contrary to common assumptions, *Perceived Aesthetics* and *Social Influence* were not significant predictors of *Satisfaction*. Most notably, *Community Immersion* demonstrated a significant and unexpected negative relationship with user *Satisfaction*.

This thesis progresses as follows. First, we outline the current state of research on WFTs and develop the theoretical background and hypotheses based on the ECM and its various clustered extensions. Next, the empirical design is presented, including details on data collection, sample characteristics, measurement, and model validation. The subsequent section reports the analysis and results, covering descriptive statistics, model fit, hypothesis testing, and post-hoc analysis. Finally, the discussion summarizes the key insights and managerial implications and concludes with limitations and directions for future research.

2. Theoretical Background and Literature Review

2.1 Wearable Fitness Technology

WFTs fall within the broader class of embodied technologies, which are commonly divided into three categories based on their degree of bodily integration: Third-generation technologies are “body melded”: they functionally extend or externalize the human mind with the goal of cognitive or neurological enhancement (e.g., brain-computer interface chips used to treat paralysis or neurological disorders). Second-generation technologies are “body internal”: parts of the device are implanted in or penetrate the body, such as pacemakers or cochlear implants. First-generation technologies are “body external”: they can be easily put on and taken off without bodily intrusion. This category includes smart glasses, smart exoskeletons and connected fitness tracking devices which are the focus of this thesis (Matwyshyn, 2019).

WFT are sophisticated digital tools designed to support healthy lifestyles and personal health management (Canhoto & Arp, 2017; Chong et al., 2020). They allow end-users to monitor, store, and analyze data pertaining to their daily physical activities and other health metrics (Talukder et al., 2019). Wearables constitute a particular form of the Internet of Things (IoT), functioning as first-generation embedded machine-to-human interfaces with internet connectivity. They can operate either directly via internal sensors or indirectly by linking to a smartphone (Deloitte, 2018; O´Brien, 2015; Matwyshyn, 2019).

WFTs distinguish themselves through five specific attributes. First, they are often small digital devices worn on the body (e.g. clipped on or worn on the wrist) that use biometrical sensors to continuously generate physical health information without the need for health professionals (Becker et al., 2017; Gupta et al., 2021). Second, these devices have distinct sensing capabilities through integrated sensors, such as GPS, physiological sensors, heart rate monitors, and/or vibration motors (Deranek et al., 2021). Third, they collect and process data related to health and fitness management, including tracking steps taken, distance, calories consumed and/or burned, sleep quality, heart rate, floors climbed, and even vital signs like blood oxygen levels and blood pressure (Chong et al., 2020; Talukder et al., 2019). Fourth, the device is usually integrated into and perceived as part of an ecosystem by consumers. WFTs have the capability for data collection, storage, and transmission (Canhoto & Arp, 2017; Weber, 2015). This activity-related information is usually accessible via mobile applications or the device itself (Reyes-Mercado, 2018;

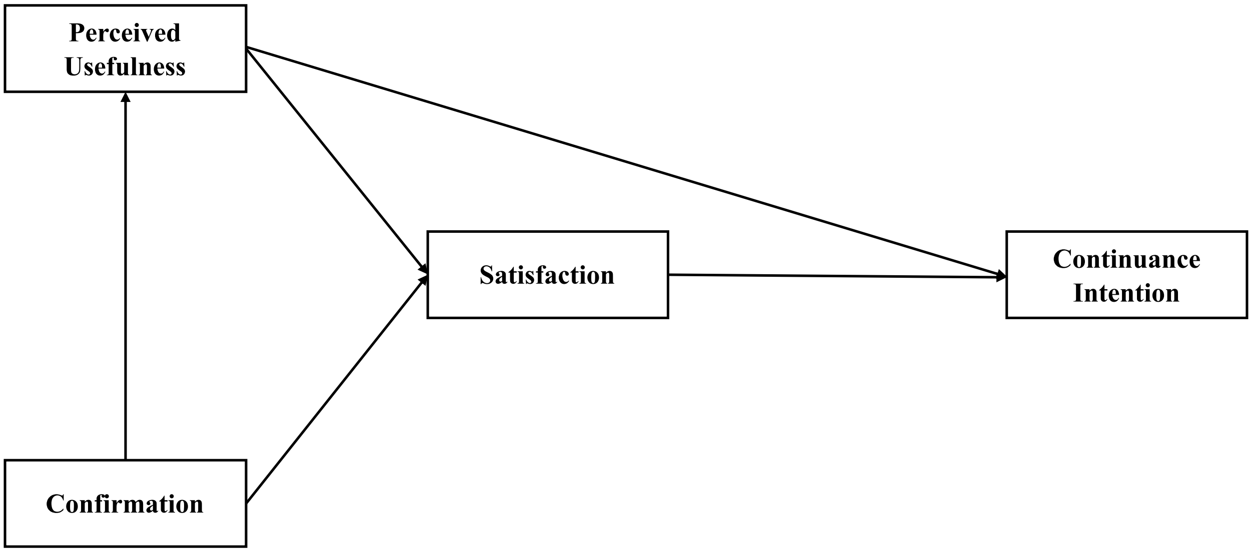
Sun & Gu, 2024). The data collected by the device can often be assessed by third-party applications through open application programming interfaces (APIs), enabling integrated functions (e.g. syncing Fitbit steps/heart rate data with a calorie tracking application like MyFitnessPal) (Canhoto & Arp, 2017). Fifth and finally, WFTs often combine technological utility with aesthetic appeal (Chuah et al., 2016). In a study by Chuah et al. (2016), half of the respondents (43.5%) rated both fashion and technology aspects of their wearable device as equal in their importance. The effect was termed "fashnology" by Rauschnabel et al. (2016) and has since become widely used in WFT research (e.g. Chuah et al., 2016; Dehghani, 2018; Sun & Gu, 2024). To explain what drives sustained use of such technologies, the next section introduces the ECM.

2.2 The Expectation-Confirmation Model

The most widely adopted and validated theoretical foundation for understanding IS *Continuance Intention* is the ECM by Bhattacherjee (2001). It is adapted from the Expectation-Confirmation Theory (ECT) in consumer behavior literature (Oliver, 1980). ECM is deemed superior to models focusing only on initial adoption (e.g. TAM, TPB), as it integrates core post-adoption evaluations like *Satisfaction* and *Confirmation* (Veeramootoo et al., 2018).

ECM postulates that the decision to continue using an IS is primarily driven by three core constructs (e.g. Bhattacherjee, 2001; Bölen, 2020; Nascimento et al., 2018), developed through the user's post-consumption experience:

Figure 1: The Expectation-Confirmation Model (Bhattacherjee, 2001)



2.2.1 Perceived Usefulness

In the ECM context, *Perceived Usefulness* represents a user's post-adoption perception of expected benefits, effectiveness, and productivity resulting from continued use (Bhattacherjee, 2001; Ogbanufe & Gerhart, 2018; Siepmann & Kowalczuk, 2021). The concept captures the value users derive from the device (Bhattacherjee, 2001; Bölen, 2020; Gupta et al., 2021). *Perceived Usefulness* enhances *Satisfaction* by ensuring that performance expectations align with reality (Bhattacherjee, 2001). A substantial body of research has documented this relationship (e.g. Bhattacherjee, 2001; Gupta et al., 2021; Nascimento et al., 2018). For instance, when users see WFTs as beneficial in achieving health and productivity goals, *Satisfaction* increases (Nascimento et al., 2018; Siepmann & Kowalczuk, 2021). There is consensus in prior literature that *Perceived Usefulness* strongly predicts *Satisfaction* in technology continuance (e.g. Bhattacherjee, 2001; Bölen, 2020; Gupta et al., 2021). While *Satisfaction* is the primary driver of *Continuance Intention*, *Perceived Usefulness* can also exert a direct influence on *Continuance Intention*, particularly under conditions of instrumental necessity (Bhattacherjee, 2001). For instance, a user may continue to use a device that they do not find particularly satisfying if they perceive it as indispensable for achieving a critical, utilitarian goal. In this case, the device's high instrumental value overrides the lack of affective *Satisfaction*, creating a direct pathway from *Perceived Usefulness* to *Continuance Intention*.

2.2.2 Confirmation

Confirmation refers to the comparison a user makes between their initial beliefs about a device (expectations) and its actual operational outcome (performance) following use (Bhattacherjee, 2001). *Confirmation* is a significant positive predictor of *Satisfaction*. This association is supported across various contexts, e.g., smartwatch *Continuance Intention*, in academic literature (Bölen, 2020). The significance of *Confirmation* in driving *Satisfaction* suggests that users find realizing their expectation more salient than the simple instrumentality of the IS (*Perceived Usefulness*) when forming their long-term *Continuance Intention*. When *Confirmation* occurs (meaning expectations are met or exceeded), users often adjust their post-acceptance beliefs. If initial expectations were unsuitably low, the *Confirmation* experience can cause users' *Perceived Usefulness* to be adjusted higher (Bhattacherjee, 2001). This adjustment aligns with Cognitive Dissonance Theory (Festinger, 1957), where rational users modify usefulness perceptions to be consistent with reality. This adjustment alleviates the psychological tension that arises if pre-acceptance perceptions are disconfirmed during subsequent use. *Confirmation* is consistently validated as a positive predictor of post-adoption *Perceived Usefulness*. In a study of online banking users, Bhattacherjee (2001) found *Confirmation* to be a significant predictor of *Perceived Usefulness*. In their study focusing on smart fitness wearables, Gupta et al. (2021) also found a strong relationship, with *Confirmation* significantly affecting *Perceived Usefulness*.

2.2.3 Satisfaction

Satisfaction is conceptualized as a post-choice evaluative judgement or affect, resulting from the use experience (Bhattacherjee, 2001). It reflects the degree of positive, indifferent, or negative feeling toward prior IS use (Bhattacherjee, 2001). *Satisfaction* is consistently validated as the strongest predictor of IS *Continuance Intention*, as it reflects the cumulative evaluation of prior interactions (e.g. Liao et al., 2021; Siepmann & Kowalczuk, 2021; Sun & Gu, 2024). Prior work demonstrates that *Satisfaction* mediates the influence of *Confirmation*, *Perceived Usefulness* and other antecedents on *Continuance Intention* (e.g. Bhattacherjee, 2001; Bölen, 2020; Shin et al., 2019). Satisfied users are more likely to maintain device use, while dissatisfaction leads to discontinuance. This mechanism has been consistently validated in IS context and extended to WFT research (e.g. Bhattacherjee, 2001; Bölen, 2020; Nascimento et al., 2018).

2.2.4. Continuance Intention

Intentions are conceptualized as self-instructive motivators that signify the degree of an individual's commitment to performing a specific action. As the most proximal antecedent to action, intentions serve as a critical index of the effort one is willing to exert to achieve a goal. Prevailing research models suggest that eliciting a subject's intent remains the most reliable method for forecasting subsequent behavior, a link that has been empirically validated across diverse domains ranging from consumer choices to leisure activities. However, people may not always have sufficient control over the transition from intention to behavior. In the context of wearable technology, for instance, "facilitating conditions", such as worsening device reliability or shifting evaluations of device data security, can act as external constraints that disrupt this relationship. Consequently, while intentions are the primary drivers of behavior, they must be analyzed with an awareness of the environmental or technical barriers that may prevent an intended action from coming to fruition (Sheeran, 2002).

Continuance Intention is typically defined as a user's conscious plan or an individual's attitude to continue using technology in the future (e.g. Dehghani, 2018; Kang & Hwang, 2022; Zhang et al., 2025). Specifically, it refers to a user's intention to continuously use the current product or service (Dehghani, 2018) or the willingness to keep using a device rather than discontinuing its use (Bhattacherjee, 2001).

Literature emphasizes that post-adoption behavior (continuance) is a theoretically distinct concept from initial adoption (acceptance) and therefore relies on a different set of determinants (Bhattacherjee, 2001; Davis et al., 1989; Yang et al., 2018). Initial adoption models, such as the Technology Acceptance Model (TAM) by Davis et al. (1989) and the Theory of Planned Behavior (TPB) by Ajzen (1991), often employ pre-acceptance variables to explain usage decisions. However, these models are often unable to fully account for the "Acceptance-Discontinuance Anomaly", where users initially accept a technology but later discontinue its use (Bhattacherjee, 2001). Consequently, research into continuous usage requires models elaborating upon the psychological motivations that emerge only after initial acceptance and usage experience have occurred (Bhattacherjee, 2001). Canhoto and Arp (2017) have found that factors driving initial adoption differ from those supporting sustained use. For instance, acceptance behaviors tend to weigh toward utilitarian values, whereas continued use places greater emphasis on hedonic values (Ogbanufe & Gerhart, 2018).

Studying Continuance Intention is crucial because the success and long-term viability of an IS fundamentally depend on its continued use, rather than merely its initial acceptance (e.g. Bhattacherjee, 2001; Nascimento et al., 2018; Zhang et al., 2025). Retaining existing customers is a significantly more cost-effective strategy compared to customer acquisition costs (Ascarza et al., 2017), especially in business-to-consumer contexts typical for the WFT market. However, retaining customers is challenging, since the WFT market is highly competitive and volatile (Bölen, 2020; Windasari et al., 2021). Causes are both advancing technology and increasing competition, lowering barriers for upgrading devices or switching to other brands (Gupta et al., 2021). This highlights the need for further research into the factors that drive Continuance Intention.

3. Conceptual Framework and Hypothesis Development

The ECM provides a robust foundation for understanding general IS *Continuance Intention*. However, relying solely on ECM in the specific context of WFT is not sufficient. The original model relies heavily on a cognitive, rational decision-making process where users weigh their expectations against performance to derive *Satisfaction* (Bhattacherjee, 2001; Gupta et al., 2021). In line with prior research, we argue that this strictly utilitarian perspective overlooks the complex, emotional, and contextual nature of personal technology usage (Nascimento et al., 2018).

Wearable devices differ fundamentally from the organizational software for which the ECM was originally designed such as banking systems or office tools (Bhattacherjee, 2001). WFTs are intimate devices worn on the body, integrated into the user's physical identity, and used in highly social contexts (e.g. gyms or running clubs) (Deranek et al., 2021). As such, we argue that a purely cognitive model that ignores the specific attributes of wearable devices (e.g. aesthetics), the privacy implications of biometric data (e.g. security), and the social dynamics of usage (e.g. community) is theoretically insufficient. By relying solely on the core ECM, researchers risk overlooking other crucial antecedents (Bölen, 2020; Nascimento et al., 2018). Therefore, to fully explain the drivers of *Continuance Intention* in the modern WFT market, we argue that the ECM must be extended to incorporate these device-specific and contextual determinants.

A comprehensive review of prior literature was conducted to generate an overview of variables that have been treated as extensions of the ECM or have been used to assess WFT *Continuance Intention*. Sufficient quality of the literature was ensured by setting a minimum requirement for the journal's impact factor (JIF). As a result, 29 papers were included in the literature review, resulting in the identification of 160 independent variables that have been tested in relation to our research topic (see Appendix C). Subsequently, certain variables were excluded from the analysis. For instance, constructs were removed if the dependent variable under investigation was not *Satisfaction* or *Continuance Intention*, or if the factor had only been proposed in qualitative studies without subsequent quantitative validation, limiting applicability to this study (e.g. Canhoto & Arp, 2017; Dehghani, 2018; Tikkanen et al., 2023).

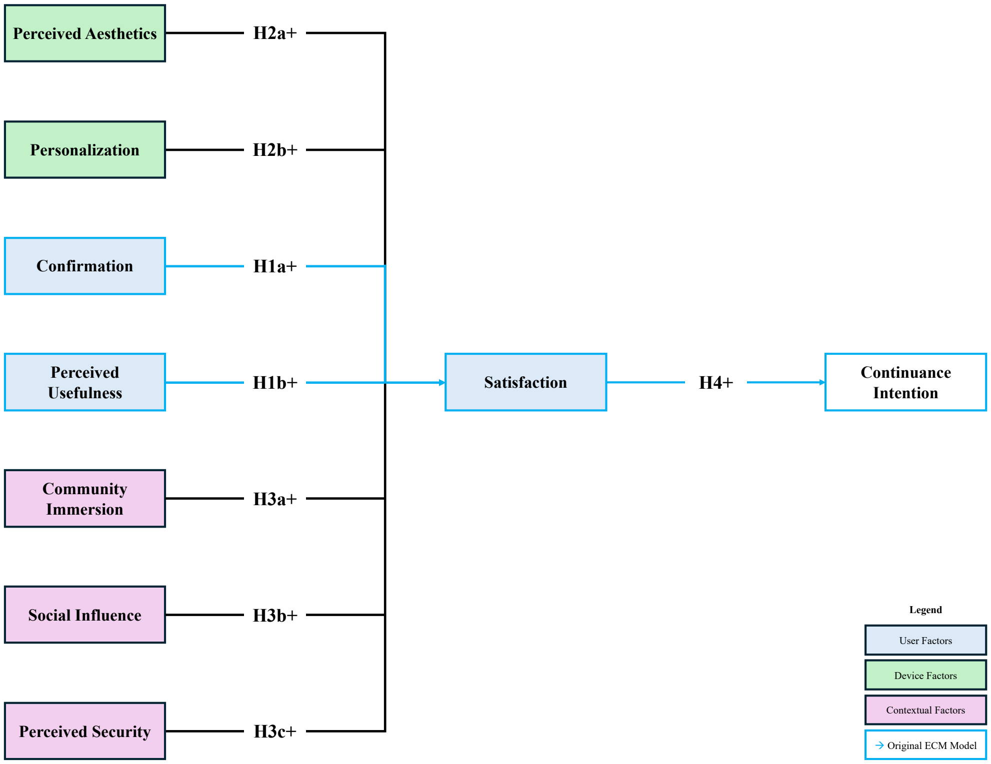
The remaining variables were then clustered into three overarching categories, as proposed by Canhoto & Arp (2017): (1) *User Factors*, (2) *Device Factors*, and (3) *Contextual*

Factors. These extensions make it possible to assess *Satisfaction* and *Continuance Intention* from a holistic perspective. The respective clusters are described in further detail below.

From these three clusters, the most relevant (i.e. fitting the specific WFT context) and empirically supported constructs were selected to extend the ECM. The resulting model therefore integrates both the original ECM dimensions and additional factors that account for the role of the device characteristics (i.e. *Perceived Aesthetics* and *Perceived Security*) (Al-Emran et al., 2023; Choi et al., 2017; Kang & Hwang, 2022) and the broader context (i.e. *Social Influence, Personalization* and *Community Immersion*) (Gupta et al., 2021; Kang & Hwang, 2022; Talukder et al., 2019).

To the best of the authors' knowledge, no study has yet assessed a holistic extension of the ECM within the context of WFT. On the contrary: existing research remains fragmented, with isolated extensions and partial validations scattered across studies. To address this gap, the present study develops an integrated framework that consolidates these extensions into a single model, enabling a more comprehensive understanding of the determinants driving *Continuance Intention* in WFT use. In line with previous research, the following extensions were incorporated into the model, and corresponding hypotheses subsequently developed.

Figure 2: Extended ECM Model



3.1 User Centric Factors (ECM Model)

The foundational model supporting the hypotheses in this study is the ECM, first introduced by Bhattacherjee (2001). Several relationships between the core constructs *Perceived Usefulness, Confirmation, Satisfaction* and *Continuance Intention* have been described and validated in numerous previous studies, as stated above. Since the key ECM variables are subjective cognitive and affective assessments rooted firmly within the user's experience (Bhattacherjee, 2001), they are treated as *User Factors* in this study.

Confirmation enhances *Satisfaction* by ensuring that expectations align with reality (Bhattacherjee, 2001). Users who feel their WFT meets or exceeds expectations are more satisfied. Numerous ECM-based studies support this relationship, making *Confirmation* a central antecedent of *Satisfaction* (e.g. Bhattacherjee, 2001; Bölen, 2020; Gupta et al., 2021; Nascimento et al., 2018)

H1a: Confirmation positively influences Satisfaction

Perceived Usefulness captures how much value users derive from the device (e.g. Bhattacherjee, 2001; Bölen, 2020; Gupta et al., 2021). When users see WFT as beneficial in achieving health and productivity goals, *Satisfaction* increases (e.g. Bhattacherjee, 2001; Nascimento et al., 2018; Siepmann & Kowalczuk, 2021). Prior work confirms that *Perceived Usefulness* strongly predicts *Satisfaction* in technology continuance (e.g. Bhattacherjee, 2001; Bölen, 2020; Gupta et al., 2021; Nascimento et al., 2018).

H1b: Perceived Usefulness positively influences Satisfaction.

Satisfaction refers to the overall affective evaluation of a user's experience with technology. It captures whether the experience is enjoyable or fulfilling (Bhattacherjee, 2001). In ECM literature, *Satisfaction* is the most critical determinant of *Continuance Intention*, as it reflects the cumulative evaluation of prior interactions (e.g. Bhattacherjee, 2001; Gupta et al., 2021; Nascimento et al., 2018). Satisfied users are more likely to maintain device use, while dissatisfaction leads to discontinuance. This mechanism has been validated in IS research (Bhattacherjee, 2001) and extends to WFT contexts (e.g. Bölen, 2020; Gupta et al., 2021; Siepmann & Kowalczuk, 2021).

For WFTs specifically, *Satisfaction* not only reflects functional performance, but also emotional benefits, such as enjoyment, pride in usage, and integration into daily routines (e.g Bölen, 2020; Nascimento et al., 2018; Siepmann & Kowalczuk, 2021). Prior work demonstrates that *Satisfaction* shapes the influence of *Confirmation, Perceived Usefulness,* and other antecedents on *Continuance Intention.* Hence, understanding *Satisfaction* is crucial to explaining sustained engagement (e.g. Bhattacherjee, 2001; Gupta et al., 2021; Shin et al., 2019).

H4: Satisfaction positively influences Continuance Intention.

Since the goal of this study is to build a holistic model of factors influencing *Satisfaction* and *Continuance Intention*, only the effect of P*erceived Usefulness* on *Satisfaction*, *Confirmation* on *Satisfaction,* and *Satisfaction* on *Continuance Intention* are treated as hypotheses, whereas we do not explicitly treat the effect of *Confirmation* on *Perceived Usefulness* and *Perceived Usefulness* on *Continuance Intention* as a hypothesis, as originally suggested by ECM theory.

3.2 Device-Specific Factors

Device-specific factors, often referred to as device-specific attributes or technology features and utility, are the inherent qualities and characteristics of the WFT product itself that influence user perceptions and behavior (Canhoto & Arp, 2017; Chuang & Chen, 2022). These factors are crucial for understanding *Continuance Intention* of WFTs, especially since the human-computer interface of WFTs differs significantly from traditional IS. Device-specific factors encompass various aspects related to the device's hardware, software, and design (Chuang & Chen, 2022; Nascimento et al., 2018).

A crucial example often studied in *Continuance Intention* research includes *Perceived Aesthetics* (e.g. design, shape, color or visual appeal) (e.g. Bölen, 2020; Dehghani, 2018; Siepmann & Kowalczuk, 2021), which recognizes the device as a fashion accessory in addition to its technology (Rauschnabel et al., 2016). Because watches are traditionally perceived as luxury fashion items, many consumers perceive them differently compared to traditional mobile devices in terms of aesthetics (Bölen, 2020). Since the same is true for rings, and WFT is increasingly perceived as a status symbol (McKinsey, 2024), we argue that the same applies to all types of WFTs.

Importantly, prior research has supported the relationship between *Perceived Aesthetics* and *Satisfaction* in the WFT context. In the case of fitness trackers, an aesthetically pleasing design can increase user pride, comfort in wearing, and delight in usage (e.g. Bölen, 2020; Canhoto & Arp, 2017; Chuah et al., 2016). Bölen (2020) integrated *Perceived Aesthetics* into an extended ECM and found that it significantly and positively influences user *Satisfaction*. This finding aligns with the results of a study by Dehghani (2018) that identified “fashnology”, the blend of fashion and technology, as a key determinant of *Continuance Intention*, alongside practical concerns such as battery life and functional elements like GPS accuracy.

H2a: Perceived Aesthetics positively influences Satisfaction.

Personalization is the tailoring of system features and information to individual needs (e.g. Clermont et al., 2020; Kang & Hwang, 2022; Wittkowski et al., 2020). This concept is central to the broader Internet of Medical Things (IoMT), which seeks to connect and digitize personalized information, including lifestyle, disease history and medical use data, thereby enabling individualized care (Kang & Hwang, 2022). *Personalization* moves beyond a "one-size-fits-all" approach by providing tailored strategies for every user (Kang & Hwang, 2022; Wittkowski et al., 2020).

In practice, *Personalization* in WFTs encompasses several technical manifestations, such as adaptive health metrics, customized training suggestions, or configurable interfaces. WFT achieve this tailored experience by utilizing high-tech sensors, algorithmic processing, and real-time data collection to identify unique individual patterns and generate in-depth insights (e.g. Bölen, 2020; Kang & Hwang, 2022; Siepmann & Kowalczuk, 2021). Specific examples of personalized features include real-time biometric monitoring which enables the continuous analysis of personal data, allowing smart healthcare applications to provide services such as calorie tracking, step counting, and the measurement of heart rate or blood pressure (Kang & Hwang, 2022). Moreover, self-tracking technologies support “personal analytics” by collecting, analyzing, and visualizing individual-level data that inform users’ decisions and guide future goal setting (Kang & Hwang, 2022). Smartwatches further enable the tailoring of goals to users’ specific needs, thereby contributing to the fulfillment of the psychological need for autonomy (Siepmann & Kowalczuk, 2021).

Prior studies confirm that *Personalization* enhances both emotional engagement and *Satisfaction* in the WFT context (e.g. Kim, 2021; Liao et al., 2021; Wittkowski et al., 2020). Consumers, in the context of running, showed valuing devices that offer data *Personalization* to fit their needs, rating this as an important factor (Clermont et al., 2020). Furthermore, *Personalization* counters the negative effect of reduced perceived autonomy as reported by Fronczek et al. (2023) and is therefore likely to positively influence *Satisfaction*. When users experience a device that is personalized to their routines, goals, and preferences, we argue that *Satisfaction* is likely to increase.

H2b: Personalization positively influences Satisfaction.

3.3 Contextual Factors

Contextual factors, encompassing the social and environmental setting, are indispensable for a holistic view of technology use (Al-Emran et al., 2023). The broader context of usage is influenced by both technical and social considerations (Canhoto & Arp, 2017; Kim, 2021), and models examining *Continuance Intention* often benefit from integrating context-specific variables into the theoretical framework (Bölen, 2020; Nascimento et al., 2018).

Community Immersion is defined as the extent to which users would like to have a continuous relationship with members of the community related to wearable healthcare devices (Hong et al., 2006).

By fostering social bonds and shared experiences, *Community Immersion* contributes to higher *Satisfaction* levels with the WFT. In their qualitative study, Canhoto & Arp (2017) found that a Community of Users provides crucial motivation for sustained engagement, largely because sharing workouts and achievements increases observability of physical activity. This finding is supported quantitatively by Kang & Hwang (2022), who found virtual *Community Immersion* to positively influence *Satisfaction*. The influence of the community is further researched by Gupta et al. (2021), who confirmed that the tendency to compare oneself with others significantly enhanced users' *Satisfaction* with WFTs. Strava, one of the leading social networks for athletes, stated that "run clubs [are] replacing nightclubs as social hotspots" (Strava, 2024). This is exemplified by an increase in running club participation and other social developments, such as 58% of respondents in a Strava user survey stating that they made friends through fitness communities (Strava, 2024). We argue that social comparison features on these devices and platforms encourage competition and teamwork, thereby supporting accountability and group goals. Consequently, the following hypothesis has been developed:

H3a: Community Immersion positively influences Satisfaction.

Social Influence captures the impact of the social environment on an individual's decision to continue using a WFT. Specifically, it refers to the pressure or encouragement from peers and important others to use a specific technology (e.g. Al-Emran et al., 2023; Choi et al., 2017; Talukder et al., 2019).

Social Influence is frequently conceptualized as subjective norm, which refers to "the perceived social pressure to perform or not to perform the behavior" (Al-Emran et al., 2023). In acceptance models, *Social Influence* is broadly defined as "the degree to which an individual perceives that important others believe he/she should use the new system" (Choi et al., 2017). The opinions of influential people play a crucial role in affecting the behavioral intention to use wearable devices. *Social influence* is considered a critical determinant in explaining a user's intention to adopt and continuously use technology and is an important antecedent, alongside attitudes and facilitating conditions, to the behavioral intention toward WFT (Choi et al., 2017; Chuang & Chen, 2022). When friends, family, or colleagues endorse the use of WFT, users may experience reassurance and validation, which enhances *Satisfaction*. Evidence from WFT studies shows that peer endorsement can lead to stronger emotional evaluations of the device (e.g. Chong et al., 2020; Jung et al., 2016; Shin et al., 2019). Thus, we argue that *Social Influence* may influence *Satisfaction* by shaping how users perceive their experience of using a WFT.

H3b: Social Influence positively influences Satisfaction.

Perceived Security is the belief that a device adequately protects personal information and ensures safe use (e.g. Al-Emran et al., 2023; Canhoto & Arp, 2017; Chuang & Chen, 2022). Security concerns are particularly relevant in WFT, which collect sensitive health and lifestyle data. When users perceive their device as secure, they experience trust, peace of mind, and reduced anxiety about continued usage (e.g. Chopra & Singhal, 2021; Mwangi et al., 2024; Windasari et al., 2021). This emotional assurance may significantly enhance *Satisfaction*.

Kim (2021) showed that *Perceived Security* strongly influences users' emotional responses, revealing that it is a significant determinant of negative emotion. Crucially, the path from security to positive emotion was statistically insignificant (Kim, 2021). This finding suggests that security functions as a "Dissatisfaction Attribute" (or hygiene factor); its absence leads users to formulate negative emotional states, while its presence does not guarantee positive emotions. Negative sentiment regarding data privacy is exemplified by current news. For instance, a mass leak of fitness tracking data that affected Fitbit, Apple, Microsoft, and Google, exposing over 60 million records due to an improperly configured third-party database was reported (Ikeda, 2021). Another example is Oura's collaboration with the U.S. military, which led to major backlash (Silva, 2025). Because of this negative news, we argue that users are becoming increasingly conscious of data security. One notable positive development, however, is that the legislation regarding data privacy is changing under the EU Data Act, which will take effect in 2029. Users could then share their data in a secure way with the European Health Data Space (EHDS). This access to data could drive innovation and medical advancements in the European public health sector (EU Science Hub, 2025). Consequently, we posit that the assurance of data security acts as a positive driver of user *Satisfaction*.

H3c: Perceived Security positively influences Satisfaction.

3.4 Control Variables

Several control variables are included in the analysis. Fronczek et al. (2023) found that the length of use (*Tenure)* plays an important role in the evaluation of the WFT. In their study, participants initially reported positive feelings towards their wearable device. Over time, the effect reversed, and consumers became less motivated to be active. Research often identifies an initial “Novelty Period”, during which users are highly susceptible to discontinuation (Shin et al., 2019). This distinction is conceptually vital, as the long-term viability of an IS, and the value derived from it (such as monitoring sustainable health data), depends on continued use rather than mere initial acceptance (Shin et al., 2019). Consequently, studies frequently categorize users by specific time brackets (e.g. 3 - 6 months, 6 - 12 months) to differentiate behaviors, defining “Sustained Use” as engagement that persists beyond this initial phase (Liao et al., 2021). To control for and potentially expand on these previous findings, *Tenure* of the WFT user is analyzed in this study.

Gender is included as a control variable, consistent with established practice in IS and technology acceptance research, where *Gender* is a common control variable due to its observed relationship with technology usage (Chuah et al., 2016; Talukder et al., 2019). Theoretically, *Gender* effects often stem from societal roles and expectations, with literature traditionally suggesting that men are often more willing than women to embrace new technology (Canhoto & Arp, 2017). Although the majority of studies have found the overall effect of *Gender* on WFT acceptance to be negligible, its inclusion is necessary to ensure the robustness of the results and account for potential demographic differences (Siepmann & Kowalczuk, 2021; Wittkowski et al., 2020).

The WFT market is evolving rapidly, with new *Types of Devices* emerging continuously (McKinsey, 2024). This had led to a “research-reality-gap”, since many studies focus solely on smartwatches (e.g. Bölen, 2020; Nascimento et al., 2018; Ogbanufe & Gerhart, 2018) and many of them on the Fitbit (e.g. Chong et al., 2020; Shin et al., 2019; Wittkowski et al., 2020). The most obvious difference in the current WFT landscape is screens. Jung et al. (2016) compared two levels of communication capability (Standalone vs. Slaved) in their study. Standalone devices are able to connect to networks themselves, whereas Slaved devices have to be used through a smartphone. This differentiation is adapted in our study, where analysis distinguishes between WFTs “with screen” and “without screen” to account for differences between *Types of*

Devices. Consequently, we introduce a new control variable in the WFT literature: Phone Operating System (*PhoneOS*). Since screenless devices are used though apps, we argue that the operating system of the user´s phone must be controlled for.

Several studies have also explicitly incorporated *Age* as a control variable within their statistical models. The results of controlling for *Age* were mixed: for instance, Siepmann & Kowalczuk (2021) found that *Age* had a significant positive effect on smartwatch *Continuance Intention*, suggesting older users had higher intention. In contrast, Chuah et al. (2016) also used *Age* as a control, but it was found to have no significant relationship with intention. In other key analyses, including *Age* as a demographic covariate confirmed that the main theoretical relationships remained stable, thereby enhancing the generalizability of the results (Wittkowski et al., 2020; Zhang et al., 2025). Therefore, *Age* is treated as the fourth control variable in this study.

Table 1: *Overview of Independent, Dependent and Control Variables analyzed in the study*

Independent Variables		
Variable	Definition	Reference
Confirmation	The perceived congruence between a user's initial expectation of the product and its actual performance following usage.	Nascimento et al. (2018); Bölen (2020); Siepmann & Kowalczuk (2021); Sun & Gu (2024); Bhattacherjee (2001); Gupta et al. (2021)
Perceived Usefulness	A cognitive belief held by the user concerning the tangible, utilitarian benefits expected from using the wearable device.	Bhattacherjee (2001); Chuah et al. (2016); Nascimento et al. (2018); Sun & Gu (2024); Gupta et al. (2021); Kim & Shin (2015); Siepmann & Kowalszuk (2021)
Perceived Aesthetics	The user's subjective evaluation of the product's non-functional, sensory attributes which contributes to an emotional response and overall impression.	Cyr et al. (2006); Bölen (2020); Kim (2021)
Personalization	The user's perception that a wearable device offers a highly individualized and tailored experience designed to meet their unique needs and support their specific goals, thereby reflecting an approach that is distinct from a generic solution.	Bock et al. (2016); Wittkowski et. al. (2020); Kim (2021); Kang & Hwang (2022); Clermont et al. (2020)
Community Immersion	The extent to which a user desires to have a continuous relationship with the members of the community related to wearable devices.	Tsai & Pai (2012); Kang & Hwang (2022)
Social Influence	The perceived social pressure on an individual to use or adopt a wearable technology.	Venkatesh et al. (2012); Talukder et al. (2019); Choi et al. (2017); Al-Emran et al. (2023)
Perceived Security	The perceived quality of the device´s protective measures and the resulting lack of anxiety or perceived risk related to the handling of sensitive user data, location, and health information.	Harris & Goode (2010); Kim (2021)
Dependent Variables		
Variable	Definition	Reference
Satisfaction	The post-choice evaluative judgement or affect, resulting from the user experience.	Nascimento et al. (2018); Siepmann & Kowalczuk; Bhattacherjee (2001)
Continuance Intention	A user's conscious plan or individual´s attitude to continue using the wearable device in the future.	Bhattacherjee (2001); Nascimento et al. (2018); Bölen (2020); Gupta et al. (2021); Zhang et al. (2025); Al-Emran et al. (2023); Sun & Gu (2024)

Control Variables		
Variable	Definition	Reference
Tenure	The usage duration of the WFT, indicated as the average number of months.	Fronczek et al. (2023), Shin et al. (2019)
Age	A user's age at the time of survey completion.	Siepmann & Kowalczuk (2021)
Gender	The user's gender, coded as a dummy-variable (0 = male, 1 = female)	Chuah et al. (2016)
Type of Device	The user's type of device, coded as \`with Screen\` and \`without Screen\`, following the study by Jung et al. (2016)	Jung et al. (2016)
PhoneOS	The phone operating system, with the answer options "iOS", "Android", or "Other"	

4. Research Method

This chapter details the methodological approach employed to investigate the research questions. While qualitative methods are suitable in the exploratory stages of theory development or investigating subjective perceptions, this approach faces limitations in the number of responses collectable and the subsequent inability to generalize findings to larger, diverse populations. Research in a mature field, such as IS, into the determinants of WFT user behavior on outcomes like *Satisfaction* and *Continuance Intention* requires a predominantly quantitative methodology to ensure theory validation and generalizability. Additionally, it has the benefit of being more objective (Bell et al., 2019). Consequently, a quantitative research approach was chosen to answer the research question.

4.1 Data Collection

The survey (see Table 2), titled "Survey on Wearable Device Use*",* was constructed in English. It followed a cross-sectional research design and was administered online via Google Forms. The survey was distributed using a snowball sampling approach in the author's personal network. Data was collected in October 2025. The target population for the survey was limited to individuals who are currently using a WFT (e.g. smart watch, smart ring, smart wristband, chest strap). All participants consented to the collection of data at the beginning of the survey, and privacy was guaranteed as all data was anonymized. A pilot test with N = 15 participants was conducted to ensure clarity and face validity of the survey instrument. The pre-test participants did not take part in the final survey. Minor adjustments were made to the wording and structure based on the feedback, such as making all questions mandatory to ensure a complete dataset and removing section breaks to improve the survey flow. In addition, participants who stated that they were not currently using a WFT were automatically redirected to the end of the survey.

4.2 Measure

The measurement items used in the survey all came from previously validated instruments and were slightly adapted to fit the context of wearable devices (see Table 2). Instrument quality was ensured by setting a minimum required Journal Impact Factor (JIF). The JIF-based paper selection results are summarized in Appendix A.

Items for the core ECM variables were adopted either from the foundational work of Bhattacherjee (2001), or from literature that adapted these items to better fit the context of WFTs. *Satisfaction* and *Perceived Usefulness* were adopted from the foundational ECM literature by Bhattacherjee (2001). While the operationalization of *Satisfaction* is grounded in Bhattacherjee's (2001) foundational framework, the specific item wording was refined to maximize construct validity. Although Bhattacherjee's (2001) original scale includes a global item anchoring 'dissatisfied' to 'satisfied,' this study prioritized the specific affective indicators listed in Table 1 (e.g., 'pleased,' 'contented'). This decision was driven by the theoretical definition of *Satisfaction* as an 'affective evaluation' of technology use (Bhattacherjee, 2001). By focusing on distinct emotional states rather than the generic label of the construct itself, the measure avoids semantic tautology and ensures a sharper delineation between the user's emotional experience (*Satisfaction*) and their cognitive evaluation of performance (*Confirmation*). The items for the other core ECM variables, *Confirmation* and *Continuance Intention,* were taken from Nascimento et al. (2018), who adapted the original instrument by Bhattacherjee (2001) to better fit the WFT context. A crucial difference between the original ECM instrument and the one adapted by Nascimento et al. (2018) is the elimination of one item ("The service level provided by OBD was better than what I expected") in the *Confirmation* question set. Since service level is not applicable to the WFT context, the subsequent change to the question set is logically sound. This is emphasized by the usage of these items in subsequent studies on WFTs (e.g. Gupta et al., 2021; Sun & Gu, 2024; Zhang et al., 2025).

The items for the independent variable *Community Immersion* were assessed using the scale originally proposed by Tsai & Pai (2012) and used by Kang & Hwang (2022) in the WFT context. The construct is measured with items assessing psychological attachment, exchange views, sense of belonging, and participation in activities. The only adaptations made to the items in this study were in wording, where "wearable healthcare device" was replaced with "wearable device".

The variable *Social Influence,* also widely referred to as Social Norm, was assessed with three items capturing the perceived social pressure or the expectation from relevant others ("people who are important to me", "people who influence me", "people whose opinions are valuable to me") to perform a certain behavior, such as in this case, using a WFT. The items were adopted from Venkatesh et al. (2012) and have since been applied frequently across WFT research (e.g.

Al-Emran et al., 2023; Choi et al., 2017; Talukder et al., 2019). The only adaptations made to the items in this study were in wording, where “fitness wearable technology” was replaced with “wearable device”.

The items for the independent variable *Perceived Security* were adopted from Kim (2021). It originated from Harris & Goode (2010), who measured the construct using a four-item battery. The items collectively assess the user´s perception of a system´s security by evaluating the presence of efficient and rigorous security procedures, the user´s subjective security concerns while exercising, and the overall perception that the device and associated applications are security conscious. The only adaptations made to the items in this study were in wording, where “fitness app and wearable device” was replaced with “wearable device”.

The items for the independent variable *Personalization*, also referred to as Perceived Personalization or Customization, were adopted from (Bock et al., 2016), which was subsequently used by e.g. Wittkowski et al (2020) and Kim (2021). The construct is measured with four items that assess the extent to which a user perceives that the WFT is tailored to their individual requirements. The questions emphasize that the device offers a personalized experience and whether it feels tailored to their needs. To better fit the context of this research, minor changes to the wording have been made. Examples include replacing “training” with “wearable device”, “training progress” with “goals”, and “is tailor-made for me” with “feels tailor-made for me”.

The items for the independent variable *Perceived Aesthetics*, or also referred to as Visual Appeal, were adopted from Bölen (2020) and Kim (2021) who used the foundational items from (Cyr et al., 2006). The set of items is utilized to measure both the fundamental subjective and physical attractiveness of the device itself, as well as the visual assessment of the digital realm, focusing on the user interface (“The way the wearable device displays its functions is attractive”). The only changes made to the items were in wording, were “fitness app and wearable device” was replaced with “wearable device”. All Responses were measured on seven-point Likert scales, in line with previous studies (Bhattacherjee, 2001; Nascimento et al., 2018; Siepmann & Kowalczuk, 2021).

Table 2: *Items used to assess each variable in the survey*

Variable	Item ID	Question / Statement	Changes to original items	References
CON	CON1	My experience with using the wearable device is better than what I expected.	Replaced "Smartwatch" with "wearable device"	Nascimento et al. (2018); Bölen (2020); Siepmann & Kowalczuk (2021); Sun & Gu (2024); Bhattacherjee (2001); Gupta et al. (2021)
	CON2	Overall, most of my expectations from using the wearable device were confirmed.		
SAT	*Prompt*	How do you feel about your overall experience of the wearable device use:	Replaced "Smartwatch" with "wearable device"	Nascimento et al. (2018); Siepmann & Kowalczuk; Bhattacherjee (2001)
	SAT1	Very displeased/Very pleased.		
	SAT2	Very frustrated/Very content.		
	SAT3	Absolutely terrible/Absolutely delighted.		
PU	PU1	I find the wearable device useful in my daily life.	Replaced "Smartwatch" with "wearable device"	Bhattacherjee (2001); Chuah et al. (2016); Nascimento et al. (2018); Sun & Gu (2024); Gupta et al. (2021); Kim & Shin (2015); Siepmann & Kowalszuk (2021)
	PU2	Using the wearable device helps me accomplish things more quickly.		
	PU3	Using the wearable device increases my productivity.		
	PU4	Using the wearable device helps me to perform many things more conveniently.		
CINT	CINT1	I intend to continue using the wearable device, rather than discontinue its use	Replaced "Smartwatch" with "wearable device"	Bhattacherjee (2001); Nasci-mento et al. (2018); Bölen (2020); Gupta et al. (2021); Zhang et al. (2025); Al-Emran et al. (2023); Sun & Gu (2024)
	CINT2	I plan to continue using the wearable device		
	CINT3	I will continue using the wearable device		
	CINT4	I predict I will continue using the wearable device in the future		
CMI	CMI1	I have a sense of belonging to the community related to wearable devices	Replaced "wearable healthcare devices" with "wearable device"	Tsai & Pai (2012); Kang & Hwang (2022)
	CMI2	I have a psychological attachment to the community related to wearable devices		
	CMI3	I exchange views with other members of the community with wearable devices		
	CMI4	I participate in wearable device community activities.		
SI	SI1	People who are important to me would think that I should use a wearable device	Replaced "fitness wearable technology" with "wearable device"	Venkatesh et al. (2012); Ta-lukder et al. (2019); Choi et al. (2017); Al-Emran et al. (2023)
	SI2	People who influence me would think that I should use a wearable device		
	SI3	People whose opinions are valuable to me would prefer that I use a wearable device		
PS	PS1	The wearable device has efficient security procedures.	Replaced "fitness app and wearable device" with "wearable device"	Harris & Goode (2010); Kim (2021)
	PS2	The security systems of this wearable device seem rigorous.		
	PS3	I have no security concerns about exercising with this wearable device		
	PS4	Overall, this wearable device seem security conscious		
PE	PE1	This wearable device offers a personalized experience.	Replaced "Training" with "wearable device" Replaced "training progress" with "goals" Replaced "is tailor-made for me" to "feels tailor-made for me"	Bock et al. (2016); Witt-kowski et. al. (2020); Kim (2021); Kang & Hwang (2022); Clermont et al. (2020)
	PE2	This wearable device is tailored to my needs.		
	PE3	This wearable device offers personalized information to support my goals.		
	PE4	This wearable device feels "tailor-made" for me.		
PA	PA1	The wearable device is aesthetically appealing.	Replaced "fitness app and wearable device" with "wearable device"	Cyr et al. (2006); Bölen (2020); Kim (2021)
	PA2	I like the way the wearable device looks.		
	PA3	The wearable device is visually attractive.		
	PA4	The way the wearable device displays its functions is attractive.		

Note: PA = Perceived Aesthetics, PE = Personalization, CON = Confirmation, PU = Perceived Usefulness, CMI = Community Immersion, SI = Social Influence, PS = Per-ceived Security, SAT = Satisfaction, CINT = Continuance Intention

4.3 Sample

The initial data set consisted of N = 294 responses. This data set was then subjected to a data cleaning process. All participants who stated that they were not currently using a WFT ("*I am not currently using a wearable device*") were removed prior to analysis. This process resulted in the removal of N = 74 rows. Furthermore, N = 7 rows were deleted because the respondents named their phone (e.g., "*iPhone*", "*Móvil*") as their WFT, which does not fit the aforementioned definition. After cleaning, the final data set consisted of N = 213 responses.

A comprehensive demographic profile of the final sample was generated to characterize the respondents and provide context for the study's findings. The *Age* of participants ranged from 16 to 87 years, with a mean *Age* of 28.25, a median of 26.00 years, and a standard deviation of 9.2, indicating that the sample was predominantly composed of young adults.

The *Gender* distribution was relatively balanced, with 48.4% (N = 103) identifying as male and 51.2% (N = 110) as female. The sample was geographically concentrated in Europe, with the largest groups residing in Germany (35.2%, N = 75) and Sweden (20.7%, N = 44), followed by Spain (11.3%, N = 24) and the US (11.3%, N = 24). The educational attainment of the sample was high, with a vast majority holding a Bachelor's (43.2%, N = 92) or a Master's degree (35.7%, N = 76).

Usage duration was balanced, ranging from less than six months to more than five years in similarly sized groups (see Table 2). Smartwatches were the dominant device category, used by N = 181, 85.0% of the sample. Correspondingly, Apple's iOS was the most prevalent phone operating system, reported by N = 169, 79.4% of users. A detailed summary of the final sample's demographic and technology-related characteristics is presented in Table 3.

Table 3: *Demographic Characteristics*

Characteristic	Category	Frequency (n)	Percentage (%)
Age	Mean (Median)	28.25 (26.00)	
	Range	16 - 87	
	Standard Deviation	9.2	
Gender	Male	103	48.4
	Female	110	51.6
Residency	Germany	75	35.2
	Sweden	44	20.7
	USA	24	11.3
	Spain	24	11.3
	Austria	22	10.3
	Other	24	11.2
Education	High School Diploma	19	8.9
	Apprenticeship	8	3.8
	Bachelor's Degree	92	43.2
	Master's Degree	76	35.7
	Diploma	16	7.5
	MBA	1	0.5
	PhD	1	0.5
Tenure	< 6 months	28	13.1
	6 - 12 months	27	12.7
	More than 1 year	41	19.2
	More than 2 years	35	16.4
	More than 3 years	30	14.1
	More than 4 years	18	8.5
	More than 5 years	34	16.0
Type of Device	Smartwatch	181	85.0
	Smart Ring	13	6.1
	Wristband (without display)	10	4.7
	Wristband (with display)	8	3.8
	AirPods	1	0.5
PhoneOS	iOS	169	79.4
	Android	44	20.7

Note: n = 213

4.4 Construct Validation

The internal consistency of each individual construct was assessed to ensure that the items were measuring a unitary concept reliably. The widely used coefficient Cronbach's Alpha (Cronbach, 1951) was calculated for each of the nine constructs using the psych package in R. The results, summarized in Table 4, generally indicated acceptable to excellent reliability above the threshold of 0.65 (Vaske et al., 2017). For instance, the scales for *Continuance Intention* (α = 0.957), *Perceived Aesthetics* (α = 0.891), and *Social Influence* (α = 0.879) all demonstrated high internal consistency. However, the two-item *Confirmation* construct yielded reliability coefficients (α = 0.612) below the commonly accepted threshold. According to Tavakol & Dennick (2011), a low alpha value might indicate a too-low amount of questions, low correlation between items, or heterogenous constructs. If a low alpha-value is caused by a too-low correlation between items, the authors recommend revising the question battery. The correlation of the two *Confirmation* items CON1 and CON2 is r = .51, indicating a strong effect (Cohen, 1988). Additionally, as described above, the scale is consistently validated in other WFT research with strong results. Therefore, despite the lower alpha, the scale was retained for further analysis.

Table 4*: Summary of Cronbach's Alpha*

Variable	Cronbach's Alpha
Perceived Aesthetics	0.893
Personalization	0.823
Confirmation	0.612
Perceived Usefulness	0.766
Community Immersion	0.844
Social Influence	0.888
Perceived Security	0.779
Satisfaction	0.819
Continuance Intention	0.959

Table 5 shows the correlation matrix for the variables. Only the variables *Confirmation* and *Satisfaction* show a high correlation of r = 0.73. This relationship is central to ECM and has been validated across numerous studies (e.g. Bhattacherjee, 2001; Bölen, 2020; Sun & Gu, 2024). The strength of the link between C*onfirmation* and *Satisfaction* is so established that it is considered theoretically expected and empirically consistent.

Table 5: *Pooled correlations*

Variable	Mean	SD	Min	Max	PA	PE	CON	PU	CMI	SI	PS	SAT	CINT
PA	5.07	1.31	1	7	1								
PE	4.94	1.14	1	7	0.44	1							
CON	5.35	1.08	1	7	0.30	0.43	1						
PU	4.61	1.23	1	7	0.23	0.40	0.37	1					
CMI	3.31	1.58	1	7	0.03	0.15	0.07	0.28	1				
SI	3.62	1.66	1	7	0.14	0.24	0.07	0.34	0.63	1			
PS	4.69	1.15	1	7	0.28	0.38	0.24	0.30	0.14	0.21	1		
SAT	5.51	1.01	1	7	0.31	0.46	0.73	0.41	0.00	0.06	0.32	1	
CINT	5.97	1.25	1	7	0.30	0.41	0.55	0.36	0.04	0.00	0.29	0.68	1

Note: *n* = 213 responses; PA = Perceived Aesthetics, PE = Personalization, CON = Confirmation, PU = Perceived Usefulness, CMI = Community Immersion, SI = Social Influence, PS = Perceived Security, SAT = Satisfaction, CINT = Continuance Intention, SD = Standard Deviation

To ensure that the regression estimates in the main analysis would not be biased by excessive correlation among the predictor variables, a multicollinearity test was conducted. The Variance Inflation Factor (VIF) was calculated for all independent variables in the *Satisfaction* equation. The results showed that all VIF values were well below the commonly accepted upper threshold of 6 (Hair et al., 2019; Verhoef et al., 2004), with the highest VIF being 1.78 for *Social Influence* and the lowest being 1.24 for *Perceived Security*. These low values indicate that multicollinearity is not an issue in the dataset (Hair et al., 2019; Verhoef et al., 2004), confirming the discriminant validity of the constructs and ensuring that the individual effects of each predictor can be reliably estimated in the regression model.

Table 6: *Variance Inflation Factors among the main predictors of Satisfaction*

CON	PU	PA	PE	CMI	PS	SI
1.344	1.408	1.292	1.600	1.675	1.238	1.784

Note: PA = Perceived Aesthetics, PE = Personalization, CON = Confirmation, PU = Perceived Usefulness, CMI = Community Immersion, SI = Social Influence, PS = Perceived Security, SAT = Satisfaction, CINT = Continuance Intention

4.5 Model and SUR Equations

The dominant methodology in IS research is Structural Equation Modeling (SEM), and it is especially frequently employed in ECM research. However, given the specific research model in this study, with the dependent variables *Satisfaction* and *Continuance Intention,* which are elicited from the same respondents regarding the same WFT, it is theoretically imperative to assume that the stochastic error terms of the two regression equations ε_1 and ε_2 are correlated. Such correlation could arise from unobserved heterogeneity, including omitted variables such as the user's general technological affinity, current mood, or individual response tendencies (e.g. social desirability bias) that simultaneously impact both outcome variables.

Ignoring these interdependencies could result in biased and inconsistent variables in different regressions. To alleviate these endogeneity problems, we argue that the Seemingly Unrelated Regression (SUR) model, first proposed by Zellner (1962), is a superior choice (Autry & Golicic, 2010). Given the recursive nature of the proposed framework, joint estimation through the SUR method is the most suitable approach. This is consistent with prior studies examining recursive processes such as the service-profit chain (Bowman & Narayandas, 2004). In interpreting these results, we apply conventional statistical thresholds, treating effects with a p-value at the 0.001 and 0.05 levels as statistically significant and those at the 0.1 level as marginally significant, in line with established empirical research practice (Woolridge, 2016).

Based on the theoretical framework, the two-equation SUR system was specified as follows:

$$SAT = \beta_0 + \beta_1 PA + \beta_2 PE + \beta_3 CON + \beta_4 PU + \beta_5 CMI + \beta_6 SI + \beta_7 PS + Age + Tenure + ToD + Gender + PhoneOS + \varepsilon_1$$

(EQ1)

$$CINT = \gamma_0 + \gamma_1 SAT + \gamma_2 PU + Age + Tenure + ToD + Gender + PhoneOS + \varepsilon_2$$

(EQ2)

Note: PA = Perceived Aesthetics, PE = Personalization, CON = Confirmation, PU = Perceived Usefulness, CMI = Community Immersion, SI = Social Influence, PS = Perceived Security, SAT = Satisfaction, CINT = Continuance Intention

To ensure the robustness of the standard errors and p-values, the SUR model was estimated using a bootstrapping procedure with 5,000 replications (Efron, 1979). This technique creates resampled data sets to generate a more accurate empirical distribution of the parameters, protecting against potential violations of normality assumptions.

5. Analysis and Results

5.1 Overall Model Fit

The SUR model demonstrated strong explanatory power for both dependent variables. The first equation, predicting user *Satisfaction*, accounted for a substantial portion of the variance, with an adjusted R^2 of 0.586. The second equation, predicting *Continuance Intention*, also explained a significant amount of variance, with an adjusted R^2 of 0.492. These results indicate that the extended ECM provides a robust framework for understanding the key drivers of post-adoption user attitudes and intentions.

Table 7: *Model fit per equation*

Equation	N	DF	SSR	MSE	RMSE	R^2	Adj. R^2
SAT	213	195	82.95	0.43	0.65	0.62	0.59
CINT	213	200	154.80	0.77	0.88	0.53	0.49

Note: N = 213. DF = Degrees of Freedom; SSR = Sum of Squared Residuals; MSE = Mean Squared Error; RMSE = Root Mean Squared Error.

5.2 Determinants of User Satisfaction

The following table presents the bootstrapped (R = 5,000) results of the two SUR Equations.

Table 8: *Seemingly Unrelated Regression Results for Satisfaction and Continuance Intention*

	Dependent Variable: Satisfaction				**Dependent Variable: Continuance Intention**			
Variables	Coefficient	Std. Error	p-value	Hypothesis	Coefficient	Std. Error	p-value	Hypothesis
Intercept	1.295**	0.452	0.004		0.336	0.512	0.511	
User Factors (ECM)								
Confirmation	.601***	0.060	0.000	H1a: supported				
Perceived Usefulness	0.110**	0.043	0.011	H1b: supported	0.077	0.067	0.264	
Satisfaction					0.813***	0.087	0.000	H4: supported
Device Factors								
Perceived Aesthetics	0.035	0.039	0.364	H2a: not supported				
Personalization	0.098*	0.054	0.068	H2b: supported				
Contextual Factors								
Community Immersion	-0.072*	0.037	0.054	H3a: rejected				
Social Influence	-0.011	0.037	0.764	H3b: not supported				
Perceived Security	0.087*	0.046	0.062	H3c: supported				
Control Variables								
Age	-0.005	0.005	0.383		0.015**	0.006	0.009	
Gender								
Female	0.115	0.097	0.237		0.328**	0.126	0.009	
Tenure								
Between 6 – 12 months	-0.461**	0.177	0.009		0.371	0.249	0.135	
More than a year	-0.184	0.161	0.253		0.141	0.245	0.565	
More than two years	-0.302*	0.183	0.097		0.347	0.242	0.152	
More than three years	-0.195	0.161	0.225		0.355	0.265	0.180	
More than four years	0.091	0.206	0.657		0.179	0.280	0.523	
More than five years	0.267	0.233	0.362		0.267	0.233	0.253	
Type of Device								
Without Screen	-0.133	0.157	0.397		-0.277*	0.168	0.099	
PhoneOS								
iOS	0.095	0.118	0.419		-0.061	0.164	0.709	

Note: Gender (Female) is compared to the reference group 'Male'. Tenure categories are compared to the reference group '< 6 months'. Device Type (With Screen) is compared to the reference group 'Without Screen'. PhoneOS is compared to the reference group 'Android' Significance codes: $p \leq 0.001$***; $p \leq 0.05$**; $p \leq 0.1$*

The first equation of the SUR model tested the hypothesized antecedents of user *Satisfaction* (H1a, H1b, H2a, H2b, H3a, H3b, H3c). The results show that the core constructs of the ECM are the most powerful predictors.

In strong support of H1a, *Confirmation* emerged as the most influential determinant of *Satisfaction*, with a positive, and highly significant coefficient ($\beta = 0.601$, $p < 0.001$). This finding underscores that the degree to which a WFT meets or exceeds a user's initial expectations is the single most critical factor in shaping overall *Satisfaction*. *Perceived Usefulness* also had a significant positive effect on *Satisfaction* ($\beta = 0.110$, $p < 0.05$), providing support for H1b. This indicates that, beyond meeting expectations, the device's practical utility in daily life is also a key driver of *Satisfaction*.

The results for the device-centric and contextual factors were more mixed. The device-centric factor *Personalization* exhibited a positive but only marginally significant effect on *Satisfaction* ($\beta = 0.176$, $p < 0.1$), suggesting a tentative indication in favor of H2b at a 10% significance level, indicating the need for further examination.

In contrast, *Perceived Aesthetics* was not a significant predictor ($\beta = 0.035$, n.s.), leading to the rejection of H2a. This suggests that while users may appreciate a tailored experience, the visual design of the device is less critical to their *Satisfaction* compared to its performance and utility.

Among the contextual factors, *Perceived Security* had a positive and marginally significant impact on *Satisfaction* ($\beta = 0.087$, $p < 0.1$), suggesting a tentative indication for H3c at the 10% significance level. This suggests that *Perceived Security* can positively contribute to the user experience.

Unexpectedly, *Community Immersion* was found to have a marginally significant, negative effect on *Satisfaction* ($\beta = -0.072$, $p < 0.1$). This finding, which contradicts H3a, suggests that for this user sample, deeper engagement with the device's social community features may be a source of pressure or anxiety, thereby detracting from overall *Satisfaction*.

Finally, *Social Influence* (SI) was not a significant predictor of *Satisfaction* ($\beta = -0.011$, n.s.), leading to the rejection of H3b.

5.3 Determinants of Continuance Intention

The second equation of the SUR model examined the predictors of *Continuance Intention*, with a primary focus on the role of *Satisfaction* (H4). As hypothesized, *Satisfaction* was the strongest and most significant predictor of *Continuance Intention*, with a positive coefficient ($\beta = 0.813$, $p < 0.001$). This result provides unequivocal support for H4 and confirms the central role of *Satisfaction* as the primary driver of users' intent to continue using their WFT in the long term.

The model also tested a direct effect of *Perceived Usefulness* on *Continuance Intention*, independent of its effect through *Satisfaction*, in line with the core ECM (Bhattacherjee, 2001). The coefficient for *Perceived Usefulness* was, surprisingly, not statistically significant ($\beta = 0.087$, n.s.). This finding indicates that the influence of a device's *Perceived Usefulness* on a user's C*ontinuance Intention* is fully mediated by *Satisfaction*. In other words, a useful device encourages continued use because it makes the user satisfied; it does not appear to have a separate, direct influence on their intentions, contrary to the common path described in ECM.

5.4 Influence of Control Variables

Several control variables also emerged as significant predictors. In the *Continuance Intention* equation, *Gender* was a significant factor, with female users reporting significantly higher *Continuance Intention* than male users ($\beta = 0.328$, $p < 0.05$). Furthermore, *Age* had a positive and significant effect, suggesting that older users have a slightly higher intention to continue using their devices ($\beta = 0.015$, $p < 0.05$). *Tenure* had a significant effect in specific subsets: users in the "6-12 month" ($\beta = -0.461$, $p < 0.05$) and "more than 2 year" ($\beta = -0.302$, $p < 0.1$) groups reported significantly higher *Satisfaction*. *Type of Device*, which was grouped in "with Screen" and "without Screen" also showed that users with screenless devices had marginal significantly lower *Continuance Intention* ($\beta = -0.277$, $p < 0.1$). *PhoneOS* did neither significantly influence *Satisfaction* ($\beta = 0.095$, n.s.) nor *Continuance Intention* ($\beta = -0.061$, n.s.).

5.5 Complementary Findings

To gain a more nuanced understanding of the relationships within the data, a series of post-hoc exploratory analyses was conducted. These analyses investigated the role of the device ecosystem, the relationship between user *Tenure* and *Satisfaction*, the underlying mechanism leading to *Confirmation,* as well as the distinct role *Community Immersion* plays in shaping *Satisfaction*.

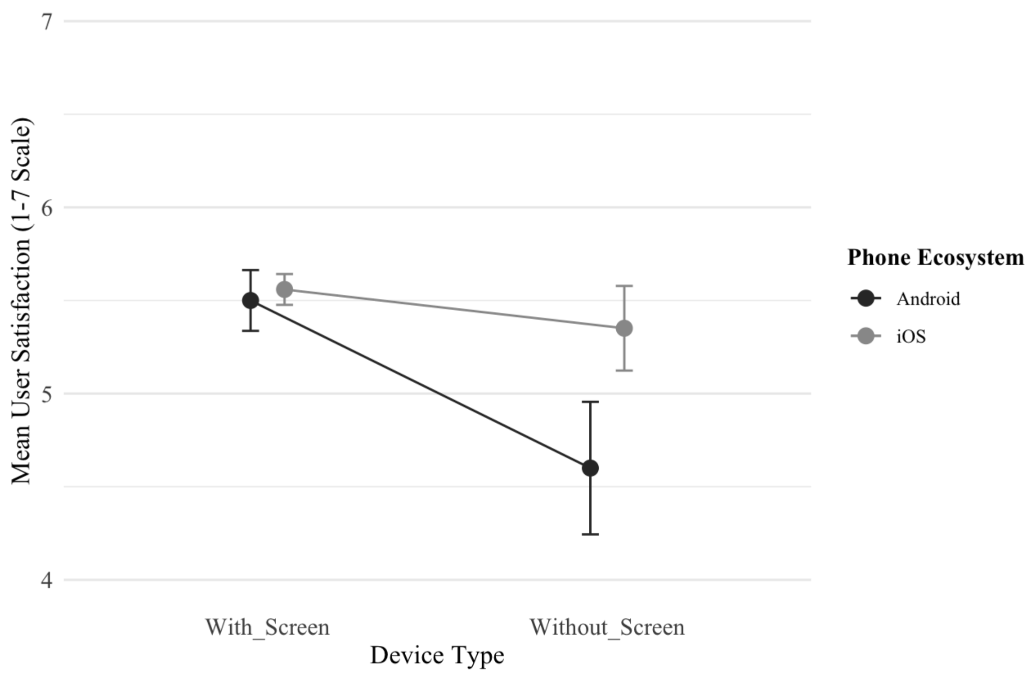
5.5.1 The Role of the Device Ecosystem

An exploratory analysis was conducted to examine whether the relationship between *Type of Device* (With Screen vs. Without screen) and *Satisfaction* is influenced by the user's phone operating system (iOS vs. Android). Due to the limited sample size within specific subgroups, notably the "Android x Without Screen" segment, statistical interaction tests lacked sufficient power. However, a descriptive analysis of the group means reveals a notable divergence in user experience.

The data indicates a disparity in *Satisfaction* based on the operating system. While "iOS x Without Screen" users reported only a slight decline in *Satisfaction* levels compared to the "iOS x With Screen" group, Android users in the "Without Screen" category reported markedly lower *Satisfaction* compared to their "With Screen" counterparts (see Figure 3). This pattern is theoretically relevant because screenless devices (e.g., smart rings) function as "slaved" devices (Jung et al., 2016), making their user experience and utility highly dependent on the integration quality of the companion smartphone app.

Although preliminary and descriptive, this finding suggests that the user *Satisfaction* with screenless wearables may be platform-dependent. The observed "Satisfaction Penalty" for Android users could be attributable to fragmentation in the Android ecosystem, differences in software optimization, or the quality of companion applications compared to the iOS environment.

Figure 3: Interaction between Device Type and Phone Operating System on Satisfaction



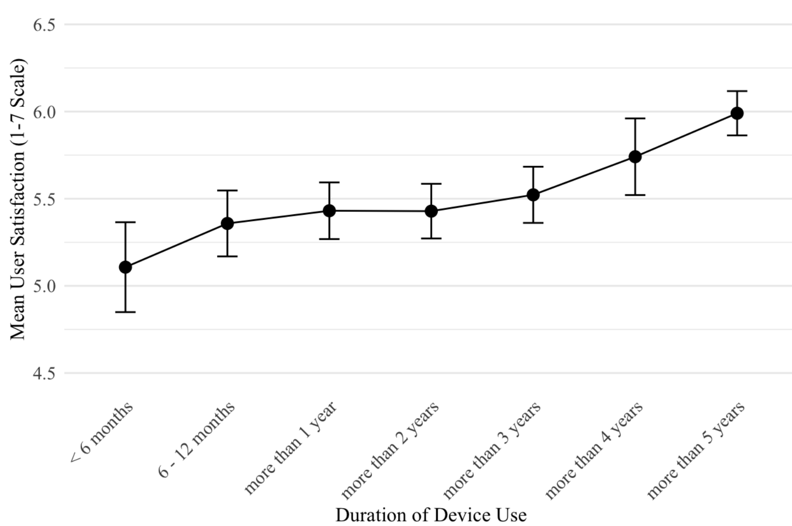
5.5.2 The Relationship Between User Tenure and Satisfaction

The original SUR model reveals a significant change in *Satisfaction* levels in the "6-12 months" ($\beta = -0.461$, $p < 0.05$) and "more than 2 years group" ($\beta = -0.302$, $p < 0.1$). An exploratory ANOVA was conducted to isolate the direct relationship between the under-studied variable *Tenure* and *Satisfaction*. The analysis confirmed that *Satisfaction* levels differ significantly across *Tenure* groups ($F(6, 206) = 2.44$, $p < 0.05$).

A closer examination of the coefficients from the underlying linear model reveals a steady increase in *Satisfaction*. The variable appears to follow an upward trajectory, a trend logically attributable to survivorship bias in sample selection (Berk, 1983). This survivorship bias operates through a dynamic "filtering process" inherent in cross-sectional designs. In the early stages of adoption (< 6 months), the user base is highly heterogeneous, comprising both users who find the device fits their lifestyle and dissatisfied users who are struggling to find value. As time progresses, the dissatisfied users naturally churn out of the WFT user population and are therefore naturally excluded from the sample at later *Tenure* stages. The data indicates that those critical drop-off points are in the time period between six to twelve months and two years after WFT purchase.

Consequently, the steady increase in user *Satisfaction* is to be attributed not to an increasingly refined group of “Survivors” who have already successfully integrated the device into their habits and find value in their WFT. This implies that the observed increase in *Satisfaction* over time may not solely represent an improvement in the user experience itself, but rather the systematic attrition of dissatisfied users. This distinction is critical for interpreting the long-term viability of WFTs: the challenge is not necessarily that long-term users become unhappy, but that new users are not retained long enough to become “Survivors”. This finding is in line with prior research by Windasari et al. (2021) and Shin et al. (2019), who report a drop in usage roughly after the six month mark, and extends it by showing that there seem to be not one, but two discontinuation points at about six months and after two years.

Figure 4: Relationship between Tenure and Satisfaction



5.5.3 The Double-Edged Sword of Community Immersion

The unexpected negative relationship between *Community Immersion* and *Satisfaction* observed in the main model prompted a deeper investigation. While previous literature (Kang & Hwang, 2022) suggest that deeper *Community Immersion* should lead to higher *Satisfaction*, the aggregate data pointed to the contrary. To isolate the specific driver of this negative effect, a post-hoc diagnostic test was conducted using an item-level regression analysis, decomposing the *Community Immersion* construct into its constituent parts. This granular analysis revealed that the negative impact of *Community Immersion* is not a general phenomenon, but seems instead to be driven by a single, distinct mechanism: the active participation in WFT communities.

Table 1: *Results of item-level regression of Community Immersion predicting Satisfaction*

Variable	Item Text (Summary)	Coefficient (β)	p-value
CMI 1	Sense of Belonging	-0.043	0.292
CMI 2	Psychological Attachment	0.02	0.621
CMI 3	Exchanging Views	0.031	0.287
CMI 4	Active Participation	-0.082	.014**

Note: Signif. Codes: $p < 0.001$ = **; $p < 0.05$ = **; $p < 0.1$ = *, CMI = Community Immersion

The analysis reveals a clear distinction between the feeling of immersion and the act of immersion. Items relating to cognitive and emotional states, such as S*ense of Belonging* (CMI1) and Psychological Attachment (CMI2), showed no significant relationship with *Satisfaction* ($p > 0.1$). Feeling connected to the community does not inherently drive dissatisfaction. However, the specific item measuring behavioral action, "I participate in wearable device community activities" (CMI4), emerged as the sole significant negative predictor ($\beta = -0.082$, $p < 0.05$).

These findings suggest a “Cost of Activity” dynamic. While users derive *Satisfaction* from the passive benefits of the community (belonging and attachment), the actual labor of participation appears to diminish *Satisfaction*. This may be because active contribution requires effort, exposes users to potential conflict, or creates a sense of obligation that passive "lurking" does not. Therefore, the negative effect of *Community Immersion* is driven not by how much users care about the community, but by how heavily they participate within it.

6. Discussion

6.1 Theoretical Implications

This study makes several significant contributions to the IS continuance literature, particularly regarding the hierarchy of *Satisfaction* drivers and the structural relationship between device attributes and cognitive evaluations.

6.1.1 User Factors: The Validation of the Core ECM

First and foremost, the findings provide strong support for the original ECM framework (Bhattacherjee, 2001). However, the relative strength of the predictors offers a crucial insight into the user psychology of wearables. *Confirmation* emerged as the single most powerful predictor of Satisfaction, exerting an influence stronger than that of *Perceived Usefulness*.

While both constructs are significant, this disparity in effect size suggests that in the WFT post-adoption phase, the user's evaluation is driven less by the raw utility of the device and more by the congruence between expectation and reality. This aligns with Cognitive Dissonance Theory (Festinger, 1957), which underpins the ECM; users seek to resolve the tension between their pre-purchase expectations and actual usage. The dominance of *Confirmation* implies that a moderately useful device that performs exactly as promised generates higher *Satisfaction* than a highly useful device that over-promises and under-delivers. This finding reinforces the perspective of Gupta et al. (2021) and Nascimento et al. (2018), who similarly identified *Confirmation* as a dominant driver, but our results highlight that in the mature WFT market, the "reality check" of *Confirmation* overshadows almost all other cognitive evaluations.

Furthermore, the path from *Perceived Usefulness* to *Continuance Intention* was non-significant. This contradicts the original ECM path where *Perceived Usefulness* has a direct impact on *Continuance Intention* (Bhattacherjee, 2001). In the context of WFTs, this suggests that "utilitarian necessity" is rarely enough to force continuance on its own; if the user is not emotionally satisfied, the mere usefulness of the data is insufficient to prevent abandonment.

6.1.2 Device Factors: Sunk Benefits versus Active Drivers

The results for *Perceived Aesthetics* and *Personalization* suggest that the drivers of *Continuance Intention* are fundamentally different from the drivers of adoption.

The rejection of H2a (*Perceived Aesthetics*) ($\beta = 0.035$, n.s.) contradicts the "fashnology" perspective often cited in wearable research (Chuah et al., 2016; Rauschnabel et al., 2016). While aesthetics is undeniably critical at the point of sale (adoption), our results imply that their salience fades during the continuance phase. Once the device becomes part of the user's daily habit, its visual appeal becomes a sunk benefit: it is appreciated but no longer actively drives the daily evaluation of *Satisfaction*. This supports the theoretical distinction between the object-based beliefs (like design) that drive initial acceptance and the usage-based beliefs (like *Confirmation*) that drive retention (Bhattacherjee, 2001).

The marginal significance of *Personalization* in the full model ($\beta = .098$, $p < 0.1$) suggests that *Personalization* acts as an antecedent to *Satisfaction*. High-quality personalization (e.g., tailored goals, adaptive metrics) is the technical input that users process to determine if they are indeed satisfied with their devices.

6.1.3 Contextual Factors: The Dark Side of Community

Perhaps the most novel contribution of this study is the empirical evidence for the dark side of *Community Immersion*. Contrary to H3a and prior literature that views social features as a source of *Satisfaction* (Canhoto & Arp, 2017; Gupta et al., 2021), we found a negative relationship between *Community Immersion* and *Satisfaction* ($\beta = -0.072$, $p < 0.1$). Intrigued by this surprising finding, our post-hoc diagnostics explain this through what we call the “Passive-Active Divide”. Analyzing the specific items showed that users value a "sense of belonging" (passive) but react negatively to the "pressure to participate" (active). This suggests that WFT communities can inadvertently create a "performance burden," where the obligation to share and compete detracts from the intrinsic enjoyment of the activity.

Similarly, the non-significance of *Social Influence* (H3b rejected) reinforces the Adoption vs. Continuance distinction. While peer pressure (subjective norm) seems to drive the initial purchase (Talukder et al., 2019), it exerts no leverage on the user's private, daily evaluation of the device. Sustained use is therefore more likely to be an intrinsic, individualistic behavior, impervious to external social pressure.

Additionally, while Kim (2021) classifies *Perceived Security* as a hygiene factor, our findings indicate a linear association between *Perceived Security* and *Confirmation* ($\beta = 0.087$, $p < 0.1$). This discrepancy warrants further investigation, particularly regarding brand-level differences in data-security practices, to clarify how heterogeneous security strategies shape user perceptions in the WFT market. A plausible explanation for the shifting role of *Perceived Security* is the growing public attention to biometric data protection, amplified by recurring reports of data misuse (Silva, 2025).

6.1.4 The Influence of Control Variables

Although *PhoneOS* did not emerge as a significant main predictor, descriptive analyses indicated a potential interaction effect involving *Satisfaction*, *PhoneOS*, and *Type of Device*, underscoring the relevance of including this novel control variable. Regarding demographic factors, *Age* exerted no significant impact on *Satisfaction* but showed a positive influence on *Continuance Intention*, potentially reflecting a lower propensity for technology discontinuance among older cohorts. This is consistent with the findings from Kowalszuk (2021). Additionally, female users exhibited a slightly higher *Continuance Intention* than males. Since this deviation is not consistently supported by prior literature, we attribute it to sample-specific characteristics rather than a generalizable phenomenon. Finally, *Tenure* demonstrated a significant effect on *Satisfaction* at specific intervals (i.e., 6–12 months and >2 years). This finding, corroborated by a post-hoc ANOVA across *Tenure* groups, is likely attributable to survivorship bias within the study population and WFT discontinuance after certain points in time, as detailed in the post-hoc analysis.

6.2 Managerial Implications

The findings offer actionable strategies for WFT manufacturers and app developers aiming to reduce churn and extend user lifecycles.

First, reliable delivery on user expectations is of utmost importance. Given that *Confirmation* is more influential than *Perceived Usefulness*, manufacturers should prioritize reliability and expectation management over introducing new features. A device that promises three days of battery life and delivers on that promise will likely generate more *Satisfaction* than a device that promises seven days but delivers five days. Marketing communications should be rigorously aligned with actual performance to ensure the "*Confirmation* mechanism" works in the firm's favor. A concrete example of this strategy can be seen in the divergent approaches of market leaders. Manufacturers often face the strategic choice between adding novel but potentially unstable sensors like blood oxygen (SpO_2) or stress tracking and core reliability like heart rate accuracy. Our findings suggest that the latter yields a higher ROI for retention. For instance, if a device promises stress tracking but delivers erratic data that conflicts with the user's subjective feeling, it triggers immediate expectation disconfirmation, damaging *Satisfaction* more severely than the utility of the feature adds to it. Therefore, product managers should adopt a "Minimum Viable Reliability" standard for all new sensors. It is strategically superior to omit a feature entirely rather than release it in a beta state that risks disconfirmation.

Second, *Personalization* may directly delight users. Managers should view *Personalization* capabilities (e.g., adaptive goals, recovery scores) not just as value-add features, but as a primary tool for *Satisfaction*. A "one-size-fits-all" experience leads to dissatisfaction. From a granular product design perspective, our item-level analysis (See Appendix D) indicates that not all *Personalization* features are equal. We found that users are significantly more driven by informational *Personalization* (Item PE3: 'personalized health insights'; $R^2 = .225$) than by simple customization options. Consequently, manufacturers should prioritize algorithms that interpret biometric data over superficial interface customizations to maximize user *Satisfaction.*

Third, treating *Perceived Security* as a mere hygiene factor is no longer an adequate strategy for managing customer *Satisfaction*, and in turn, *Continuance Intention*. Our findings reveal the increasingly important role this feature plays for WFT users, and have implications for data security procedures and communication strategies. Especially in the face of changing legislation (i.e., the EU data act), WFT providers need to manage their communication strategies and data-handling carefully.

Fourth, our findings challenge the prevailing notion that *Community Immersion* positively impacts the user experience. Specifically, the "cost-of-activity" highlights that community features should not add pressure for users who react negatively to competition or comparison. Further research is required to determine whether active participation has a negative impact on *Satisfaction* for all users, or just specific subgroups. Until then, providers could make community features optional, allowing users to avoid this potential negative antecedent to *Satisfaction*.

Finally, it is crucial to consider the Ecosystem Divide. The descriptive indication that screenless devices (e.g., smart rings) underperform on Android devices suggests a critical strategic flaw. Manufacturers of these form factors must invest disproportionately in their Android app experience to compensate for the OS fragmentation. Alternatively, marketing budgets for screenless devices might yield higher ROI if targeted specifically at the iOS ecosystem, where the slaved device experience appears more seamless.

6.3 Limitations and Future Research Directions

Despite the rigorous methodology, this study is subject to limitations that suggest specific avenues for future research.

First, the sample size was relatively small, with only N = 213 responses being analyzed. Future research should aim to expand this number and consider the difficulty of finding suitable participants in specific WFT subgroups (e.g., smart rings). Furthermore, regarding the sample composition, the data exhibited a pronounced skew towards smartwatch users. This demographic imbalance may limit the generalizability of the findings across different wearable form factors. Consequently, future investigations would benefit from ensuring a balanced distribution across device types or, alternatively, isolating a sample devoid of smartwatches to verify whether the observed structural relationships remain consistent outside the smartwatch ecosystem.

Second, the descriptive patterns observed for *PhoneOS* and *Type of Device* in relation to *Satisfaction* (Android users having lower *Satisfaction* in devices without a screen) warrant further investigation. As the sample size was insufficient to support reliable statistical testing, these findings remain exploratory. Nonetheless, the implications for WFT manufacturers are non-trivial: incompatibilities arising solely from users' phone operating systems may lead to user dissatisfaction, potential customer churn, and negative word-of-mouth.

Third, the study employed a system of two Seemingly Unrelated Regressions (SUR) rather than Structural Equation Modeling (SEM). While SUR was appropriate for the specific dual-equation focus of this study, SEM would allow for the simultaneous estimation of the latent measurement model and the structural paths. Future studies with larger sample sizes (N > 400) should employ covariance-based SEM to validate the mediated structural paths identified here.

Fourth, the ECM extensions examined in this study (*Perceived Security, Community Immersion, Personalization*) exhibited either no effects or only marginal effects. Potential explanations include the relatively small sample size or the presence of heterogeneous user subgroups with differing preferences. Future research should therefore seek to identify distinct clusters of WFT users and explore their specific preferences and requirements for continued use. Especially the question of which factors need to be confirmed (*Confirmation*) for specific subgroups to be satisfied could prove valuable for WFT manufacturers, and further advance research in the WFT field.

Fifth, a specific measurement limitation concerns the internal consistency of the *Confirmation* construct, which yielded a Cronbach's alpha of $\alpha = 0.612$ in this dataset. Post-hoc item-level regression analysis (see Appendix D) revealed that while both *Confirmation* items were significant, CON2 ('My experience with using the device was better than what I expected') possessed notably higher explanatory power ($R^2 = 0.449$) compared to CON1 ($R^2 = 0.349$). This divergence in predictive strength likely contributed to the lower internal consistency (Cronbach's $\alpha = 0.612$) observed for this construct. While this falls below the conventionally accepted threshold of $\alpha = 0.65$, the construct was retained for the analysis due to its theoretical centrality as the foundational mechanism of the ECM. Excluding this variable would have undermined the study's ability to test the core ECM framework. It is important to note that the items utilized for this scale were adopted from established, empirically validated instruments that have consistently demonstrated high reliability across numerous prior IS studies. However, the scale used to assess *Confirmation* was adopted from e.g. Nascimento et al. (2018), who adapted the original ECM by Bhattacherjee (2001) by not only adapting the wording, but also reducing the number of items from three to two. Since this goes against best-practice in quantitative research (e.g. DeVellis, 2016), it raises the question of whether the scale for *Confirmation* in WFT research should be revised. This discrepancy suggests that the lower consistency observed here is likely an artifact of this specific sample rather than a fundamental deficiency in the scale itself. Nevertheless, future research utilizing larger sample sizes is necessary to re-establish the psychometric robustness of this construct within this context.

Sixth, by surveying current users, the study inherently suffers from Survivorship Bias; the analysis is restricted to individuals who have chosen to persist with the technology. While the interaction with *Tenure* allowed for inferences regarding early usage dynamics, future research should adopt a sequential mixed-methods approach to explicitly target discontinuers (i.e. users who abandoned their device in the last six months). A qualitative inquiry could first be employed to uncover the phenomenological reasons for abandonment, the insights from which could subsequently be tested quantitatively among current users to identify latent negative emotions. Comparing the structural model of discontinuers to that of continuers would provide crucial insight into the extended ECM. If future research employs a cross-sectional research design, we recommend a different approach to analyzing *Tenure*. This study analyzed subgroups of *Tenure* to analyze the mean usage duration. To get a more nuanced understanding of the effect of usage duration, the exact duration of use (*Tenure*) should be studied instead.

Finally, a compelling avenue for future inquiry involves the phenomenon of device upgrading. Further research is required to investigate the drivers behind a user's decision to switch to a newer iteration of the same ecosystem (e.g., upgrading to the latest hardware generation). Determining whether this behavior constitutes a distinct construct or merely a facet of IS continuance would provide valuable nuance to the understanding of long-term user engagement and loyalty.

6.4 Conclusion

This study set out to develop and empirically test a holistic, extended Expectation-Confirmation Model (Bhattacherjee, 2001) to understand the multifaceted drivers of user *Satisfaction* and *Continuance Intention* for Wearable Fitness Technology. By integrating user-centric, device, and contextual factors into a single framework, the research sought to provide a more comprehensive explanation for why users continue to engage with their devices long after the initial adoption phase.

In addressing the central research question (*How do user, device, and contextual factors shape Satisfaction and Continuance Intention in the sustained use of Wearable Fitness Technology?)*, this study establishes that the *Continuance Intention* of WFT users is predominantly driven by *Satisfaction*, which acts as a conduit for a holistic set of diverse determinants. While the results validate the foundational influence of *Perceived Usefulness* and *Confirmation* within the ECM, they crucially demonstrate that these core factors are insufficient in isolation. The findings reveal that device-centric attributes, specifically *Personalization*, and contextual *Community Immersion* are significant antecedents of *Satisfaction*.

The analysis yielded findings that both reinforce established theories and introduce new, nuanced insights into the post-adoption user experience. While the majority of the core tenets of the ECM were strongly validated, the effects of the extended factors proved to be structurally complex. The unexpected negative impact of *Community Immersion* challenges the prevailing assumption that social engagement is inherently beneficial in the WFT context.

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Appendix

Appendix A: JIF-based-paper-selection process

Journal	Field	JIF	Threshold L	Threshold U	Result
Journal of Retailing and Consumer Services	Business	13,1	2	5	Included
Journal of Service Research	Business	9,8	2	5	Included
Management Science	Business	4,6	2	5	Included
Journal of Marketing Management	Business	3	2	5	Included
Sustainability	Health	3,3	3	10	Included
JMIR	Health	6	3	10	Included
International Journal of Information Management	Information Technology	20,1	3	10	Included
Technology in Society	Information Technology	12,5	3	10	Included
Automation in Construction	Information Technology	11,5	3	10	Included
Computers in Human Behavior	Information Technology	8,9	3	10	Included
Internet Research	Information Technology	6,8	3	10	Included
Electronic Markets	Information Technology	6,8	3	10	Included
Education and Information Technologies	Information Technology	5,4	3	10	Included
International Journal of Human–Computer Interaction	Information Technology	4,9	3	10	Included
Industrial Management & Data Systems	Information Technology	4,7	3	10	Included
Behaviour & Information Technology	Information Technology	3,1	3	10	Included
Psychology & Marketing	Psychology	9,1	2	5	Included
Universal Access in the Information Society	Information Technology	2,1	3	10	Excluded
Mobile Media & Communication	Information Technology	1,8	3	10	Excluded
European Conference on Information Systems	Information Technology	N/A (Conference)	N/A (Conference)		Excluded
Essex Business School, University of Essex (PhD Thesis)	Business	N/A (Thesis)	N/A (Thesis)		Excluded
Benchmarking	N/A	N/A	N/A		Excluded
AMCIS	Information Technology	N/A (Conference)	N/A (Conference)		Excluded
National Library of Medicine	Health	N/A (Institution)	N/A (Institution)		Excluded
International Journal of Environmental Research and Public Health	Health	N/A (Delisted)	N/A (Delisted)		Excluded
Cogent Business & Management	Business	N/A (No JIF Listed)	2	5	Excluded

Appendix B: Literature Review of the Dependent Variables

Theoretical Model	Variable	Methodology	Items	Citation
Theory of Planned Behavior, Protection-Motivation Theory (PMT)	Behavioral Intention	Quantitative	BI1: I intend to start using the smartwatch to interact with my colleagues and lecturers BI2: I intend to continue using the smartwatch frequently BI3: I will strongly recommend the use of smartwatch to my peers BI4: Overall, I intend to continue using the smartwatch in my future learning	Al-Emran et al. (2023)
ECM	Continous Usage Intention	Quantitative	CI1: I will frequently use my smartwatch in the future CI2: I will regularly use my smartwatch in the future CI3: I intend to continue using my smartwatch, rather than discontinue ist use	Bölen (2020)
N/A	Sustained Use	Qualitative	- When do you usually use X? - How do you usually use X? - Overall, how satisfied are you with the use? - How do you think your own usage pattern of X will change in the next 6 months?	Canhoto & Arp (2017)
TAM	Intention to Adopt	Quantitative	- I intend to use X when I´m on the jobsite - I plan to use X in the future - All things considered, I will use X	Choi et al. (2017)
ECM, TAM	Consumer perception and use of wearable technology devices	Qualitative	N/A	Chong et al. (2020)
Cognitive Emotion Theory (CET), TAM, Innovation Diffusion Theory (IDT), Theory of planned Behavior	Behavioral Intention	Quantitative	- If Mi Band were available to me, I would use it - If Mi Band were launched on the market at an affordable price, I would likely purchase it - I think I would use Mi Band without a sense of being forced	Chuang & Chen (2022)
N/A	Continous Usage Intention	Qualitative	N/A, thematic analysis of Amazon reviews	Dehghani (2018)

Self-Determination Theory	Sustained Use	Quantitative Experiment	- The number of days that individuals wore and synched their devices - The total number of days the participants did not use the device during the study, based on the "last synch" date - Zero steps logged on any given day, which indicated non-compliance	Deranek et al. (2021)
Expectation Confirmation Theory (ECM), Social Comparison Theory	Continous Usage Intention	Quantitative	CUI1: I intent to continue using Smart fitness wearables rather than discontinue its use CUI2: I intend to continue using Smart fitness wearable than use any alternative means CUI3: If I could, I would like to discontinue my use of Smart fitness wearable	Gupta et al. (2021)
Technology Acceptance Model (TAM)	Continous Usage Intention	Quantitative	- I will regularly use IoT-based healthcare wearable devices in the future - I will recommend IoT-based healthcare devices to people around me - I will continue to use short video IoT-based healthcare wearable devices	Kang & Hwang (2022)
Environmental Psychology Theory, Two-Factor Theory of Motivation	Behavioral Intention	Quantitative	- I would like this wearable device to deal with all my physical activities - I would enjoy interacting with this wearable device - I prefer that this wearable device will deal with my physical activities in the future	Kim (2021)
Technology Acceptance Model (TAM)	Continous Usage Intention	Quantitative	IU1: I predict I will use this smartwatch in the future IU2: I plan to use this smartwatch in the future IU3: I expect my use of this smart watch to continue in the future	Kim & Shin (2015)
Expectation Confirmation Theory (ECM)	Loyalty	Quantitative	- REC1: I will introduce this smart health device to my friends. - REC2: I will commend this smart health device to my friends. - REC3: I will tell others about the benefits of this smart health device. - CON1: I will continue to use this smart health device in the future. - CON2: I will probably continue to use this smart health devices in the future. - CON3: I plan to continue using this smart health device in the future. - CRO1: I will purchase value-added services related to this smart health device in the future. - CRO2: I will buy the peripheral products of this smart health device in the future. - CRO3: I will buy other products of this smart health device brand in the future.	Liao et al. (2021)

Expectation Confirmation Model (ECM)	Continous Usage Intention	Quantitative	INT1: I intend to continue using the smartwatch, rather than discontinue its use INT2: I plan to continue using the smartwatch INT3: I will continue using the smartwatch INT4: I predict I will continue using the smartwatch in the future	Nascimento et al. (2018)
Theory of Planned Behavior (TPB), Use of Technology (UTAUT2)	Behavioral Intention	Quantitative	BI1: I intend to use wearable technology in the future BI2: I intend to use wearable technology at every opportunity in the future BI3: I plan to increase my use of wearable technology in the future	Rahman et al. (2022)
Technology Acceptance Model (TAM), Diffusion of Innovation Theory, Self-Determination Theory	Motivation for long-term activity tracker use	Qualitative	Questions focused on (1) the motivations for adopting and using Fitbit, (2) specific capabilities of the device	Shin et al. (2019)
Expectation Confirmation Model (ECM)	Continous Usage Intention	Quantitative	- I intend to continue using my smartwatch rather than discontinue ist use - I predict I would continue using my smartwatch - I plan to continue using my smartwatch	Siepmann & Kowalczuk (2021)
Expectation Confirmation Model (ECM)	Continous Usage Intention	Quantitative	CI1: I intend to continue using my fitness wearable device rather than discontinue using it CI2: I plan to continue using my fitness wearable device frequently CI3: If I am given a change to choose again, I would still choose to use my fitness wearable device	Sun & Gu (2024)
Unified Theory of Acceptance and Use of Technology (UTAUT2), Diffusion of Innovation Theory	Behavioral Intention	Quantitative	BI1: I intend to use fitness wearable technology in the future BI2: I intend to use fitness wearable technology at every opportunity in the future BI3: I plan to increase my use of fitness wearable technology in the future	Talukder et al. (2019)
Service-Dominant Logic (S-DL), Actor to Actor Intention	Continous Usage Intention	Quantitative	- I intend to continue using the described wearable fitness tracker for the purpose of maintaining my personal health - I would like to recommend my friends and families to use the described wearable fitness tracker - I intend to increase my usage of the wearable fitness tracker in the future - (Assume that I have used the described wearable for six months): I want to keep using the wearable fitness tracker	Windasari et al. (2021)

Appendix C: Literature Overview of the Independent Variables

Theoretical Model	Variable	Cluster	Methodology	Items	Citation
no specific model	Accountability	Excluded	Qualitative	n/a	Chong et al. (2020)
Technology Acceptance Model (Extended)	Affective Quality (AQ)	User	Quantitative	- I feel excited when using this smart watch. - I would miss using this smart watch if I no longer have it. - this smart watch is attractive and pleasing.	Kim & Shin (2015)
Theory of Planned Behavior (TPB)	Attitude (A)	User	Quantitative	- A1: Using smartwatch is a good idea. - A2: I have a generally favorable attitude toward using smartwatch. - A3: I like the idea of using smartwatch in learning. - A4: Overall, using smartwatch is beneficial.	Al-Emran et al. (2023)
Technology Acceptance Model (Extended)	Availability (AV)	Device	Quantitative	- AV1: I can access information and desired contents any time via this smart watch. - AV2: I can use this smart watch any time I want to get desired information and service. - AV3: This smart watch offers the sense of real-time connectedness. - AV4: This smart watch offers immediate, timely access to information or service I need	Kim & Shin (2015)
no specific model	Brand	Device	Quantitative	- Samsung Electronics - Apple	Jung et al. (2016)
no specific model	Compatibility	Excluded	Qualitative	Definition of construct: The degree of interaction between applications (apps) operating on the smartwatch system and external devices, such as smartphones	Deghani (2018)
Cognitive Emotion Theory (CET)	Compatibility (COM)	Device	Quantitative	- Mi Band is relevant to my needs and expectations - Mi Band seems to satisfy my desires - Mi Band is appropriate for my expectations and needs - I think Mi Band is useful.	Chuang & Chen (2022)
Extended unified theory of acceptance and use of technology (UTAUT2), Diffusion of innovation (DOI)	Compatibility (COM)	Device	Quantitative	- using fitness wearable technology is compatible with all aspects of my lifestyle - using fitness wearable technology is completely compatible with my current situation - using fitness wearable technology fits into my lifestyle	Talukder et. al. (2019)
no specific model	Compatibility with offline practice (COF)	Excluded	Quantitative	- COF1: Using this smart health device is very similar to how I used to conduct my offline personal health management. - COF2: Using this smart health device does not require changing my current offline personal health management. - COF3: Using this smart health device is in line with my yearning offline personal health management mode.	Liao et al. (2021)
no specific model	Compatibility with online practice (COL)	Excluded	Quantitative	- COL1: Using this smart health device is very similar to how I used to conduct my online personal health management. - COL2: Using this smart health device does not require changing my current online personal health management. - COF3: Using this smart health device is in	Liao et al. (2021)

				line with my yearning online personal health management mode.	
no specific model	Complementary Goods	Device	Qualitative	Definition of construct: The applications (apps) that can enhance the product value, facilitate smartwatch usage, and influence customers' decisions to continue using the device	Deghani (2018)
Expectation Confirmation Model (ECM)	Confirmation (CON)	User	Quantitative	- CON1: Overall, most of my expectations from using my smartwatch were confirmed. - CON2: My experience with using my smartwatch was better than what I expected. - CON3: The function provided by my smartwatch was better than I expected. - CON4: My smartwatch can meet demands in excess of my required functions.	Bölen (2020)
Expectation (ECT), Social Comparison Theory, Expectation Confirmation Model (ECM)	Confirmation (CON)	User	Quantitative	- My experience of using smart fitness wearable is better than what I expected - The service provided by smart fitness wearable is better than what I expected - Overall, most of my expectations from using smart fitness wearable have been fulfilled"	Gupta et al. (2021)
Expectation-Confirmation Model - Extended (ECM-E)	Confirmation (CONF)	User	Quantitative	- CONF1: My experience with using the smartwatch is better than what I expected. - CONF2: Overall, most of my expectations from using the smartwatch were confirmed.	Nascimento et al. (2018)
no specific model	Consumer Action	Excluded	Qualitative	Wearable use (also noted as an antecedent in some contexts)	Mwangi et al. (2024)
TAM, UTAUT, DOI	Context of use	Context	Qualitative	- Observational learning / Social influence (e.g., recommendations from friends, 'group hype', seeing others use) - Receptiveness to financial incentives (from employers/insurers) - Privacy and security concerns (e.g., reluctance to share data with employers/insurers) - Technical infrastructure (e.g., ability to capture data anywhere/anytime, facilitate data aggregation) (for sustained use) - Community of users / Sharing workouts and achievements (for sustained use)	Canhoto & Arp (2017)
no specific model	Continuation (CON)	Excluded	Quantitative	- CON1: I will continue to use this smart health device in the future. - CON2: I will probably continue to use this smart health devices in the future. - CON3: I plan to continue using this smart health device in the future.	Liao et al. (2021)
Expectation-Confirmation Model (ECM), Self-Determination Theory (SDT)	Control Variables	Excluded	Quantitative	Age, Gender, Smartwatch Brand, Smartwatch Possession Duration, Connectedness, Fitness Level, Physical Activity Frequency	Siepmann and Kowalczuk (2021)
Technology Acceptance Model (Extended)	Cost	Context	Quantitative	- CT1: This smart watch was expensive. - CT2: Purchasing this smart watch was a burden to me. - CT3: I was able to easily afford this smart watch	Kim & Shin (2015)

no specific model	Cross-buy (CRO)	Context	Quantitative	- CRO1: I will purchase value-added services related to this smart health device in the future. - CRO2: I will buy the peripheral products of this smart health device in the future. - CRO3: I will buy other products of this smart health device brand in the future.	Liao et al. (2021)
Environmental Psychology Theory, Two-Factor Theory of Motivation	Customization	Device	Quantitative	- The services of the fitness app and wearable device are often personalized to me. - I feel that the fitness app and wearable device are designed for me. - The fitness app and wearable device treat me an individual. - If I wanted to, I could customize the fitness app and wearable device to what I like	Kim (2021)
no specific model	Discretion	Excluded	Qualitative	n/a	Chong et al. (2020)
no specific model	Display Shape	Device	Quantitative	- Curved - Square - Round	Jung et al. (2016)
no specific model	Display Size	Device	Quantitative	- 1.6 Inches - 1.3 Inches	Jung et al. (2016)
Technology Acceptance Model (TAM)	Effort Expectancy (EE)	User	Quantitative	- I can interact with Mi Band clearly and understandably - I could easily become skillful at using Mi Band - I think Mi Band is easy to use - I think learning how to use Mi Band is easy	Chuang & Chen (2022)
Extended Expectation-Confirmation Model (ECM)	eHealth Literacy (eHL)	User	Quantitative	- I know how to find helpful fitness information on the Internet. - I know how to use the Internet to answer my fitness questions. - I know what fitness information are available on the Internet. - I know how to use the health information on the Internet to help me.	Sun and Gu (2024)
Fit-Viability Model (FVM) and Empowerment Theory	Elderly-oriented fit (EOF)	Excluded	Quantitative	- The WHTs are easy to operate for me. - The health data of the WHTs is easy to see for me. - The health data of the WHTs is easy to understand for me. - The WHTs have simple interfaces for me.	Zhang et. al. (2025)
no specific model	Enabling Technologies	Device	Qualitative	Definition of construct: The durability and recharge speed of batteries, which are crucial component technologies necessary for the smartwatch's performance and desirability	Deghani (2018)
Expectation-Confirmation Model (ECM), Self-Determination Theory (SDT)	Enjoyment (EM) part of the variable "Emotional Factors"	User	Quantitative	- I find using the smartwatch to be enjoyable. - The actual process of using the smartwatch is pleasant. - I have fun using the smartwatch.	Siepmann and Kowalczuk (2021)
Environmental Psychology Theory, Two-Factor Theory of Motivation	Entertainment Value	User	Quantitative	- I use the fitness app and wearable device for the pure enjoyment of them. - I think that the fitness app and wearable device are very entertaining. - I enjoy exercising with the fitness app and wearable device because of their own sake, not just because I purchased them.	Kim (2021)

				- The fitness app and wearable device do not just support my physical activity; they entertain me. - The enthusiasm of the fitness app and wearable device is catching, they pick me up.	
Theory of planned behavior (TPB)	Facilitating Condition (FC)	Excluded	Quantitative	- I have the resources that are necessary to use Mi Band - I have the knowledge necessary to use Mi Band - Mi Band is compatible with other systems I use	Chuang & Chen (2022)
Extended unified theory of acceptance and use of technology (UTAUT2), Diffusion of innovation (DOI)	Facilitating Conditions (FC)	Excluded	Quantitative	- I have the resources necessary to use fitness wearable technology - I have the knowledge necessary to use fitness wearable technology - fitness wearable technology is compatible with other systems I use	Talukder et. al. (2019)
Cognitive Emotion Theory (CET)	Familiarity (FAM)	Device	Quantitative	- Mi Band requires little change in user behavior - Mi Band requires little learning on the part of users - Mi Band requires little change of users' use of this type of device	Chuang & Chen (2022)
no specific model	Fashionability (Fashnology)	Device	Qualitative	Definition of construct: An individual's perception regarding the fashion aspects (design, uniqueness, size, etc.) of smartwatches for use in various occasions and activities	Deghani (2018)
no specific model	Functionality	Device	Qualitative	Definition of construct: The performance quality of the device, its operating system, and its connectivity with external devices and applications (e.g., WhatsApp)	Deghani (2018)
no specific model	Gaming motivation (motivational factor)	Excluded	Qualitative	Described as: recognition, feedback, goal setting	Shin et al. (2019)
Expectation-Confirmation Model (ECM), Self-Determination Theory (SDT)	Goal Pursuit Motivation (GPM) part of the variable "Health and Fitness Factors"	User	Quantitative	- Using my smartwatch keeps me motivated to exercise regularly. - Using my smartwatch pushes me to increase the effort I put toward exercising. - Using my smartwatch motivates me to exercise harder than I have in the past. - Using my smartwatch keeps me motivated to live healthier. - Using my smartwatch, motivates me to work towards a healthier lifestyle. - Using my smartwatch motivates me to live healthier than in the past.	Siepmann and Kowalczuk (2021)
Expectation-Confirmation Model - Extended (ECM-E)	Habit (HAB)	User	Quantitative	- HAB1: Using the smartwatch has become automatic to me. - HAB2: Using the smartwatch is natural to me. - HAB3: When faced with a particular task, using the smartwatch is an obvious choice for me.	Nascimento et al. (2018)

Extended unified theory of acceptance and use of technology (UTAUT2), Diffusion of innovation (DOI)	Habit (HB)	User	Quantitative	- the use of fitness wearable technology has become a habit for me - I am addicted to using fitness wearable technology - using fitness wearable technology has become natural to me	Talukder et. al. (2019)
Extension of the Expectation Confirmation Model (E-ECM)	Habit (HBT)	User	Quantitative	- HBT1: The use of smartwatch has become a habit for me. - HBT2: Using the smartwatch belongs to my daily routine. - HBT3: I am addicted to using my smartwatch.	Bölen (2020)
Information Systems (IS) Continuance Model, IS Sucess Model	Haptics Feedback (HAPT) part of the Variable System Quality	Device	Quantitative	- Hap1: I enjoy the haptics touch from my smartwatch. - Hap2: Haptics touching in general is fun. - Hap3: I am a person who likes the haptics touch. - Hap4: My interaction level with the haptics touch is high. - Hap5: The haptics touch quickly communicates information to me. - Hap6: The haptics touch helps me with my tasks (e.g., goal reminders).	Ogbanufe & Gerhart (2018)
no specific model	Health-Technology (Healthtology)	Excluded	Qualitative	Definition of construct: The interaction of health issues, informatics, and technology aimed at providing innovative approaches to satisfy unique healthcare needs, motivating users to engage in lifestyle and health improvements	Deghani (2018)
Extended unified theory of acceptance and use of technology (UTAUT2), Diffusion of innovation (DOI)	Hedonic Motivation (HM)	User	Quantitative	- using fitness wearable technology is fun - using fitness wearable technology is enjoyable - using fitness wearable technology is entertaining	Talukder et. al. (2019)
Technology Acceptance Model (Extended)	Hedonic Motivation (WHM)	User	Quantitative	- WHM1: Using this wristband would provide more fun for daily work. - WHM2: Using this wristband would be entertaining.	Choi et al. (2017)
Extension of the Expectation Confirmation Model (E-ECM)	Individual Mobility (IM)	User	Quantitative	- IM1: I would like to be able to keep in touch everywhere I am - IM2: I would like to be able to coordinate my daily tasks everywhere I am - IM3: I would like to be able to coordinate my daily tasks no matter what time it is	Bölen (2020)
Information Systems (IS) Continuance Model, IS Sucess Model	Information Quality (INFQ)	Device	Quantitative	- InfQ1: Overall, I would give information from the smartwatch high marks. - InfQ2: In general, the smartwatch provides me with high-quality information. - InfQ3: Overall, I would give the information provided by the smartwatch a high rating in terms of quality.	Ogbanufe & Gerhart (2018)
no specific model	Informational Aspects (inhibiting factor)	Excluded	Qualitative	Described as: loss of interest in knowing repetitive patterns of behavior	Shin et al. (2019)

Extended unified theory of acceptance and use of technology (UTAUT2), Diffusion of innovation (DOI)	Innovativeness (INN)	User	Quantitative	- if I heard about a new information technology, I would look for ways to experiment with it - among my peers, I am usually the first to try out new information technologies - in general, I am hesitant to try out new information technologies - I like to experiment with new information technologies	Talukder et. al. (2019)
Environmental Psychology Theory, Two-Factor Theory of Motivation	Interactivity	Device	Quantitative	- I believe that the fitness app and wearable device are dynamic ones. - I feel that I am engaged in the fitness app and wearable device. - The fitness app and wearable device enable me to view physical activity in various ways. - The fitness app and wearable device have search tools which help me find what I want to exercise.	Kim (2021)
Technology Acceptance Model - Extended (TAM-E)	Interactivity (INT)	Device	Quantitative	- IoT-based healthcare wearable devices can share information with multiple people. - Information exchanges between each other can be frequent in IoT-based healthcare wearable devices. - The community in IoT-based healthcare wearable devices is active.	Kang & Hwang (2022)
Fit-Viability Model (FVM) and Empowerment Theory	Intergenerational support (IS)	Context	Quantitative	- My younger family members encourage me to use the WHTs. - My younger family members teach me how to use the WHTs. - My younger family members can't offer suggestions when I need help with the WHTs. (R) - My younger family members can provide me with information to help me overcome problems when using the WHTs. - My younger family members can help me identify the cause of issues and offer suggestions when using the WHTs.	Zhang et. al. (2025)
Technology Acceptance Model (Extended)	Mobility (MB)	Device	Quantitative	- MB1: This smart watch has good mobility. - MB2: I feel I can use this smart watch anywhere. - MB3: I would like to use this when I am in transit from one place to another	Kim & Shin (2015)
no specific model	Motivation	User	Qualitative	n/a	Chong et al. (2020)
Cognitive Emotion Theory (CET)	Novelty (NVE)	Device	Quantitative	- Mi Band is really extraordinary - Mi Band can be considered revolutionary - Mi Band is not conventional - Mi Band has radical differences from other devices - Mi Band is not similar to other devices.	Chuang & Chen (2022)
Environmental Psychology Theory, Two-Factor Theory of Motivation	Originality of Design	Device	Quantitative	- The fitness app and wearable device are fresh and original. - The fitness app and wearable device are innovative and creative. - The fitness app and wearable device are adventurous. - The fitness app and wearable device are advanced.	Kim (2021)

Technology Acceptance Model (TAM)	Outcome Expectancy (OE)	User	Quantitative	- Mi Band could help in reaching my health care objectives - Mi Band could improve my health care performance - Mi Band could improve the quality of my health care	Chuang & Chen (2022)
Extension of the Expectation Confirmation Model (E-ECM)	Perceived Aesthetics (PA)	Device	Quantitative	- PA1: The design of my smartwatch is attractive. - PA2: The appearance of my smartwatch is visually appealing to me. - PA3: The design of my smartwatch is cool to me. - PA4: The design of my smartwatch is excellent to me. - PA5: The user interface (i.e. colors, menus, etc.) of my smartwatch is attractive to me.	Bölen (2020)
Theory of Planned Behavior (TPB)	Perceived Behavioral Control (PBC)	User	Quantitative	- PBC1: I have control over using smartwatch in learning activities. - PBC2: I have the necessary resources to use the smartwatch. - PBC3: I have the necessary knowledge to use the smartwatch.	Al-Emran et al. (2023)
Device specific attributes	Perceived Comfort (PC)	User	Quantitative	- I think using Mi Band is pleasant - I think using Mi Band is comfortable - I think using Mi Band makes me feel at ease - I think Mi Band is well suited to my body.	Chuang & Chen (2022)
Information Systems (IS) Continuance Model, IS Sucess Model	Perceived Convenience (CONV) part of the Variable System Quality	Device	Quantitative	- Conv1: Difficult — Easy - Conv2: Inconvenient — Convenient - Conv3: Complex — Simple - Conv4: Time Consuming — Fast - Conv5: Restrictive — Liberating - Conv6: Inaccessible — Accessible	Ogbanufe & Gerhart (2018)
no specific model	Perceived Ease of Use	Device	Qualitative	Definition of construct: How easy consumers find learning and using smartwatches through new interaction techniques such as speech recognition or ultrasonic gesture recognition	Deghani (2018)
Technology Acceptance Model (Extended)	Perceived Ease of Use	Device	Quantitative	- Learning to use smartwatches is simple - Using smartwatches is self-explaining - Smartwatches are easy to use	Chuah et al. (2016)
Technology Acceptance Model (Extended)	Perceived Ease of Use (WPE)	Device	Quantitative	- WPE1: It would be easy for me to read data on this wristband. - WPE2: Learning how to use this wristband is easy for me.	Choi et al. (2017)
Expectation-Confirmation Model - Extended (ECM-E)	Perceived Enjoyment (ENJ)	User	Quantitative	- ENJ1: I have fun interacting with the smartwatch. - ENJ2: Using the smartwatch provides me with a lot of enjoyment. - ENJ3: I enjoy using the smartwatch.	Nascimento et al. (2018)
Expectation (ECT), Social Comparison Theory, Expectation Confirmation Model (ECM)	Perceived Health Outcomes (PHO)	User	Quantitative	- Using smart fitness wearable has helped me to live healthy life (PHO1) - Smart fitness wearable has helped me to maintain good health (PHO2) - After using smart fitness wearable, I feel healthier (PHO3)	Gupta et al. (2021)
Device specific attributes	Perceived Privacy (PP)	Context	Quantitative	- I think that privacy breaches are a serious issue today - I think Mi Band threatens my privacy - I worry that Mi Band might leak my personal information	Chuang & Chen (2022)

Technology Acceptance Model (Extended)	Perceived Privacy Risk (WPR)	Context	Quantitative	- WPR1: I am comfortable in letting management know about my physiological conditions. - WPR2: I am comfortable in letting co-workers know about my physiological conditions.	Choi et al. (2017)
Information Systems (IS) Continuance Model, IS Sucess Model	Perceived Proximity (PROX) part of the Variable System Quality	User	Quantitative	- Prox1: I feel close to my smartwatch. - Prox2: Even when I am not attending to my smartwatch, I still feel close to my smartwatch. - Prox3: When I think of my smartwatch, it seems close. - Prox4: Even when I am not actively using my smartwatch, I feel close to my smartwatch. - Prox5: I feel connected to my smartwatch. - Prox6: With regard to my emails, messages, and alerts, I often think about my smartwatch. - Prox7: I have a warm feeling about my smartwatch. - Prox8: Psychologically, my smartwatch feels close.	Ogbanufe & Gerhart (2018)
Protection Motivation Theory (PMT)	Perceived Severity (PS)	Context	Quantitative	- PS1: I believe that learning material stored on a smartwatch is vulnerable to security incidents. - PS2: I believe that the productivity of smartwatch is threatened by security incidents. - PS3: I believe that the profitability of smartwatch is threatened by data protection incidents. - PS4: I believe that smartwatch can allow remote access to learning materials. - PS5: I believe that smartwatch can be used to download learning materials.	Al-Emran et al. (2023)
Expectation-Confirmation Model - Extended (ECM-E)	Perceived Usability (USAB)	Device	Quantitative	- USAB3: The contents of the smartwatch are organized in such a way that makes it easy for me to know where I am when navigating it. - USAB4: The amount of information displayed in the smartwatch is appropriate. - USAB5: Searching and checking the information that I need from the smartwatch is quick. - USAB6: It is easy to find the information I need from the smartwatch. - USAB7: It is easy to find the functions I need from the smartwatch. - USAB8: The smartwatch provides accurate information and functions that I need. (Note: USAB1 and USAB2 were eliminated due to low loading)	Nascimento et al. (2018)
Extended Expectation-Confirmation Model (ECM)	Perceived Usability (USAB)	Device	Quantitative	- The contents of fitness wearables are organized in such a way that makes it easy for me to know where I am when navigating it. - I think the amount of information displayed in of fitness wearables is appropriate. - Fitness wearables provide accurate information and functions that I need.	Sun and Gu (2024)
Technology Acceptance Model (Extended)	Perceived Usefulness	Device	Quantitative	- Smartwatches could make my life more effective - Smartwatches could help me organize my life better - Smartwatches could increase my productivity	Chuah et al. (2016)

no specific model	Perceived Usefulness	Device	Qualitative	Definition of construct: How well consumers believe smartwatches can be integrated into their daily routines as an accessory and boost their personal efficiency (e.g., being more productive and organized)	Deghani (2018)
Expectation (ECT), Social Comparison Theory, Expectation Confirmation Model (ECM)	Perceived Usefulness (PU)	Device	Quantitative	- Smart fitness wearable improves my performance in managing my physical activity - Smart fitness wearable increases my productivity (such as more physical activity) - Smart fitness wearable enhances my effectiveness in physical activity - Overall, Smart fitness wearable is useful in managing goals related to physical activity	Gupta et al. (2021)
Expectation-Confirmation Model - Extended (ECM-E)	Perceived Usefulness (PU)	Device	Quantitative	- PU1: I find the smartwatch useful in my daily life. - PU2: Using the smartwatch helps me accomplish things more quickly. - PU3: Using the smartwatch increases my productivity. - PU4: Using the smartwatch helps me to perform many things more conveniently.	Nascimento et al. (2018)
Extended Expectation-Confirmation Model (ECM)	Perceived Usefulness (PU)	Device	Quantitative	- Using fitness wearables improves my performance in managing my physical activity. - Overall, fitness wearables are useful in managing goals related to physical activity. - Using fitness wearables helps me to perform physical activities more conveniently.	Sun and Gu (2024)
Technology Acceptance Model (Extended)	Perceived Usefulness (WPU)	Device	Quantitative	- WPU1: I find the wristband useful in my job. - WPU2: Using this wristband would improve the quality of my daily life.	Choi et al. (2017)
Protection Motivation Theory (PMT)	Perceived Vulnerability (PV)	Context	Quantitative	- PV1: Smartwatch could be vulnerable to security incidents. - PV2: Smartwatch could be susceptible to security incidents. - PV3: A security problem to my personal data could occur if I don't comply with the institution's smartwatch security policy.	Al-Emran et al. (2023)
Technology Acceptance Model (Extended)	Perceived Vulnerability (WPV)	Context	Quantitative	- WPV1: I am at risk of suffering health problems on the work site. - WPV2: It is likely that I will suffer health problems during my work.	Choi et al. (2017)
no specific model	Personal Motivation (motivational factor)	User	Qualitative	Described as: existing medical conditions, existing motivation for exercise	Shin et al. (2019)
Technology Acceptance Model - Extended (TAM-E)	Personalization (PL)	Device	Quantitative	- IoT-based healthcare wearable devices know what I need. - oT-based healthcare wearable devices know what I like. - IoT-based healthcare wearable devices provide content that suit my interests.	Kang & Hwang (2022)
no specific model	Price	Context	Quantitative	n/a	Jung et al. (2016)
Extended unified theory of acceptance and use of technology (UTAUT2), Diffusion of innovation (DOI)	Price Value (PV)	Context	Quantitative	- fitness wearable technology is reasonably priced - fitness wearable technology is good value for money - at the current price, fitness wearable technology provides good value	Talukder et. al. (2019)

no specific model	Product Features	Device	Qualitative	Economic burden, Attractiveness, Comfort, Innovativeness, Perceived compatibility/facilitating conditions, Perceived ease of use, Perceived ease of use/complexity, Feedback/quality of information, Monitoring (ns), Perceived content quality, Perceived risk/perceived credibility, Perceived service quality, Perceived usefulness, Readability, Result demonstrability, Service quality, System quality	Mwangi et al. (2024)
no specific model	Recommendation (REC)	Excluded	Quantitative	- REC1: I will introduce this smart health device to my friends. - REC2: I will commend this smart health device to my friends. - REC3: I will tell others about the benefits of this smart health device.	Liao et al. (2021)
Technology Acceptance Model (Extended)	Relative Advantage (RA)	Device	Quantitative	- using this smart watch improves the quality of my work. - the advantages of using this smart watch outweigh the disadvantages. - this smart watch has greater advantages and offers more functions than its precursors.	Kim & Shin (2015)
Environmental Psychology Theory, Two-Factor Theory of Motivation	Relevance of Information	Device	Quantitative	- Each function of the fitness app and wearable device clearly indicates what one can expect to find or do. - Visual information about physical activity is easily accessed. - All relevant information is easily available. - There is a great deal of relevant information. - Technical details about the fitness app and wearable device can be easily accessed.	Kim (2021)
Protection Motivation Theory (PMT)	Response Cost (RC)	Device	Quantitative	- RC1: Smartwatch is expensive to purchase and operate. - RC2: We have to frequently upgrade our smartwatches to download learning materials. - RC3: Security incidents can slow down the smartwatch performance. - RC4: Compliance with smartwatch security policy would require a considerable investment of effort other than time.	Al-Emran et al. (2023)
Protection Motivation Theory (PMT)	Response Efficacy (RE)	Context	Quantitative	- RE1: Smartwatch can successfully prevent security incidents. - RE2: Smartwatch is the best solution for counteracting security problems. - RE3: If we use the smartwatch in our study, we can minimize the threat of security incidents. - RE4: Compliance with smartwatch security policy reduces the security threat to my personal data.	Al-Emran et al. (2023)
Environmental Psychology Theory, Two-Factor Theory of Motivation	Security	Context	Quantitative	- The fitness app and wearable device have efficient security procedures. - The security systems of this fitness app and wearable device seem rigorous. - I have no security concerns about exercising with this fitness app and wearable device. - Overall, this fitness app and wearable device seem security conscious	Kim (2021)

Protection Motivation Theory (PMT)	Self-efficacy (SE)	User	Quantitative	- SE1: It would be easy for me to use the smartwatch by myself. - SE2: I could adopt the smartwatch even if there is no one around to tell me what to do as I go. - SE3: I could adopt the smartwatch if I could contact someone when I got stuck.	Al-Emran et al. (2023)
Expectation-Confirmation Model (ECM), Self-Determination Theory (SDT)	Self-Quantification Behavior (SQB) part of the variable "Health and Fitness Factors"	User	Quantitative	- I regularly collect data on my behavior using self-tracking devices. - It is important for me to collect data on my behavior. - I monitor my collected data regularly. - I analyze my data regularly. - I make connections between my behavior and the data that I get from self-tracking devices.	Siepmann and Kowalczuk (2021)
Technology Acceptance Model - Extended (TAM-E)	Service Convenience (SC)	Device	Quantitative	- It is convenient to use IoT-based wearable healthcare devices. - The menu design of IoT-based healthcare wearable devices is simple. - I can use IoT-based healthcare wearable devices immediately when I want to.	Kang & Hwang (2022)
no specific model	Situational Aspects (inhibiting factor)	Context	Qualitative	Described as: lack of time, life constraints, …	Shin et al. (2019)
no specific model	Sleep Hygiene	Excluded	Qualitative	n/a	Chong et al. (2020)
Expectation (ECT), Social Comparison Theory, Expectation Confirmation Model (ECM)	Social Comparison Tendency (SCT)	User	Quantitative	- I often compare myself with others how they are doing (SCT1) - I always pay a lot of attention to how I do things compared with how others do things (SCT2) - I always want to find how well I have done as compared to others (SCT3) - I often compare how I am doing physically (e.g. fitness, weight, running) as compared to other people (SCT4) - I often compare my accomplishments with others achievements (like walk/running in Kilometres) (SCT5)	Gupta et al. (2021)
Environmental Psychology Theory, Two-Factor Theory of Motivation	Social Factors	Context	Quantitative	- There is a sense of human touch whenever I interact with the fitness app and wearable device. - There is a possibility of networking with other users through the fitness app and wearable device. - There is a sense of friendliness whenever I interact with the fitness app and wearable device. - There is a feeling of belongingness whenever I interact with the fitness app and wearable device. - There is a sense of human warmth in the fitness app and wearable device. - There is a sense of human sensitivity in the fitness app and wearable device.	Kim (2021)
Theory of planned behavior (TPB)	Social Influence (SI)	Context	Quantitative	- People who influence my behavior have mentioned that I should use Mi Band - People who are important to me have mentioned that I should use Mi Band - In general, my family has supported the use of Mi Band.	Chuang & Chen (2022)

Extended unified theory of acceptance and use of technology (UTAUT2), Diffusion of innovation (DOI)	Social Influence (SI)	Context	Quantitative	- people who are important to me would think that I should use fitness wearable technology - people who influence me would think that I should use fitness wearable technology - people whose opinions are valuable to me would prefer that I use fitness wearable technology	Talukder et. al. (2019)
Technology Acceptance Model (Extended)	Social Influence (WSI)	Context	Quantitative	- WSI1: My co-workers would think using this wristband is a good idea. - WSI2: People who are important to me would think that I should use this wristband.	Choi et al. (2017)
no specific model	Social Motivation (motivational factor)	Context	Qualitative	Described as: relatedness, social competition	Shin et al. (2019)
no specific model	Social Pressure	Context	Qualitative	Quantified self, Social influence, Subjective norms	Mwangi et al. (2024)
no specific model	Standalone Communication	Device	Quantitative	- Standalone Communication - Slaved to Smartphone	Jung et al. (2016)
Technology Acceptance Model (Extended)	Subcultural Appeal (SA)	Context	Quantitative	- this smart watch makes people who use it different from other people. - If I use this smart watch, it would make me stand apart from others. - this smart watch helps people who use it stand apart from the crowd. - people who use this smart watch are unique. - people who use this smart watch would be considered leaders rather than followers.	Kim & Shin (2015)
Theory of Planned Behavior (TPB)	Subjective Norm (SN)	Context	Quantitative	- SN1: Colleagues who influence my behavior think that I should use smartwatch in learning. - SN2: Colleagues who are important to me, think that I should use smartwatch in learning. - SN3: My instructors think that I should use smartwatch in learning. - SN4: The university management thinks that I should use smartwatch in learning. - SN5: In general, university management has supported the use of smartwatch in learning.	Al-Emran et al. (2023)
Fit-Viability Model (FVM) and Empowerment Theory	Task-technology fit (TTF)	Device	Quantitative	- The WHTs are fit for the requirements of my health management. - Using the WHTs fits with my exercise routine. - The WHTs fit with my healthy lifestyle. - The WHTs are suitable for helping me monitor my health.	Zhang et. al. (2025)
no specific model	Technical Aspects (inhibiting factor)	Device	Qualitative	Described as: loss of interest in technological features	Shin et al. (2019)

TAM, UTAUT, DOI	Technology features and utility	Device	Qualitative	- Goal orientation (specific goals like weight loss, marathon training; general fitness goals; nutrition-related goals; or general interest in technology) - Functional features (e.g., steps counter, heart rate monitor, GPS) - Easy access to data (for adoption) - Look and feel (design, size, unobtrusive) - Willingness to pay (for devices vs. apps) - Data accuracy and usefulness (for sustained use) - Device portability and resilience (e.g., battery life, works in all environments) (for sustained use) - Ability to transfer and aggregate data (for sustained use) - Time-saving (for sustained use) - Pleasurable workouts / Fun to use (e.g., enjoyable user experience, new features, games, badges, virtual competitions, gamification) (for sustained use)	Canhoto & Arp (2017)
Extended Expectation-Confirmation Model (ECM)	Technology Innovativeness (TI)	Device	Quantitative	- In general, I am not hesitant to try out new information technologies. - I have a lot of new technology products than others. - I keep up with the latest technological developments in my area of interest.	Sun and Gu (2024)
Environmental Psychology Theory, Two-Factor Theory of Motivation	Usability	Device	Quantitative	- The functions on the wearable device and fitness app are easy to operate. - The wearable device and fitness app are user-friendly. - In general, the easy wearable device and fitness app are easy to use for physical activity. - The fitness app links and wearable device are obvious in their intention and destination. - The fitness app and wearable device have convenient ways to maneuver among related functions. - Navigation through the wearable device and fitness app is intuitively logical. - There are useful navigation aids on the fitness app and wearable device	Kim (2021)
TAM, UTAUT, DOI	User Characteristics	User	Qualitative	- Technology affinity (self-reported level of interest in new technology) - Gender (self-described early/late adopter) - Attitudes towards health and fitness / Type of goal (intrinsic vs. extrinsic goals) - Habit (for sustained use)	Canhoto & Arp (2017)
no specific model	User Characteristics	User	Qualitative	Big 5 personality traits, Cognitive age, Cognitive barriers, Consumer innovativeness, Need for uniqueness, Resistance to change, Value incongruence, Vanity	Mwangi et al. (2024)
no specific model	User Concerns	User	Qualitative	Health concerns, Intrusiveness, Perceived information sensitivity, Privacy concerns, Technology anxiety, Trust	Mwangi et al. (2024)
no specific model	User Motivation	User	Qualitative	Autonomous motivation, Enjoyment motives, Motivational barriers, Self-actualization, Self-regulatory motives, Social motives	Mwangi et al. (2024)

Technology Acceptance Model (Extended)	Visibility of Smartwatches	Context	Quantitative	- Generally speaking, other people would notice it if I wear a smartwatch - Smartwatches are a technology that is very visible to other people - Smartwatches are technology that is recognized by people who see me	Chuah et al. (2016)
Environmental Psychology Theory, Two-Factor Theory of Motivation	Visual Appeal	Device	Quantitative	- The fitness app and wearable device are aesthetically appealing. - I like the way the fitness app and wearable device look. - The fitness app and wearable device are visually attractive. - The way the fitness app and wearable device display its functions is attractive.	Kim (2021)

Appendix D: Item Level Regression Analysis Results

Rank	Item	Construct	Coefficient	R2 (Explained Var.)	p-value
1	CON2	Confirmation	0.542	0.449	< .001
2	CON1	Confirmation	0.48	0.349	< .001
3	PU1	Perceived Usefulness	0.375	0.291	< .001
4	PE3	Personalization	0.344	0.225	< .001
5	PE2	Personalization	0.284	0.148	< .001
6	PS3	Perceived Security	0.208	0.126	< .001
7	PE1	Personalization	0.274	0.12	< .001
8	PA4	Perceived Aesthetics	0.224	0.096	< .001
9	PS1	Perceived Security	0.237	0.094	< .001
10	PU4	Perceived Usefulness	0.203	0.09	< .001
11	PE4	Personalization	0.185	0.085	< .001
12	PU2	Perceived Usefulness	0.168	0.083	< .001
13	PA2	Perceived Aesthetics	0.188	0.08	< .001
14	PA3	Perceived Aesthetics	0.183	0.078	< .001
15	PA1	Perceived Aesthetics	0.144	0.048	0.001
16	PS4	Perceived Security	0.149	0.045	0.002
17	PU3	Perceived Usefulness	0.105	0.032	0.009
18	SI1	Social Interaction	0.064	0.014	.090 (n.s.)
19	PS2	Perceived Security	0.078	0.012	.115 (n.s.)
20	CMI4	Community Immersion	-0.044	0.007	.239 (n.s.)
21	SI3	Social Interaction	0.041	0.005	.284 (n.s.)
22	CMI1	Community Immersion	0.017	0.001	.653 (n.s.)
23	CMI2	Community Immersion	0.017	0.001	.649 (n.s.)
24	CMI3	Community Immersion	0.003	0	.939 (n.s.)
25	SI2	Social Interaction	-0.009	0	.819 (n.s.)

Note: Each row represents a separate bivariate linear regression where Satisfaction (SAT) is the dependent variable. Items are ranked by R2. n.s. = not significant at the .05 level.

Appendix E: Use of AI and Generative AI

This thesis used generative AI tools **exclusively to support literature review efficiency and documentation structuring**. All conceptual reasoning, theoretical integration, methodological decisions, data analysis, and interpretation of results were conducted by the authors.

AI tools were *not* used to generate hypotheses, conduct statistical analysis, write findings, discussion, or conclusions.

1. Tools Used

- **NotebookLM** (Google)
  → Used exclusively to summarize academic papers and extract structured variable information for the literature review worksheets.
- **ChatGPT** **(OpenAI)**
  → Used only for administrative and editorial support (e.g., wording suggestions, formatting checks, and clarifications of statistical terminology).
  → No text was copied verbatim into the final thesis without review and rewriting.

2. Purpose of AI Use

AI was employed to:

1. Summarize long academic articles more efficiently.
2. Extract comparable information from diverse sources into structured literature tables.
3. Clarify statistical terminology during model inspection (e.g., what coefficients, SE, or t-values represent).
4. Improve wording of already written paragraphs (but never to generate conceptual arguments or empirical reasoning).

3. Specific Prompts Used

Below is the complete list of prompts used during the thesis writing process. They are reported in full for transparency and replicability.

3.1 Literature Review Summaries

Prompt 1 (NotebookLM):

"Please summarize this paper. Structure your response according to the headings and subheadings in the original source."

Prompt 2 (NotebookLM):

"Summarize information from the source in the following categories in bullet points: Authors, Year, Journal, Research Aim, Data, Methodology, Independent variables, Moderator, Mediator, Dependent variable, Findings."

3.2 Extraction of Dependent Variables

Prompt (NotebookLM – Sheet "Dependent Variable"):

"What is the dependent variable? What is the theoretical model used? What are the items used to assess the dependent variable?"

3.3 Extraction of Independent Variables

Prompt (NotebookLM – Sheet "Independent Variables"):

"Fill out the following brief about the source: Theoretical Model used in the source, Independent Variables per theoretical model tested, name all items per independent variable, dependent variable, whether the independent variable had a significant effect on the dependent variable (focus on findings, not initial hypothesis), if applicable: beta-factor."

3.4 Editorial / clarification prompts (ChatGPT)

Used only for explanation—not for content generation.

Examples include:

- "Explain in simple terms what the coefficient, standard error, and t-value indicate."
- "Improve the formulation of this paragraph while keeping the meaning unchanged."
- "How should I report this statistical output in academic style?"

No conceptual reasoning, hypothesis development, or interpretation of results was delegated to AI.

4. Human Oversight

All AI-assisted outputs were:

- Reviewed manually,
- Cross-checked against the original academic sources, and
- Only used as input for our *own* writing.

The authors take full responsibility for all analyses, interpretations, and conclusions presented in the thesis.