

Investigating Consumers' Continued Use of Technology: A Longitudinal Study

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Abstract

Research on technology adoption has grown significantly, yet post-adoption behaviours, such as the continued use of information technology (IT), remain underexplored. This thesis adopts a longitudinal approach to investigate the dynamics of consumer intentions and technology use over time, focusing on wearable fitness technology (WFT). WFT plays a pivotal role in daily life, offering features that support health and encourage physical activity. Despite these advantages, studies highlight a high abandonment rate of WFTs after a few months (Talukder *et al.*, 2019), limiting long-term health benefits (Canhoto and Arp, 2017). In addition, personality traits (PTs) are shown to have a significant influence on attitudes and intentions towards continued technology use (Rupp *et al.*, 2018; Attig and Franke, 2019), yet their role in sustained engagement remains underexamined. Drawing on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), PT theory, and technology adoption literature, this study develops a conceptual framework to address key gaps. It explores (1) how continued use behaviour (CUB) evolves over time and the predictors shaping continued use intention (CUI); (2) the drivers of continued WFT use by examining how CUI influences CUB; and (3) the role of PTs in moderating the CUI–CUB relationship. This study employs a quantitative, longitudinal survey methodology, incorporating measures from UTAUT2, PT models, and a new construct, Technology Upgradability, to investigate factors influencing CUB. Structural equation modelling was conducted using IBM SPSS, AMOS, and SmartPLS. Findings from two datasets reveal the increasing impact of CUI on CUB, confirming the dynamic nature of predictors. Some predictors remain consistently significant; others gain importance or remain insignificant over time. PTs also exhibit temporal influences, with certain traits strengthening or weakening the CUI–CUB relationship across datasets. This research study contributes to a deeper understanding of the factors that impact IT use continuity. The results, which derive implications for both practitioners and researchers, provide valuable guidance for developing consumer-centred technologies that promote continued use.

Keywords: Technology adoption, Post-adoption, Continued use intention, Continued use behaviour, Upgradability, Personality traits, Longitudinal study, Wearable fitness devices

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List of Abbreviations

5G	Fifth generation
Apps	Applications
AI	Artificial intelligence
AR	Augmented reality
AVE	Average variance extracted
BI	Behavioural intention
BMI	Body mass index
CFA	Confirmatory factor analysis
CFI	Comparative fit index
CinH	Conscientiousness in health
CMB	Common method bias
CR	Composite/construct reliability
CUB	Continued use behaviour
CUI	Continued use intention
DAnoy	Device annoyance
df	Degrees of freedom
DOI	Diffusion of Innovations (theory)
DTPB	Decomposed Theory of Planned Behaviour
DV	Dependent variable
ECM	Expectation-confirmation model
e.g.	For example
EFA	Exploratory factor analysis
EffExp	Effort expectancy
FCons	Facilitating conditions
FFM	Five-Factor Model (of personality)

GOF	Goodness of fit
HC	Health consciousness
ICT	Information and communications technology
i.e.	that is
IoT	Internet of Things
IS	Information system
IT	Information technology
IV	Independent variable
KMO	Kaiser–Meyer–Olkin (measure)
KS	Kolmogorov–Smirnov (test)
mHealth	Mobile health
MM	Motivational model
MPCU	Model of Personal Computer Utilisation
Neu	Neuroticism
OTTI	Openness to technological innovativeness
PA	Physical activity
PBC	Perceived behavioural control
PEnj	Perceived enjoyment
PEOU	Perceived ease of use
PerExp	Performance expectancy
PT	Personality trait
PU	Perceived usefulness
PValu	Price value
RMSEA	Root mean square error of approximation
SCT	Social Cognitive Theory

SD	Standard deviation
SDT	Self-Determination Theory
SEM	Structural equation modelling
SotPrss	Societal pressure
SPSS	Statistical Package for the Social Sciences
SW	Smartwatches
TAM	Technology Acceptance Model
TechH	Technology habit
TLI	Tucker–Lewis index
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
TUpG	Technology upgradability
UK	United Kingdom
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance inflation factor
WFT	Wearable fitness technology
WHT	Wearable health technology

Chapter 1: Introduction

The digital era has ushered in a transformative landscape, in which individuals regularly interact with a wide array of advanced technological innovations. This technological design has transformed the way we live, work, and communicate in fields such as business, entertainment, retail, and social networking, presenting both opportunities and challenges. These state-of-the-art technologies include "connectivity technologies", such as the Internet of Things (IoT). The proliferation of these technologies has significantly shaped the digital landscape, particularly through smart home appliances, smart wearables, and industrial applications (Mamonov and Benbunan-Fich, 2021), which have become integrated into our daily routines, providing real-time data and automated control (Kalantari, 2017).

Another notable aspect of the digital era is the rise of cloud computing, artificial intelligence (AI) and machine learning, which are examples of "analytical computing technologies". These technologies have permeated various sectors, from healthcare to finance, enabling more efficient and personalised services. A study by McKinsey (2024) found that the global AI market is projected to grow at a compound annual rate of 33% between 2022 and 2030, highlighting the increasing prominence of these technologies in our lives. One more illustration is "search technologies" (which are like voice recognition-based searches), personal computing devices, such as smart glass, smart connected objects, and smartphones, as the ubiquity of mobile devices is considered one of the defining attributes of the digital era. According to a recent study, the global smartphone user base is expected to reach 7.69 billion by 2027 (Taylor, 2023). These pocket-sized devices have become the primary means of accessing information, communication, and entertainment. Individuals now rely on their smartphones for a multitude of tasks, from mobile banking and e-commerce to social media and navigation (Terry and Gunter, 2018).

The pervasive integration of technology into daily life has led to a shift in how we interact with the world around us, showcasing the importance of understanding how consumers respond to smart services/products (Verhoef *et al.*, 2017). By staying informed and adapting to these changes, individuals can harness the power of digital innovations to enhance their personal and professional lives, which, needless to say, can only be achieved through long-term use (continuance use).

Technology continued use behaviour (CUB) is a significant area of study due to its implications for both technology developers and consumers. Continuance use, as opposed to initial adoption, involves the sustained engagement with and utilisation of a technological product over time (Venkatesh, Thong and Xu, 2016). Thus, understanding CUB is crucial for ensuring the long-term success and improvement of technological innovations, particularly in highly competitive markets, meaning it is not just an academic pursuit. Understanding CUB also has significant practical implications, highlighting that technology adoption alone does not guarantee sustained use. High initial adoption rates can be deceptive, masking the reality of users abandoning technologies after a brief period (Canhoto and Arp, 2017). In addition, continued use forms the foundation for realising the full potential of a technology's benefits, whether it has increased productivity, enhanced communication, or improved access to information (Park, Chung and Jayaraman, 2014). However, most studies have primarily focused on the **initial adoption** phase, neglecting the equally important post-adoption period, during which users' experiences and perceptions can evolve significantly (Bhattacharjee, Perols and Sanford, 2008; Kim and Han, 2021).

Technology adoption refers to the initial decision-making process by which individuals begin to use a new technology. This process is influenced by various factors, including perceived usefulness, perceived ease of use, social influence, and facilitating conditions. The Unified

Theory of Acceptance and Use of Technology (UTAUT) model, a significant contribution by (Venkatesh *et al.*, 2003), has been widely used to explain technology adoption. This model, with its key determinants of performance expectancy, effort expectancy, social influence, and facilitating conditions, provides a comprehensive understanding of technology adoption. Recent studies have further enriched this model by incorporating additional factors, such as hedonic motivation, price value, and habit, which are particularly relevant in consumer contexts (Venkatesh, Thong and Xu, 2012).

Although initial adoption is important, the continued use of technology is equally, if not more, critical for the sustained success of technological innovations. Continued use behaviour refers to the ongoing engagement with and utilisation of technology after the initial adoption phase. Therefore, understanding it is vital for developers and marketers because it has a direct impact on user retention and long-term engagement, highlighting the need to study the various factors that influence CUB. Although performance expectancy, effort expectancy, and facilitating conditions remain important, additional factors, such as social influence (societal pressure) and perceived price value, play significant roles (Cho, Cheng and Hung, 2009). Perceived enjoyment and perceived device annoyance (typically treated as a single dimension in the hedonic motivation construct) capture both the benefits and challenges users experience, reinforcing continued use by enhancing users' perceptions of the benefits of technology (Oyibo and Vassileva, 2020). Habit, formed through repeated use, can make continued use automatic and less dependent on conscious decision-making (Limayem *et al.*, 2007). Further, recent research has also highlighted the role of improved technology functionality, as in one study on the circular economy in adding or replacing components (Vimal *et al.*, 2021). However, the current research study introduces a more defined conceptualisation by isolating [technology upgradability](#),

something that does not yet have a strong precedent in the information system (IS) literature, especially in terms of measuring long-term user engagement with consumer technologies.

Moreover, psychological tendencies, particularly **personality traits**, shape individual behaviour in technology use significantly. Personality characteristics are known to influence not only the initial intention to use technology but also the tendency to continue using it over time (Rupp *et al.*, 2018). This underscores the importance of considering personality as a key factor when examining sustained engagement with technology, as specific traits can either facilitate or hinder adoption and/or continued use behaviour.

Recent studies have shown that traits such as conscientiousness, openness to technology, and emotional stability have a significant impact on users' acceptance of technology (Devaraj, Easley and Crant, 2008; Svendsen *et al.*, 2013). Likewise, conscientious users are more likely to engage with technologies that support their goals and values. Conscientiousness has been shown to have a significant impact on outcomes such as creativity in goal-directed tasks, suggesting it could similarly enhance the focused, ongoing use of technology. On the other hand, individuals high in openness are typically more receptive to novel features and frequent updates, which aligns with a tendency to explore and adopt new technological advancements (Ismail *et al.*, 2023). These personality-driven distinctions are crucial in understanding continuance behaviours, as they reveal how personal characteristics can moderate continued engagement with wearable fitness technology (WFT) (there is more elaboration on this in the next section).

Adopting a longitudinal perspective is essential for understanding the evolution of user perceptions and behaviours over time. Longitudinal studies, which trace the same individuals over an extended period, offer insights into the dynamic processes of technology use, unlike cross-sectional or experimental studies that capture data at a single point in time (Peters, Calvo

and Ryan, 2018). In particular, in this study context of WFT, longitudinal research can demonstrate how factors (e.g., performance expectancy, effort expectancy, and perceived price value) change as users become more accustomed to the technology. Longitudinal research can also reveal how personal traits (e.g., neuroticism) can increase or decrease as users gain trust and experience with devices over time.

Thus, understanding the complex phenomenon of **consumer continuance use** of technology is crucial for scholars and practitioners. It helps identify the factors that drive long-term adoption and develop strategies to influence these factors and reduce the rate of technology abandonment. In the following sections, this chapter introduces the research problem, summarises the identified research gaps (with a comprehensive discussion available in Chapter 2), and outlines the study objectives. It then delves into the innovation context of the study, specifically examining “wearable fitness technology” as an innovative device, and the study's significance within this context. The chapter also discusses the study's importance by highlighting its potential theoretical contributions and managerial implications. Finally, an overview of the thesis structure is provided to summarise the subsequent chapters.

1.1 Research Problem

a) Factors influencing technology adoption and continued use (longitudinal perspective)

Technology adoption and continued use from a consumer behaviour perspective is a critical area of research that has gained significant attention in recent years. The rapid advancement and proliferation of various technologies have transformed how individuals interact with and rely on technology in their daily lives. In information technology (IT) research, scholars have extensively studied “technology adoption” in the context of different services/products in order to investigate their adoption and users purchase intentions (Chiu, Oh and Cho, 2021; Zhao *et al.*, 2021; Mehra, Rajput and Paul, 2022), related behaviours/attitudes (Talukder *et al.*, 2019; Chen *et al.*, 2021;

Qasem, 2021; Suo *et al.*, 2021), and the factors influencing such behaviours/attitudes. However, minimal effort has been dedicated to studying continuance use factors. **Understanding** the factors (if they vary) that influence both the initial adoption, and the continued use of technology is essential for developers, marketers, and policymakers aiming to enhance the user experience and ensure the longevity of technological innovations.

Moreover, the majority of the existing research on the **continued use of technology** has relied on cross-sectional studies that offer valuable snapshots of consumer behaviour at a single point in time. These studies are inherently limited in their ability to assist in comprehending the dynamic nature of CUB. For example, such studies cannot account for how consumer perceptions, such as performance expectancy and effort expectancy, and subsequent use behaviour might change as users gain experience with the technology (Park, Chung and Jayaraman, 2014). Cross-sectional designs also struggle to disentangle the causal relationships between adoption factors (e.g., effort expectancy) and use behaviour (e.g., frequency of use).

Given the preceding references and trends, a study is essential to understand consumer continued use of technology within the realm of smart wearable devices. This study uses a longitudinal design to differentiate between technology adoption and post-adoption factors influencing CUB. It also examines how consumer perceptions and technology use behaviours evolve over time, providing insight into continued engagement with wearable technology.

b) Personality traits model in the IT/WFT context

The Five-Factor Model (FFM) of personality, also called the Big 5 (Goldberg, 1990; Costa and McCrae, 1992), is one of the personality conceptualisations that have been progressively explored and validated in the scientific literature. The FFM is considered the most common theory in sociological and behavioural sciences describing personality. The model has been

extensively applied to identify the most important dimensions of personality. It is also regarded as a state-of-the-art personality measurement model, as it explains and measures human personality due to mainly biologically determined "basic tendencies" and can be described by its five superordinate constructs (Buettner, 2017):

- Openness to experience, which is associated with scientific and artistic creativity and divergent thinking, represents flexibility of thought and tolerance of new ideas;
- Conscientiousness, or conscience, manifests as motivation and persistence in goal-oriented behaviour;
- Extraversion is expressed by being sociable, outgoing, active, and ambitious;
- Agreeableness, also known as likability, is associated with courtesy, forgiveness, trust, flexibility, good-naturedness, cooperation, soft-heartedness, and tolerance; and
- Neuroticism is characterised by anxiousness, depression, insecurity, and hostility (Barrick and Mount, 1991).

Although extensive research from the fields of psychology and marketing demonstrates the significant impact of personality on individual behaviours (Malouff, Thorsteinsson and Schutte, 2006; Buettner, 2017; Ali, Bowen and Deininger, 2020), IT/IS research historically overlooked this factor (Wang, Ngai and Wei, 2012). However, recent studies on IT/IS have increasingly examined personality traits as predictors of technology usage patterns, as shown in work by McElroy *et al.* (2007), Devaraj, Easley and Michael Grant (2008), and Venkatesh and Windeler (2012), as well as more recent contributions (Buettner, 2017; Selden and Goodie, 2018; Mansourimoayyed *et al.*, 2020; Salem and Alanadoly, 2021). Notably, Devaraj, Easley, and Michael Crant (2008) illustrated the value of integrating personality within IT/IS research specifically related to technology adoption and use. Expanding this work, Wang, Ngai and Wei

(2012) explored the influence of personality within the IS continuation context, further demonstrating its relevance for understanding sustained technology engagement.

From the above, the existing IT literature has demonstrated that psychological tendencies critically affect several individual variables (Yan *et al.*, 2021). Among these, personality traits are a significant group of variables that can influence the use of IT. For instance, Rupp *et al.* (2018) argue that specific personality characteristics (such as agreeableness, conscientiousness, and extraversion) can shape individuals' intention to use fitness trackers by affecting the perceived usability and the motivational affordances these devices provide (i.e., autonomy, competence, and connectedness). They suggest that conscientious individuals are more likely to engage with fitness trackers due to their perception of the high motivational affordances of such devices. Conversely, Attig and Franke (2019) found no substantial direct effects of personality traits (including conscientiousness, extraversion, agreeableness, and neuroticism) on users' motivation to utilise fitness trackers. These conflicting findings indicate that personality characteristics may exert an indirect influence on the use of fitness-tracking devices.

In contrast to prior studies, which primarily focus on direct relationships, the current research aims to address these discrepancies by evaluating the longitudinal effects of personality traits on users' continued use intention and behaviour over time. By adopting a longitudinal approach, this study seeks to provide a more nuanced understanding of how personality traits interact with use behaviours, thereby contributing to the theoretical framework of IT continuance use. The findings are also expected to yield practical implications for practitioners and companies by offering deeper insights into the factors that drive continuance intention. This knowledge will assist organisations in identifying and targeting individuals who are more likely to maintain their use of such technology, ultimately enhancing user engagement and satisfaction with health and fitness wearables.

c) Selection of technological devices as the study context

Wearable devices can transform individuals' lifestyles and enhance their well-being, behaviours, and decisions. Research has indicated that wearable devices were expected to become mainstream after the phenomenon of the mass-market adoption of smartphone usage and to have the potential to transform the world as we know it, just as mobile devices have in the last couple of decades (Ometov *et al.*, 2021). The global trend towards greater physical health and well-being has converged with the development of WFT devices, allowing users to track, trace and monitor gains in their fitness effortlessly (Lunney, Cunningham and Eastin, 2016). Today's consumers are engaged in a compound and wide variety of networks in which wearables can play a critical role in users' day-to-day activities, shifting from having a short-term status into being an essential accessory (Ferreira *et al.*, 2021).

Wearable devices can be used in various fields, including healthcare, education, and fashion; thus, they have tremendous potential and present opportunities in enabling users to manage their personal health and stay active. They range from smartwatches (SWs), smart wristbands, electronic activity monitors, and chest bands, to jewellery and glasses, among others, to track an individual's fitness and general performance (Talukder *et al.*, 2019). In addition, these devices provide digital outputs fed into web- or mobile-based applications (apps) to address various functionalities, including physical activities, event notification, and sleep and heart monitoring (Pfeiffer *et al.*, 2016). Similarly, wearable devices can serve as effective tools for use with smartphone apps to observe individual health information, such as heart rate variations, body temperature, breathing rate and blood glucose, to name a few (Farrokhi *et al.*, 2021).

Over the last decade, consumers' interaction with technology and AI has grown remarkably. For instance, wearable technologies have turned from non-existent to arising globally, changing how

we interact with the surrounding environment (Ameen *et al.*, 2021). Wearable devices reside within the larger concept of the IoT. They are also considered one of the major areas of IoT applications, in smart home devices, smart cities, and industrial applications (Mamonov and Benbunan-Fich, 2021).

The IoT encompasses billions of interconnected devices (things) capable of sensing the physical world (such as wearables, smartphones, sensors, and industrial machines), transmitting observational data, and performing actions via the internet. In 2014, the IoT accounted for 13% of business operations, rising to 25% by 2019. With reference to a report published in November 2019 by Statista Research Development, the overall number of connected IoT devices was predicted to be 75.44 billion worldwide by 2025 (Fizza *et al.*, 2021). Likewise, these wearable technologies are now considered critical in certain consumer goods and services sectors, including healthcare (Ferreira *et al.*, 2021).

Wearable technology growth, especially fitness trackers, has been extended internationally. Initial indications recommended the great potential for this technology to develop further and create a multi-billion-dollar industry (Sultan, 2015). At the same time, the size of the global fitness tracker market was valued at USD 30.41 billion in 2019, which appeared to dominate the smart wearables industry in the future, with expectations of its reaching USD 91.98 billion by 2027 (Lange, 2018).

Despite the global shift towards adopting innovative wearable technologies (Ferreira *et al.*, 2021), challenges persist regarding their long-term adoption, primarily due to the nascent nature of this cutting-edge technology and ongoing ethical and privacy concerns (Ameen, Hosany and Tarhini, 2021). Key issues include discomfort during use (Kim and Chiu, 2019), shortcomings in physical design, inaccuracies in data, and connectivity problems arising from device

incompatibility with certain phone models or pairing malfunctions (Benbunan-Fich, 2020), among others. Developmental flaws in wearable technology often led consumers to discontinue use. Research indicates that most individuals stop using these devices within the first six months (Piwek *et al.*, 2016; Canhoto and Arp, 2017), with approximately 33% of American consumers ceasing use within six months and 50% within a year (Lee *et al.*, 2016). Issues such as inadequate data reliability and accuracy contribute significantly to abandonment, as highlighted by Coorevits and Coenen (2016) and Epstein *et al.* (2016). Poor usability poses another critical challenge, further increasing device abandonment rates. A report by Gartner (2016) reveals that 30% of users discontinued use due to a lack of novelty and perceived usefulness, underscoring the importance of addressing these shortcomings to enhance user retention.

Wearable fitness devices worn or tethered to the body gather physical movement data, forming a suitable method for monitoring health and individual fitness parameters, such as heart rate, step count, and calorie expenditure (Attig and Franke, 2020). Therefore, wearable fitness devices are increasingly entwined into our societies and everyday life. They have undergone substantial developments, especially after Greenfield's book was published in 2006, as part of a broader trend in research into ubiquitous computing (Greenfield, 2006). These improvements included hardware (such as the Apple Watch, Samsung's Galaxy Gear, Fitbit, Jawbone Up, or Nike+ FuelBand) and several mobile phone apps that track activities (Gilmore 2016). These wearable devices enhance users' health and well-being and improve people's experiences of connecting with their preferred features. For instance, smartwatches have multiple functions beyond telling the time (Chuah *et al.*, 2016); unlike a traditional watch, SWs can receive and send messages and monitor health and fitness through sensors and scanning features (Hong, Lin and Hsieh, 2017). Thus, consumers should opt for SWs that incorporate these features, ensuring continued use to support and achieve their health-related objectives.

Consequently, there is an increasing interest in understanding how individuals adopt and utilise their smart devices, particularly regarding the factors that influence continued usage. As Niknejad *et al.* (2020) highlighted in their comprehensive literature overview, the theme of consumer behaviour focuses on individuals' willingness to adopt and use smart wearable devices. This theme encompasses various aspects, including actual system use, user experiences, intentions to use, intentions to adopt, purchase intentions, extended use, technology adoption, and the factors affecting these behaviours. Among the 65 studies reviewed, user behaviour emerged as the second most commonly explored theme, accounting for 27% of the primary research. Notably, most of these studies (55%) specifically looked at users' continuance intentions related to the adoption (10 papers) and use (26 papers) of smart wearable technologies. Furthermore, the technology adoption subgroup constituted 15% of the total primary research, with 10 publications focusing on user behaviour.

Studies shown in Table 2-6 collectively reveal key factors influencing continuance intentions with regard to wearable technologies yet vary in their theoretical frameworks and emphasis, underscoring a gap that the current study aims to address. For instance, Dehghani, Kim and Dangelico (2018) and Hong, Lin and Hsieh (2017) use the Technology Acceptance Model (TAM) and Diffusion of Innovations (DOI) theory to examine factors such as perceived usefulness, ease of use, and consumer innovativeness, focusing primarily on initial adoption behaviours.

Similarly, Bölen (2020), A. Gupta *et al.* (2021) and Siepmann and Kowalczyk (2021) extend the expectation-confirmation model (ECM), adding emotional, health-related, and self-motivational drivers. However, these studies do not utilise the UTAUT2 framework, which is particularly relevant for understanding the role of social and facilitating conditions in the sustained use of consumer technologies, such as wearable fitness trackers and smartwatches. In addition, while these studies address important constructs such as health benefits and social motivations, their

reliance on cross-sectional data limits their ability to capture the dynamic and evolving nature of user engagement, despite repeated calls for longitudinal research (Park, 2020; Siepmann and Kowalczyk, 2021). The current research addresses these gaps by utilising UTAUT2 to explore continued use intention (CUI) and CUB through factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions. This longitudinal approach offers a more comprehensive view of continuance behaviour in relation to wearable technology by including constructs such as perceived enjoyment, device annoyance, and technology upgradability and by integrating personality traits as moderating factors.

In summary, although prior research has explored initial adoption intentions, significant gaps remain in understanding the longitudinal dynamics of wearable technology engagement. These gaps necessitate further research examining the evolving factors behind continued use, which will inform theoretical and practical applications. As wearable devices undergo continuous updates, new features influence consumer decisions, calling for sustained theoretical exploration to understand the broader implications of continued use, which is crucial for these technologies' long-term advancement and sustainability (Chiu, Cho and Chi, 2020).

1.2 Thesis Aim(s) and Question(s)

Building on the above-mentioned information, this research study aims to develop and verify a comprehensive framework through a quantitative data analysis approach. The framework is intended to explain and predict people's continued use of wearable fitness technologies by investigating the factors associated with users' continued use intention and continued use behaviour toward technology. Further, the study aims to examine, through longitudinal studies, the moderating role of users' psychological traits (both general personality and technology user-specific characteristics) in consumers' continued use of WFT.

The novel research framework proposed in this study extends the UTAUT2 model with additional contextual variables that play an important role in determining the continued use of WFT/SW. That is, the framework incorporates Technology Upgradability and splits "Hedonic motivation" into two concepts: Perceived Enjoyment and Perceived Device Annoyance. Lastly, the research findings provide unique perspectives on consumer continuance use intention and behaviour when interacting with WFT—aiming to add to the growing literature on these devices and extend current theoretical models.

1.3 Research Questions

The main questions the study aims to address are as follows:

1. What are the determinants that affect consumers' decision to continue using IT (wearable technology), and which are affected by technological/utilitarian, affective/hedonic, emotional, and social factors?
2. To what extent can personality traits (user-specific personal characteristics) predict consumers' continued use intention and continued use behaviour of WFT/SW?

To bridge the above-mentioned research gaps in the literature, this thesis intends to:

- Understand the mechanisms of consumer continuance use of technology in the context of WFT (i.e., smartwatches).
- Understand post-adoption factors influencing continued technology use and how user perceptions and behaviour evolve over time.
- Understand the role of continued use intention toward WFT as a key mechanism for converting perceived factors into continued use behaviour.
- Understand the interplay between consumer personality traits and the continued use of WFT by evaluating how personality characteristics enhance the impact of continued use intention on behaviour.

The next section offers an in-depth review of the research context of the study (i.e., wearable fitness devices: smartwatches).

1.4 Research Context

To meet the above-mentioned study objectives regarding smart wearables, it is crucial to understand how these devices apply to technology adoption and continuance use research. This section first **defines wearables devices** as “technological devices” and then examines the relevance of the present study in the context of WFT.

1.4.1 Defining Wearable Computing: A Historical Perspective

Although wearable technology devices have recently become an essential component of our daily lives, they are not a new phenomenon, as they have been around since the 13th century. English friar Roger Bacon (c.1289) started the wearables journey with the invention of spectacles (which can be carried easily and enhance vision), which are considered the pioneering smart glasses (Ometov *et al.*, 2021). Later, Edward O. Thorp and Claude Shannon (1955) created a device that was small enough to be worn on the body (first visualised in 1955 and executed later

in 1960–1961). The device was used to predict where the ball would land on a roulette wheel to beat Las Vegas casinos (Fernández-Caramés and Fraga-Lamas, 2018). In the 1960s, experimentation with helmets and smart glasses took place. Later, in the 1970s, wearable devices were used to help photographers with lighting. In the 1980s and 1990s, wearables were used to monitor a person's vital signs using smart shirts and augmented reality.

Wearables have become smart enough to incorporate technological information communicated autonomously and process information in motion (Park, Chung and Jayaraman, 2014). In recent years, IoT and 5G technology expansion has given rise to various apps and devices, benefitting humanity (Khanh *et al.*, 2022). In the development of ubiquitous computing—a term that explains how technology withdraws from the background and becomes an element of our life fabric—wearables are regarded as the next step. Wearable devices are a product of at least three cutting-edge technologies: mobile technology, the IoT, and big data. Based on their specifications and applications, wearable devices can be classified into three parts: wearable textile devices, wearable electronics, and healthcare devices (Cicek, 2015).

Wearable devices can be considered as advanced computing technologies that consumers can wear (Jacobs *et al.*, 2019). Wearable computing is described as the miniaturisation of components that have enabled wearable and nearly invisible systems so that individuals can move about and interact freely, supported by their personal information domain (Mann, 1997). As a result of its sensory and scanning elements, such as biofeedback, and psychological function tracking, wearable technology is considered more sophisticated and unique than mobiles and laptops (Gao, Li and Luo, 2015). Wearable computing is defined by Galzarano *et al.* (2016) as a fully functional, self-powered, self-contained computer that lets the user acquire data anywhere and at any point in time (Jara, Bocchi and Genoud, 2014). This definition suggests that these wearables are networked, which few are, whereas others stock information

to be later shifted to other devices. In addition to being a self-contained computer, wearable technology can represent various forms of body-mounted technology. Wearables could include smart bands, smart glasses, contact lenses, head-mounted monitors, SWs, smart jewellery (e.g., smart rings, tiaras and bracelets), or any other type of smart clothing provided with sensors (Rani, Chu and Li, 2021). With advancements in wearable technology, sensors are becoming increasingly smart, connected, and predictive, gathering data from the wearer's body, the surroundings, or both. The connected age enables unprecedented links between resources, people, devices, and oneself (Gao, Li and Luo, 2015). Although most wearable devices are easily removable, some emerging forms are more embedded, such as microchips or smart tattoos (Luczak *et al.*, 2020), reflecting the evolution of computer wearables alongside modern products.

Such modern products present a mixture of computing devices and sensors embedded in fashion accessories and clothing, such as SWs or activity-tracking bracelets (Nieroda, Mrad and Solomon, 2018). Similarly, wearables include altimeters, accelerometers, and other sensors embedded into the device and then attached to a certain body part (such as the wrist) (Farrokhi *et al.*, 2021). Whether worn on the body or embedded within it, wearable technology gives continuous, useful, seamless, compact and mostly hands-free access to the electronics and computers paired with it. While various wearable device types exist, they are all low key (i.e., small, lightweight, do not have wires or are included in clothing). They also maintain a primary task (i.e., they do not disturb and are useful all the time) and are aware of the context (i.e., casual use or "smart") (Papi *et al.*, 2015). Furthermore, Rani, Chu and Li (2021) state that such wearable computing creates new opportunities and challenges for user authentication. It also has a significant impact when users begin their innovation in wearable computing and use their portable devices as one of the computation sources.

Many wearable computing devices are emerging in the market, and include the Apple iWatch, iRing, Sony Smart Band, Google Glass, Bluetooth Ring, Microsoft HoloLens, Pebble Smartwatch, Fitbit fitness tracker, Oculus Rift virtual reality goggles, 9Solutions' Real-Time Locating Systems, and the iKey wearable keyboard (Jhajharia, Pal and Verma, 2014; Kalantari, 2017). Table 1-1 shows only one type of wearable computing application used in fitness and wellness practice. The next section examines the current study's importance for WFT devices, supported by industry insights and statistical evidence.

Table 1–1 Wearable computing application in fitness and wellness practice

Source: Jhajharia, Pal and Verma (2014)

Application	Product categories	
Fitness and Wellness	Activity monitors Emotional measurement Fitness and heart rate monitors Foot pods and pedometers Heads-up display	Sleep sensors Smart glasses Smart clothing Smartwatches Other audio earbuds

1.4.2 Relevance of the Current Research Study to the Health and Fitness Sector

Humans create and develop technologies to help them thrive in any situation. Technology is defined as "Scientific knowledge used in practical ways in industry, such as designing new machines" (Merriam-Webster, 2008). Wearables are more than just additional gadgets to carry around; they contribute significantly to an individual's personal technological portfolio. This evolution has led to a different type of individual information system. Baskerville (2011, p. 1) defines this as "an activity system in which individual persons, according to idiosyncratic needs and preferences, perform processes and activities using information, technology, and other resources to produce informational products and/or services for themselves or others".

Wearables, wearable devices, wearable technology, or physical activity assessment devices are all expressions that refer to small electronic and mobile devices or computers. They can communicate wirelessly, incorporated into devices, accessories, or garments worn in close proximity or direct contact with an individual's skin (e.g., shirts, shoes, or socks), or even invasive types such as smart tattoos or microchips (Luczak *et al.*, 2020). Wearable devices are multidisciplinary, as they have applicability to engineering, data analysis, strategy, information technology and systems, medicine, marketing, and many other fields. Some studies have identified wearable devices as small computers with several functions, in addition to showing the time, that support interactivity and connectivity (Chuah *et al.*, 2016) and have batteries, microprocessors, memory, and the ability to connect to the internet (Khanna, Kapahi and Gupta, 2021).

Wearables, particularly in the fitness industry, are not only designed to convert movement into numbers but also to grant users the integration and seamless experience expected from computers and assist them in achieving a state of self-connection by utilising sensors and software that allow for real-time data exchange, communication, and information access

(Kalantari, 2017). Unlike laptop computers and phones, wearable devices provide users with more control and convenience, such as through being lightweight and offering the possibility of being used while moving around, even without reaching the keyboard commands (i.e., through voice and hand gestures). Moreover, wearable devices have advantages over smartphones and tablets as they offer a range of scanning and monitoring attributes, including sensory physiological or biofeedback functions (Khan *et al.*, 2020). They help users extend their senses and gather information from the world. Thus, users' awareness of wearable devices has surged alongside developers' eagerness to bring innovative wearable devices to the market (Park, Chung and Jayaraman, 2014). The authors argue that these wearable devices can better laptop computer and smartphone performance and hence replace them in the future.

Increased customer demands and the expanding number of innovative services are driving the rapidly growing information and communications technology (ICT) industry. In general, the number of interconnected portable devices has increased tremendously year after year, due to consumer needs and the widespread use of the IoT. Consequently, these wearable devices represent a large share of the IoT (Swan, 2012; Castillejo *et al.*, 2013; Hiremath, Yang and Mankodiya, 2015), which connects the world and brings accessibility to the wearer's wrist. Further, the popularity of wearable devices is constantly growing. According to a Statista 2022 report on wearable devices (*Wearable shipments by category 2024 | Statista*, 2022), shipments in 2014 were around 22.8 million units, and in 2018, they reached 172.2 million; there were forecasts of 627 million units by 2024 (see Figure 1-1).

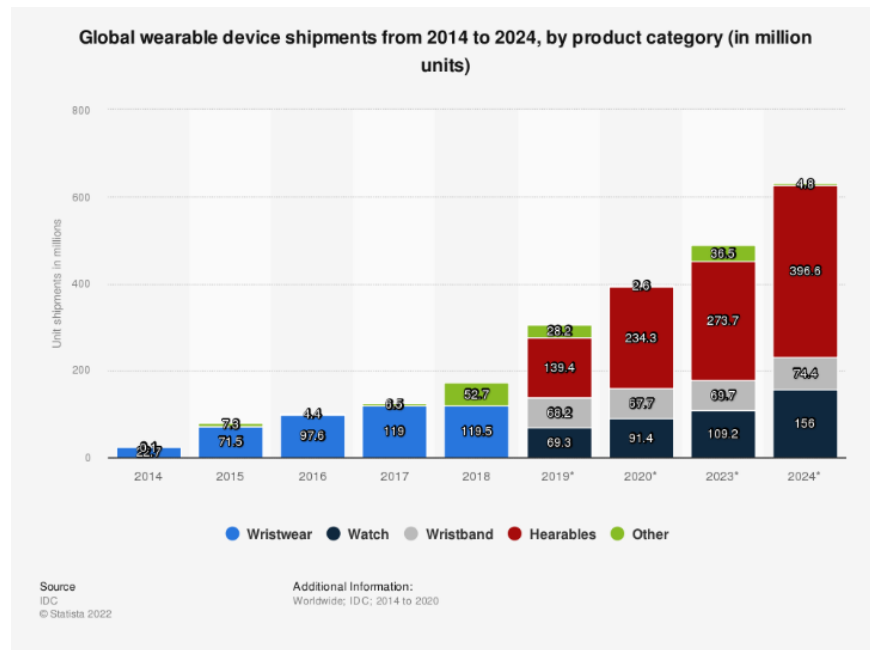


Figure 1-1 Wearable device growth based on shipment data (in millions), source Statista (2022)

Wearable technologies offer numerous benefits to both individuals and businesses across various sectors. In the fitness industry (the current study's main focus), wearable devices play a critical role in health tracking and monitoring, enhancing personal fitness and well-being. They can also be utilised in entertainment, gaming, information, communication, education, and navigation, demonstrating their versatility. The advantages of these technologies can, potentially, transform the landscape of societies and businesses dramatically. In the retail, manufacturing, and services sectors, wearable devices can significantly increase efficiency and save businesses millions of dollars (Abraham and Annunziata, 2017). Using wearable devices in medical settings could also provide assistive services for people with disabilities and increase the accuracy of the health data collected, hence improving the success of medical procedures and the safety of patients (Nazir *et al.*, 2019). Users can collect and store all their health and fitness-related data in one place with mobile health apps that interact with wearables (Jung, Kim and Choi, 2016), but these collected data can also be stored and shown as reports to doctors,

dieticians and experts for treatment and diagnosis if needed. With the help of these data, greater numbers of new services, known as online treatment, are now increasingly available. Although people might regrettably arrange to see a doctor after becoming ill, using a wearable device could potentially predict the progress of the disease by continuously monitoring wearers' health or notifying their doctor automatically so that measures can be taken to reduce health threats (Ometov *et al.*, 2021). Another fast-growing category of health software is first made available in the marketplace (i.e., as mobile medical apps) and typically installed on personal smartphones and wearable devices to help consumers identify mental states/illnesses (Terry and Gunter, 2018). Similarly, wearable devices can constantly monitor physical activities, heart rhythms, electrocardiograms, stress levels, sleep patterns and duration, blood pressure, and body temperature (Xie *et al.*, 2018). Therefore, healthcare users can avoid or decrease health problems by as much as 89%, which encourages proactive resolutions (Truong and Truong-Dinh, 2021).

Wearable devices are increasingly popular tools in sports, providing quantitative feedback for monitoring and improving athletic performance (Rapp and Tirabeni, 2020). For instance, wearable technologies with imaging capabilities have the potential to revolutionise sports performance and rehabilitation. These devices enable real-time monitoring of athletic performance and offer valuable insights into injury recovery, optimising training regimens and enhancing rehabilitation protocols. Specifically, they can track muscle recovery after injuries, detect muscle imbalances, and inform the development of personalised treatment plans (Seçkin, Ateş and Seçkin, 2023).

Before exploiting wearables, which was not long ago, people needed to work with a doctor/specialist when they wanted to find out information about themselves. Likewise, if they

were to learn further details concerning their sleep patterns/quality, they would undergo a sleep study in a strange environment that does not reflect their actual lives. Wearables are now increasing in function, and through such integrating technology, users can collect a tremendous amount of visual data and graphs about themselves that can be saved and stored directly on their wearable device/SW (Morozova and Gurova, 2021). Visual data produced by wearable devices might engage consumers in physical activities to better recognise different points of their bodies, physiologies, and habits; otherwise, the data simply remain figures unless learning occurs during data interpretation.

Although wearables could help solve several public health issues, researchers underline that sensitive data—from individuals' medical information to their financial details—can also be easily sensed and recorded by these devices (Rawassizadeh, Price and Petre, 2015). Such data may also merge with personal information from other sources, creating serious privacy risks that broaden the scope of discriminating profiles, data breaches, and manipulative marketing (Montgomery, Chester and Kopp, 2018). Given these privacy concerns, understanding the factors influencing consumer trust and continued use of WFT becomes crucial, thus positioning this research study to address how privacy considerations can have an impact on long-term engagement with WFT, especially within the context of smartwatches.

1.5 Prospective Study Contributions

This research aims to fill gaps identified in the literature, enhance theoretical understanding of technology adoption and continued use, and offer several managerial recommendations for organisations, managers, and innovators involved in providing wearable fitness devices.

1.5.1 Prospective Theoretical Contributions

This research work contributes to IS literature by focusing on technology adoption. It is intended to make a significant contribution to the customer's long-term use (post-adoption) and psychology literature, underscoring its relevance and importance in the academic sphere through employing a longitudinal research design, which is less common in the existing body of work on technology adoption and use. Longitudinal studies offer a dynamic perspective, capturing changes in consumer attitudes, behaviours, and perceptions over time, which cross-sectional studies cannot provide (Bhattacharjee, 2001). This approach allows for a deeper understanding of how initial acceptance transforms into sustained use, offering insights into the temporal aspects of technology engagement.

Furthermore, this research is intended to advance the theoretical understanding of CUB by adapting UTAUT2 for the specific context of WFT, a domain that remains underexplored (Venkatesh, Thong and Xu, 2012). Although UTAUT2 is broadly applied, it has rarely been tailored to consumer health technologies, such as WFT. This study fills this gap by examining the unique determinants that continued WFT use, especially as these devices become integral to daily health and fitness routines.

The study's main theoretical contribution lies in its expansion and contextualisation of UTAUT2 for WFT. Core constructs from UTAUT2—performance expectancy, effort expectancy, social influence (here reconceptualised as societal pressure), facilitating conditions, price value, and habit—are adapted to reflect the nuances of WFT use. However, hedonic motivation, typically treated as a single dimension, is split into perceived enjoyment and perceived device annoyance to capture both the benefits and challenges users experience with WFT.

This study introduces Technology Upgradability as a new construct within the UTAUT2 model, enhancing its relevance for WFT by aligning it with the rapid innovation and updates typical of this sector. Unlike prior uses of "upgradability" across economic, environmental, cloud computing, and consumer electronics (see Table 3-1), this construct has yet to be fully explored in the context of technology adoption and continued use for consumer wearables. By addressing this gap, the research strengthens the UTAUT2 model's application to health-focused wearables, whereby the ability to upgrade plays a key role in sustaining long-term user engagement. This extension not only validates the applicability of UTAUT2 in a novel domain but also enhances the robustness of the model by providing empirical evidence from a rapidly growing sector of consumer technology.

By integrating these elements (a total of nine constructs), this research refines UTAUT2 to assess the progression from initial acceptance to sustained use, offering a specialised framework that addresses both the temporal and contextual dynamics of consumer health technology engagement (Bhattacharjee, 2001; Venkatesh, Thong and Xu, 2012). This research also contributes to the literature by examining the moderating role of personality traits in the continued use of WFT. Despite growing research on technology adoption, personality traits have yet to be explored as moderators. This approach responds to Venkatesh, Thong and Xu's (2012) suggestion that the UTAUT2 model could be expanded to encompass different contexts, technologies, and consumer groups, thereby offering new insights into the factors influencing long-term use of WFT.

By investigating the role of specific personality traits in influencing users' continued behaviour in using WFT, this study contributes to a deeper understanding of the psychological and behavioural factors that drive continued use of technology. Salem and Alanadoly (2021), who examined personality traits and social media influences in the context of sustainable fashion,

highlighted how personality dimensions shape word of mouth and consumer engagement with sustainable products. In extending this approach, the present study applies a similar lens to the WFT domain, exploring the impact these traits have in ongoing user engagement. Doing so enriches the theoretical landscape around technology continuance behaviour, offering insights that may inform future research on user retention and engagement in the fitness technology sector.

1.5.2 Prospective Practical Contributions

From a practical perspective, this study's findings have significant implications for various stakeholders, including manufacturers, marketers, healthcare providers, and policymakers. Understanding the determinants of continued use could help these stakeholders enhance consumer engagement and retention, ultimately improving the effectiveness and value of WFT.

For manufacturers, insights into the factors driving sustained use can inform the design and development of more user-centric devices. By understanding the importance of constructs such as performance expectancy and hedonic motivation (which the current thesis splits into perceived enjoyment and perceived device annoyance), manufacturers can prioritise features that enhance user experience and satisfaction. For instance, improving the accuracy and comprehensiveness of health metrics, as well as incorporating engaging and enjoyable elements, could increase consumer retention (Siepmann and Kowalczyk, 2021). Marketers can leverage the findings to tailor their strategies more effectively. Highlighting the benefits of WFTs that align with consumers' intrinsic motivations and perceived value could make marketing campaigns more compelling. For example, emphasising the long-term health benefits and the enjoyment of using WFTs could resonate with potential consumers, fostering a positive perception and encouraging continuous use (Yang *et al.*, 2016).

Healthcare providers could also benefit from this research by integrating WFTs into health promotion and disease prevention programmes. Understanding the factors that encourage sustained use can help design interventions that leverage WFTs to monitor and improve patient health outcomes. This is particularly relevant for chronic disease management, for which continuous monitoring and feedback can significantly enhance treatment adherence and effectiveness (Chandrasekaran, Katthula and Moustakas, 2020). Policymakers could use the insights from this study to support public health initiatives that promote the use of WFTs. By recognising the role of technology in health promotion, policymakers could develop strategies and regulations that encourage the adoption and sustained use of WFTs, ultimately contributing to broader public health goals. This could include funding for technology-based health programmes, public awareness campaigns, and initiatives to reduce the cost of these devices for consumers (Alam *et al.*, 2022).

1.6 Structure of the Thesis

This thesis is structured into eight chapters. Following this **Introduction** (Chapter 1), the remainder is structured as follows.

Chapter 2 – Literature Review This chapter presents a detailed conceptualisation of consumer adoption and continued use of technology (highlighting the most dominant models/theories). Then, the theoretical background to the factors that influence consumers' continued use of IT is discussed, followed by the significance of the current study within the context of WFT. Previous empirical studies are reviewed in each section to identify gaps in the current literature. The necessary theoretical frameworks are then discussed, along with the reasons for their selection.

Chapter 3 – Research Hypotheses and Conceptual Framework This chapter presents the conceptual model, developed based on adapting the UTAUT2 model (Venkatesh, Thong and Xu, 2012) and the personality traits model (Terracciano and Costa, 2004).

Chapter 4 – Research Methodology To evaluate the hypothesised relationships established in the preceding chapter, Chapter 4 begins by exploring the philosophical paradigms, research approaches, and designs within the field of business and management studies that informed the choice of an appropriate research philosophy, approach, and overall design for this study. Following a thorough consideration of these foundational aspects, a quantitative approach was selected as the most suitable for addressing the study's objectives. This chapter further elaborates on the specific objectives of the quantitative study, outlining the sampling procedures that ensure representative and reliable data. Ethical considerations are carefully discussed to underscore the importance of maintaining research integrity and participant confidentiality throughout the data collection process. Lastly, the chapter details the data collection tools utilised, aligning them with the study's requirements and the broader quantitative framework to provide a structured and rigorous approach to gathering the data essential for testing the hypothesised model.

Chapters 5 and 6 – Quantitative Data Analysis These two chapters present the quantitative analysis and findings regarding the proposed conceptual model based on the first and second datasets, respectively.

Chapter 7 – Longitudinal Analysis and Results This chapter demonstrates the final analysis and results from the longitudinal study and consolidates the study findings derived from the quantitative findings.

Chapter 8 – Limitations, Future Research, and Conclusion This chapter details the study's limitations and suggests directions for future research. It concludes with the managerial implications and a summary of the entire research study.

Chapter 2: Literature Review

This chapter synthesises previous literature to identify the dominant models and theories related to technology acceptance, adoption, and continuance usage while critically evaluating their limitations. The synthesis concludes in a literature review table that summarises publication details, antecedents, moderators, and outcomes of technology adoption and continuance use. The chapter then highlights gaps in the existing research, emphasising areas in which further investigation into the continued use of WFT, particularly smartwatches, is needed. Building on addressing these gaps, the chapter develops a conceptual model grounded in the UTAUT2 to examine determinants of consumers' continued IT use. In summary, this chapter defines the frame of reference for the pivotal study object.

2.1 Dominant Models and Theories Used in Technology Adoption and Continued Use of ICT Research

Since the 1970s, researchers have realised that studying IT and IS adoption, acceptance, and usage is a foundation for discovering and utilising technology. Studies in developed countries showed that, over the past 40 years, introducing IT to organisations significantly affected the economy. IT invaded every business sector, which caused a shift from a manufacturing to an information economy (Dos Santos and Sussman, 2000). However, IT adoption has also brought many challenges to the application process, such as IT acceptance, which is considered to be related to individuals' interactions with technology. Thus, many models and theories have been used to meet such challenges and explore factors influencing computer use and correlated devices/apps while considering numerous independent variables in different environments (Khechine, Lakhal and Ndjambou, 2016). Moreover, these models and theories highlight individuals' capacity to adopt new technology, drawing on concepts from behavioural science, particularly in sociology and psychology, and their influence on continued technology use.

Over time, theories developed due to the work of extending and validating models that occurred when each theory was presented. Likewise, experts drew several models and established overlapping theories to explain usage behaviour and understand how consumers adopt technology in a fast-progressing digital world. Momani, Jamous and Hilles (2017) demonstrate how these theories are very similar in structure but differ in explaining the intentions behind the continuance use of technology. According to the number of constructs and moderators representing their structure, the best theory should be comprehensive and uncomplicated, making it more understandable and applicable, particularly to new technology acceptance behaviour research.

The Theory of Reasoned Action (TRA) (Ajzen and Fishbein, 1980) originally provided a foundational framework in psychology for understanding behavioural intentions, which was later expanded into the Theory of Planned Behaviour (TPB) (Ajzen, 1985). This evolution continued with the Decomposed Theory of Planned Behaviour (DTPB) (Taylor and Todd, 1995), further refining the model's constructs in examining intentions in various contexts. Similarly, in the IS field, the TRA framework inspired the development of the Technology Acceptance Model (TAM) (Davis, 1986), focusing specifically on technology acceptance. The TAM was later extended to TAM2 (Venkatesh and Davis, 2000) and then into the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh *et al.*, 2003), progressively building on TAM's insights to better capture the complexities of technology adoption and use. The UTAUT model combines several theories, including those mentioned above, in addition to the Model of Personal Computer Utilisation (MPCU) (Triandis, 1979), Diffusion of Innovations (DOI) theory (Rogers, 1983), and Social Cognitive Theory (SCT) (Wood and Bandura, 1989) and Motivational Model (MM) (Davis, Bagozzi and Warshaw, 1992). These sequential advancements reflect a shared effort across

disciplines to deepen our understanding of behavioural intention and technology usage, each model addressing different facets of decision-making and acceptance.

To conclude, for social science academics, understanding consumers' perceptions, diffusion, and acceptance of innovation and technology is crucial to identifying and evaluating social changes while explaining the tools of change. As a result, numerous models have been presented to better comprehend consumer adoption of new technologies and the ramifications due to advanced and emerging technology's continual growth in a continuously changing digital and fast-paced world (Chuah *et al.*, 2016). Thus, the next section of this chapter presents the models and theories developed across diverse disciplines that have been instrumental in explaining, predicting, and understanding people's acceptance and adoption of new products or technologies. Each theory provides unique insights into the mechanisms influencing user and consumer behaviour, particularly in response to technological advancements. By comparing these theories and discussing their applicability, limitations, and contextual relevance to consumer technologies, the chapter will underscore why UTAUT2 was adopted as the primary theoretical lens for this research study. This analysis not only highlights how UTAUT2 fits the research goals but also distinguishes it as a model equipped to address the unique requirements of studying continued use in the consumer technology landscape. Figure 2-1 displays the reviewed theoretical frameworks of concepts and theories related to the individual acceptance process.

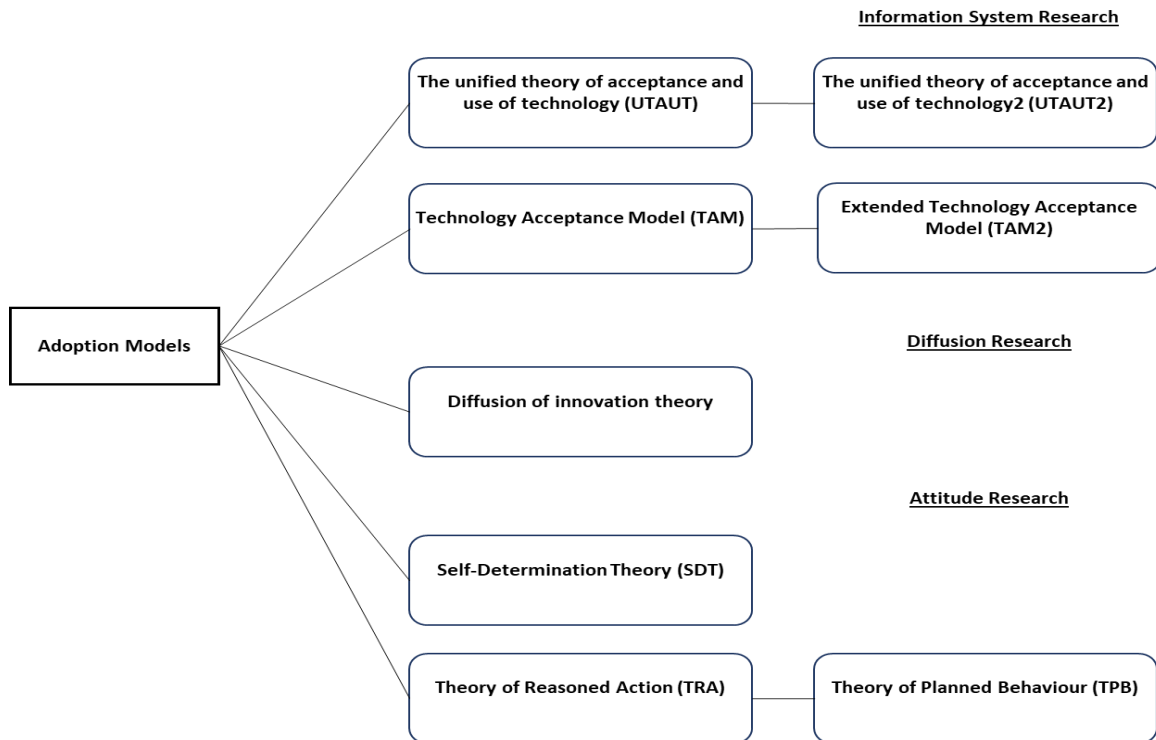


Figure 2-1 Relevant acceptance/adoption models

Theory of Reasoned Action (TRA)

The TRA is the oldest technology acceptance model and is regarded as one of the most basic explanations of human behaviour. The history of the TRA goes back to the era (the 1910s to 1960s) of studying individuals' behaviour through attitude, whereby attitude can influence behaviour directly or indirectly, whether as a one- or multidimensional factor. Fishbein and Ajzen's research programme on the Persuasion Models of Psychology in the late 1950s focused on behaviour prediction in both laboratory and applied settings (Momani, Jamous and Hilles, 2017). Their strategy acted as a bridge between various theories and lines of research on attitudes (i.e., theories of attribution, learning theories, expectancy-value theories, balance theory, and the theory of cognitive dissonance).

It postulates that individuals are rational and will act systematically based on the information they have, as people examine the consequences of their actions before determining whether to engage in a particular behaviour. Fishbein and Ajzen (1975) considered two main constructs moderating the TRA theory: the attitude of a person towards behaviour and subjective norms. A meta-analysis discovered that the TRA model could predict activities and goals based on various explicit options (Sheppard, Hartwick and Warshaw, 1988).

Limitations of the TRA

According to Ajzen (1985), the theory is constrained by correspondence. Attitude and intention must agree on action, target, context, time frame, and specificity for the theory to predict specific behaviour (Sheppard *et al.*, 1988). The theory's most serious flaw is that behaviour is under volitional control. The theory only applies to behaviour that has been planned ahead of time. This hypothesis does not explain irrational decisions, habitual acts, or behaviour that is not consciously considered.

In conclusion, although the TRA provides foundational insights into understanding intention, it was originally conceptualised for general human behaviours and is thus somewhat limited when applied to complex, evolving technologies. In the scope of the current thesis, which explores users' continued use of WFT, the TRA presents certain constraints. For instance, it does not account for external variables, such as technological features or user experience factors, which directly influence individuals' constant interaction with technology. This exclusion is crucial, as continued engagement with WFT involves not only social and personal attitudes, but also practical considerations (such as effort expectancy) and the tangible benefits users derive from the technology over time. These factors are central to understanding technology use that is sustained beyond the initial adoption stage.

Given the limitations referred to above, this thesis adopted the UTAUT2 as its primary theoretical lens as it offers a more holistic framework that addresses a range of determinants relevant to continued use in a consumer technology context. Unlike the TRA, UTAUT2 incorporates constructs such as hedonic motivation, price value, and habit, which are pivotal in understanding user interactions with technology over time. The design of the UTAUT2 model aligns more effectively with the research objectives, providing a comprehensive view of the motivational and contextual factors driving continued engagement with WFT. Therefore, although the TRA has been valuable in behavioural research, its exclusion here is due to its limited applicability in capturing the ongoing, multifaceted nature of consumer technology use that is central to this thesis.

Theory of Planned Behaviour (TPB)

The TPB is considered an extension of the TRA as Ajzen (1985) added a new construct, perceived behavioural control (PBC), to the subjective norms and attitudinal factors. These three main constructs moderate the theory; namely, attitude towards the behaviour and subjective norms (both adopted from the TRA) and perceived behavioural control (the new construct), which is termed “The perceived ease or difficulty of performing the behaviour” (Ajzen, 1991, p. 188).

Today's technological world has abundant information that forms people's opinions and behaviours ubiquitously. For example, reviews, discussions, and ratings of products and services with further information about who purchased or is about to purchase them, even suggestions about similar products or services that all, in combination, contribute towards making a decision. The TPB is, to date, one of the best predictor theories used in marketing; therefore, modern marketing needs to master these avenues to be successful in placing a service or product to digital natives/technology-savvy people who spend their time on the internet.

Limitations of the TPB

Although the TPB offers a well-regarded framework for examining intention-based behaviours, it is less suited for the specific focus of this thesis on consumer continuance with regard to WFT. The TPB, as mentioned earlier, is centred around three key constructs: attitude towards behaviour, subjective norms, and perceived behavioural control. Although these elements are valuable for understanding initial intention, the TPB lacks the nuanced constructs needed to explain technology acceptance and continued use behaviour in a rapidly evolving consumer technology context.

This thesis focuses specifically on individual consumers' continued use of WFT, which involves a complex interplay of performance-based expectations, effort-based expectations, social influence, and other technological support, as identified in UTAUT2. UTAUT2 has been extensively validated for technology acceptance studies. It includes constructs beyond the TPB's initial focus, such as effort expectancy, facilitating conditions, and hedonic motivation, each of which is particularly relevant to understanding ongoing consumer interaction with WFT.

In addition, UTAUT2 provides constructs designed specifically to capture post-adoption behaviours. This is crucial for addressing the unique goal of this thesis, which is to investigate consumer continuance rather than mere adoption intention. Since the TPB does not offer constructs explicitly tailored to measuring sustained engagement with technology, using the TPB as the theoretical foundation would limit the ability to explore the factors influencing continued WFT usage thoroughly; as a result, it was not used in this research study.

Technology Acceptance Model (TAM)

The TAM is a theory in IS that models how users accept and use technology. The model is often used to study individuals' adoption of developing ICT. It originates in social psychology and is studied as part of the TRA (Belief, 1975). The TAM, however, violates the TRA model since it maintains that there is a direct link between perceived usefulness and behavioural intention. In contrast, the TRA claims that attitude entirely mediates belief and intention (Taylor and Todd, 1995). The TAM shows that the easier a technology is to use, the more useful it can be. The level to which someone believes that using technology should be effortless is known as perceived ease of use (Persico, Manca and Pozzi, 2014). Technology-friendly attributes, such as uncomplicated and user-friendly devices, can determine PEOU, but this depends on users' efficacy—that is, their own judgement of their level of competency in using technology (Venkatesh and Davis, 2000). .

Moreover, TAM has been utilised to explain users' adoption behaviour toward computer information systems in mobile commerce (Wu and Wang, 2005). Empirical evidence supporting TAM has also been collected in the context of online banking (Pikkarainen *et al.*, 2004). Additionally, an enhanced version of TAM has been developed to investigate e-learning adoption across various conditions (Pandita and Mishra, 2021). Previous studies have supported the significant reliability of the TAM in describing attitudes towards wearable devices (e.g., Adapa *et al.*, 2018; Cheung *et al.*, 2019; Park, 2020).

Limitations of the TAM

A range of studies have criticised the TAM as being too parsimonious (Teo, Huang and Hoi, 2018) since using it without external factors cannot provide specific views about a system (Mathieson, 1991). Likewise, the TAM's simplicity has induced criticisms as it focuses on a few utilitarian constructs and involves only PEOU and PU (Bagozzi, 2007). A further example is the finding in Mamonov and Benbunan-Fich's (2021) study, which suggests a critical boundary condition for the application of dominant theories (such as TAM) in technology adoption. Canziani and MacSween (2021) also show that using TAM constructs limited their model's outcome by employing intentions rather than actual behaviours. Other researchers (Šumak *et al.*, 2017; Tsai *et al.*, 2018) argue that the TAM has several flaws. For instance, it ignores the model indicators and instead focuses on the external variables of PEOU and PU, fails to provide sufficient insight into individuals' perspectives on novel systems, and disregards the relationship between usage attitude and usage intention. Most importantly, the TAM focuses on consumers' perception of how a new system improves task efficiency (Sarkar and Khare, 2017), which is valuable for understanding early-stage adoption but less suited to contexts in which sustained engagement is tied to lifestyle habits, social factors, and intrinsic motivations.

Given these limitations, UTAUT2 emerged as a more suitable framework for this research. Unlike the TAM, UTAUT2 includes constructs specifically relevant to consumer technology contexts, such as hedonic motivation, habit, and social influence, which are essential to understanding continued use behaviour. By providing a broader scope that extends beyond task efficiency, UTAUT2 aligns well with the aim of this thesis to investigate long-term consumer engagement with WFT, thus justifying its selection over the TAM as the guiding theoretical lens (more details are contained in the theoretical framework section).

Social Cognitive Theory (SCT)

Social cognitive theory is one of the most influential theories in social and organisational psychology and is widely recognised as a framework for understanding individual behaviour change. It uses many aspects to understand change and adoption, including attitude and belief development, self-regulation, and affect (Wood and Bandura, 1989).

Furthermore, Bandura's most recent conceptualisation of his model (2004) provides a causal framework with four primary postulated constructs to explain people's participation (or not) in health-enhancing or health-damaging behaviours.

SCT is based on six constructs: one is self-efficacy, and the other five are observational learning, continuance capability, reciprocal determinism, expectations, and reinforcements. Likewise, Bandura argues that two sets of expectations are the major cognitive forces guiding behaviour. The first set of expectations is related to outcomes; however, the second set includes "self-efficacy", which is an individual's beliefs about his or her ability to perform a certain behaviour.

Limitations of SCT

SCT offers valuable insights into how personal factors, environmental influences, and behaviour interact to shape learning and technology use. However, several limitations make it less suited

to the focus of the current thesis on consumer continuance use behaviour with WFT. SCT primarily addresses behaviour in dynamic environments in which social influences and observational learning play significant roles. Although such factors are relevant to technology adoption, they do not fully capture the intricacies of individual motivation and sustained engagement with consumer technology. A central tenet of SCT is self-efficacy, which relates to users' belief in their ability to use a system effectively. Although this is pertinent to initial technology adoption, it provides limited insight into ongoing use when other factors (such as habit formation and social influence) become more prominent. Furthermore, SCT's broader focus on social behaviour and observational learning is better suited to organisational contexts, in which learning through others can have a significant impact on technology use.

In contrast, UTAUT2 more directly addresses the motivations and conditions influencing continued consumer engagement with personal technology, such as WFT. UTAUT2 expands on the focus of SCT by incorporating factors such as hedonic motivation, price value, and habit, which are essential for understanding why individuals continue using technology post-adoption. Given these distinctions, UTAUT2 provides a more precise fit for this study's aim to examine individual consumers' continued use of WFT. Accordingly, UTAUT2 was chosen as the foundational model for this research, allowing a more comprehensive investigation than would SCT into the factors influencing long-term consumer engagement.

Self-Determination Theory (SDT)

Richard Ryan and Edward Deci created SDT. Their research concerns the dominant role of intrinsic motivation in behaviour, the innate drive to satisfy internal needs, and extrinsic motivation, which comes from the outside, (Ryan and Deci, 2000). As social context provides extrinsic motivators and inhibitors, an individual has an inherent tendency towards growth and

action. However, human beings need to be nurtured by their external environment to fulfil that potential (Deci and Ryan, 2012). Their findings led to the identification of three basic psychological needs that individuals have, which they call Psychological Nutrients: competence, autonomy, and relatedness. Fulfilling these needs is essential for well-being and effective functioning; otherwise, the motivation falls (Ryan and Deci, 2017).

Grounded in SDT, a study, by Siepmann and Kowalczyk (2021), investigated the impact of positive and negative emotional as well as health and fitness factors on promoting or hindering consumers from continuous use of SWs. They built upon the ECM by developing an integrated framework to explain continuance intention via health and fitness as well as positive and negative emotion-related variables. Structural equation modelling (SEM) was used to validate the model through a questionnaire based on 335 responses from actual SW users. The study results demonstrated the applicability of the ECM to the SW context. They also underlined the significance of self-quantification as a focal construct for explaining goal pursuit motivation, perceived usefulness, and confirmation. However, the researchers found that device annoyance is an important barrier to continuous SW use. As both studies suggest, future research should emphasise the social aspects of wearable fitness devices to understand the sustainability of a system and how it affects consumers' long-term attitudes and motivations regarding the fitness device.

Limitations of SDT

Although SDT offers valuable insights into motivation, it is less aligned with the specific focus of this thesis, which is on understanding consumer continued use intention and behaviour in the context of WFT. SDT primarily concerns intrinsic motivation and the psychological needs for competence, autonomy, and relatedness. Although these factors can influence a person's motivation to initiate and sustain behaviours (such as using a wearable fitness device), SDT may

not fully address the broader range of external and contextual factors that typically affect technology acceptance, usage, and continuance use in consumer contexts.

Moreover, this thesis is grounded in UTAUT2, which is specifically designed to assess how various constructs affect technology acceptance and continued use, incorporating a balance of both cognitive (e.g., performance expectancy) and external motivational constructs (e.g., social influence and facilitating conditions), which are directly relevant for studying consumer behaviours in relation to WFT. By focusing on these constructs, UTAUT2 provides a well-rounded framework for understanding not only the initial acceptance of WFT but also the factors influencing long-term usage, a key objective in this thesis. Therefore, this study did not consider SDT but instead built on a more comprehensive theory, UTAUT2, which supports all aspects of the current research study.

Model of Personal Computing Utilisation (MPCU)

Triandis (1979) proposed a less-cited yet insightful theory of behaviour, distinguishing between beliefs formed at the moment of action and those shaped by anticipated future consequences. According to Triandis, individual decisions are influenced by multiple factors, including social norms, roles and values, self-image, emotional responses (affect), and both the perceived and actual consequences of a form of behaviour. Building on this framework, Thompson, Higgins and Howell (1991) developed an adoption model that separates the cognitive and affective components of attitudes. In their model, affect represents the feelings of like or dislike associated with an action, which are clearly differentiated from belief-based components (perceived consequences). This distinction enables a nuanced analysis of how both affective and cognitive factors influence behavioural decisions.

Limitations of the MPCU

The MPCU, although influential in its time, has limitations that reduce its relevance for contemporary research into technology adoption and, more specifically, understanding the post-adoption behaviour central to the current study. The MPCU was developed primarily as a theoretical framework to examine personal computer adoption during a period in which the understanding of technology use was significantly less complex. Consequently, the model lacks constructs essential for analysing modern, dynamic contexts such as the continued use of WFT, which involves more nuanced interactions, ongoing engagement, and factors tied to user well-being and long-term utility.

Additionally, the MPCU has not been widely validated in empirical research, as it has primarily been discussed in historical contexts rather than in modern empirical studies. It does not provide constructs that capture the social, emotional, and experiential dimensions of technology use, which are now recognised as critical for investigating continuance use behaviours. Given these limitations and its restricted empirical applicability, the MPCU does not align with the theoretical needs of this study. Therefore, a more recent and empirically validated model, such as UTAUT2, offers a more suitable foundation for understanding the ongoing use and engagement factors critical to WFT. As a result, the MPCU was not used in this study.

Diffusion of Innovations (DOI) Theory

Rogers (2003) developed the DOI theory to explain the innovation adoption process. Innovation refers to “an idea, practice, or object perceived as new by an individual or other unit of adoption” (Rogers, 2003, p. 12). Adopting a new idea, behaviour, or product (i.e., “innovation”) does not occur instantaneously in a social system; instead, it is a process whereby some people are more apt to accept the innovation than others. DOI theory endeavours to explain why, how, and at what rate new technologies and ideas spread. Everett Rogers published his influential book for

the first time in 1962, now in its fifth edition, providing a foundation for understanding innovation adoption and the factors that shape an individual's choices about that innovation. The book offers various definitions, including innovativeness, diffusion, technology, information, and communication. It also shares the four main elements in the diffusion of new ideas, which are (I) innovation, (II) communication channels, (III) time, and (IV) the members of a social system. The characteristics of an innovation determine its adoption rate as conceived by the members of a social system (Rogers, 2003). Further, Rogers (2003) argued that “individuals’ perceptions of these characteristics predict the adoption rate of innovations” (p. 219).

Limitations of DOI Theory

Although DOI theory provides valuable insights into how innovations are adopted across different settings, it is ultimately unsuitable for the theoretical lens of this thesis due to certain limitations within the scope of this study. Although the flexibility of DOI theory allows it to be applied across various contexts, it primarily offers a broad, generalised framework that fails to explain the underlying reasons for specific attitudes resulting in the adoption or rejection of innovations. This gap is significant because, in a consumer-focused study on WFT, understanding the nuanced motivations behind individuals' continued use is crucial. The lack of focus of DOI theory on the direct relationship between the properties of innovation and the expected attitudes towards it limits its applicability in this context (Tarhini *et al.*, 2019). Furthermore, DOI theory is predominantly designed for adoption analysis at a firm or organisational level, whereby adoption decisions are made collectively rather than individually. As the current research study specifically examines individual consumer behaviour in the context of continued personal use of WFT, an organisation-centred model would not capture the individual-level attitude and behaviour relevant to this study.

In contrast, UTAUT2 is uniquely equipped to address individual-level determinants, incorporating constructs (hedonic motivation, habit, price value, etc.) that play pivotal roles in consumer technology engagement. The focus of UTAUT2 on individual decision-making aligns directly with this study's objectives, enabling a comprehensive examination of consumer behaviour related to sustained use rather than initial adoption alone. Therefore, although DOI theory offers a valuable perspective on technology diffusion, its limitations in addressing individual-level determinants make UTAUT2 a more fitting theoretical framework for this thesis.

Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT was developed by Venkatesh *et al.* (2003), who designed the theory to obtain a more exhaustive understanding of and predict users' intention to use technology and subsequent usage behaviour, which previous models had not achieved individually.

The UTAUT model is a mixture of core elements from eight prominent technology use, acceptance, and diffusion theories that are brought together to structure a unified model for understanding technological acceptance. These models include the TAM (Davis, 1989); MM (Davis, Bagozzi and Warshaw, 1992); TPB (Ajzen, 1991); TRA (Belief, 1975); DOI theory (Rogers, 1983); SCT (Campeau and Higgins, 1995); MPCU (Thompson, Higgins and Howell, 1991); and the combined Theory of Planned Behaviour/Technology Acceptance Model (C-TPB-TAM) (Taylor and Todd, 1995).

The UTAUT model incorporates various constructs originating from the main theoretical information and computer technology acceptance models. Table 2-1 presents the models Venkatesh *et al.* (2003) selected to formulate UTAUT based on a systematic analysis and comparison. The model holds four main key constructs: effort expectancy, performance

expectancy, social influence, and facilitating conditions. The first three directly determine usage and behavioral intention factors, and the fourth key construct directly affects usage/actual behaviour. Gender, age, experience, and voluntariness of usage are all moderating variables in the UTAUT model. The influence of these four independent constructs on intention and usage behaviour is anticipated to be moderated by these variables. Further, in a longitudinal study, Venkatesh *et al.* (2003) observed that UTAUT accounted for 70% of the variance in behavioural intention (BI) and nearly 50% of the variance in actual use validated.

UTAUT is a well-established theoretical model for exploring the adoption of technology. It seeks to understand how people use and intend to use information systems as a function of constructs borrowed from various theories, that is, performance and effort expectancy (from expectancy theory), social influence (from SCT), and facilitating conditions (from personal computing utilisation). As major indicators of adoption intention, the UTAUT model incorporates the main independent constructs as defined by Venkatesh *et al.* (2003): performance expectancy is "the degree to which an individual believes that using the system will help him or her attain gains in job performance" (p. 447); effort expectancy is "the degree of ease associated with the use of the system" (p. 450); social influence is "the degree to which an individual perceives that important others believe he or she should use the new system" (p. 451); and facilitating conditions denote "the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system" (p. 453).

Table 2–1 Venkatesh *et al.*'s (2003) technology acceptance models chosen to develop the UTAUT model

Model/Theory	Author(s)	Description	Measured constructs
Theory of Reasoned Action (TRA)	Fishbein and Ajzen (1975)	A theory of human behaviour is used to ascertain the influence of technology acceptance.	• Attitude towards behaviour • Subjective norms
Technology Acceptance Model (TAM)	Davis (1989); Davis, Bagozzi and Warshaw (1989)	The model was contextualised in the IS field. It excluded attitudes towards a behaviour from the TRA for a better explanation of intentions.	• Perceived usefulness • Perceived ease of use • Subjective norms
Diffusion of Innovations (DOI) theory	Moore and Benbasat (1991)	The theory was taken from sociology and explains various innovation traits for predicting technology acceptance.	• Relative advantage • Ease of use • Image • Visibility • Compatibility • Results demonstrability • Voluntariness of use
Motivational model (MM)	Davis, Bagozzi and Warshaw (1992)	The model was borrowed from psychology to help understand how people are motivated to adopt technology.	• Extrinsic motivation • Intrinsic motivation
Theory of Planned Behaviour (TPB)	Ajzen (1991); Schifter and Ajzen (1985)	The theory is an extension of the TRA as it added PBC to be more inclusive while explaining individual acceptance of technology.	• Attitude towards behaviour • Subjective norms • Perceived behavioural control (PBC)

Decomposed Theory of Planned Behaviour (DTPB)	Taylor and Todd (1995)	The theory is a hybrid of TPB constructs and one of the TAM constructs (i.e., PU) for validating acceptance studies.	• Attitude towards behaviour • Subjective norms • Perceived behavioural control • Perceived usefulness (PU)
Social Cognitive Theory (SCT)	Compeau and Higgins (1995)	A popular theory of human behaviour applied to the acceptance of computer utilisation.	• Outcome expectations—performance • Outcome expectations—personal • Self-efficacy • Affect • Anxiety
Model of PC Utilisation (MPCU)	Thompson <i>et al.</i> (1991)	The model was derived from human behaviour theory and adapted to envisage PC utilisation. It was then used to clarify users' intentions in different contexts.	• Job fit • Complexity • Long-term consequences • Affect towards use • Social factors • Facilitating conditions

User acceptance is critical to the successful adoption of any IS or IT (Davis, 1989). In recent decades, numerous theoretical models have been established in the fields of psychology, IS, and sociology to predict and explain user acceptance of IT or IS. Between 2004 and 2011, UTAUT research confirmed the importance of performance expectancy and behavioural intention as major indicators of technology acceptance and use (Williams, Rana and Dwivedi, 2015). . Such a well-established model has been widely used to study a variety of technologies and even contexts beyond users' adoption in various study settings, including education, healthcare, libraries, telecommunications, government services, internet banking (Tarhini *et al.*, 2016), mobile banking (Jadil, Rana and Dwivedi, 2021) and other apps, such as ride-sharing (Pandita and Mishra, 2021).

Limitations of the UTAUT Model

Although the UTAUT model attained significant explanatory power, researchers have critiqued it for its predominantly utilitarian focus, which overlooks several key determinants crucial for understanding technology adoption beyond workplace environments. Although UTAUT is effective in capturing factors influencing employee behavioural intentions to adopt new technologies within organisational contexts, it does not fully address the distinct drivers of consumer behaviour in personal or everyday technology use. This limitation restricts UTAUT's applicability to studies involving consumer-graded innovations, such as WFT/SW, which are influenced more by personal and affective motivations than purely functional or extrinsic drivers. For instance, habit or hedonic motivations (which have been split in the current research study into two relevant constructs: perceived enjoyment and perceived device annoyance)—which are highly relevant in consumer settings in which technology is adopted as part of lifestyle choices—are either absent or minimally addressed in the original UTAUT model. These gaps present a critical barrier when attempting to apply UTAUT to consumer technologies, for which users often

prioritise enjoyment and personal relevance over productivity or organisational expectations. Moreover, UTAUT's primary focus on factors such as social influence and facilitating conditions is tailored to organisational structures, within which adoption decisions are frequently influenced by hierarchical support and peer expectations, rather than individual consumer preferences.

Given these limitations, UTAUT does not sufficiently capture the nuances of individual-level motivations and sustained engagement, which are crucial to understanding why consumers continue to use technologies such as WFT/SW in the long term. Consequently, the expanded UTAUT2 model—which introduces additional constructs such as hedonic motivation, price value, and habit—offers a more comprehensive and appropriate framework for this research study. These constructs not only enhance explanatory power for consumer-grade technologies but also align with the current study's focus on continued use rather than initial adoption alone, making UTAUT2 a better fit for examining consumer behaviour in the context of WFT.

Thus, this study adopted UTAUT2 as the primary theoretical lens, as it better accommodates the affective and consumer-centred factors critical to investigating CUB among individual consumers in a non-organisational context. The model supports the aim of exploring the integration of technology into personal routines and sustained engagement with consumer technologies, addressing the unique motivations and usage patterns characteristic of WFT. Table 2-2 reviews behavioural factors in technology acceptance models and their explained variance. Its structure and categories are inspired by Tarhini *et al.* (2019) but have been adapted to align with this study's focus on continued use behaviour, highlighting that the UTAUT2 model demonstrates the highest explained variance.

Table 2–2 Summary of technology acceptance models and their explained variance
 Sources: inspired by (Tarhini *et al.*, 2019)

Model	Behavioural factors	Explained variance
TAM	PU + PEOU	0.53
IDT	Innovation attributes + innovators' characteristics	0.40
TRA	Individuals' perceptions + attitudes towards the behaviour + social influences	0.36
TPB	Attitude towards the behaviour + subjective norms + perceived behavioural control	0.39
SCT	Self-efficacy + outcome expectations + affect	-
MM	Intrinsic motivation (enjoyment + fun) + perceived benefits (PU) + external pressure, i.e., social pressure	-
MPCU	People's beliefs + affect + social norms + perceived consequences + habit + facilitating conditions	0.47
DTPB	Attitude decomposed to relative advantage (PU), complexity (ease of use) and compatibility + subjective norms + PBC decomposed to self-efficacy and facilitating conditions	0.36
UTAUT	Effort expectancy + performance expectancy + social influence + facilitating conditions	0.56
UTAUT2	Effort expectancy + performance expectancy + social influence + facilitating conditions + hedonic motivation + price value + habit	0.74

2.2 Theoretical Framework of the Study

2.2.1 UTAUT2

The starting point for the theoretical framework of this study is UTAUT2, which includes the main constructs/relationships from UTAUT and integrates three new constructs: fun (e.g., hedonic motivation), cost (e.g., price value), and habit, as well as new relationships. Reflecting on its relevance to consumer behaviour in emerging technologies, Venkatesh, Thong and Xu (2012) used a two-stage online survey of 1,512 mobile internet consumers in Hong Kong to provide empirical support for the application of UTAUT2 to be used among individuals in a non-organisational context. The results showed that, compared with the baseline UTAUT, the extensions proposed in UTAUT2 substantially improved the variance explained in behaviour intention and technology use, going from 56% and 40% to 74% and 52%, respectively.

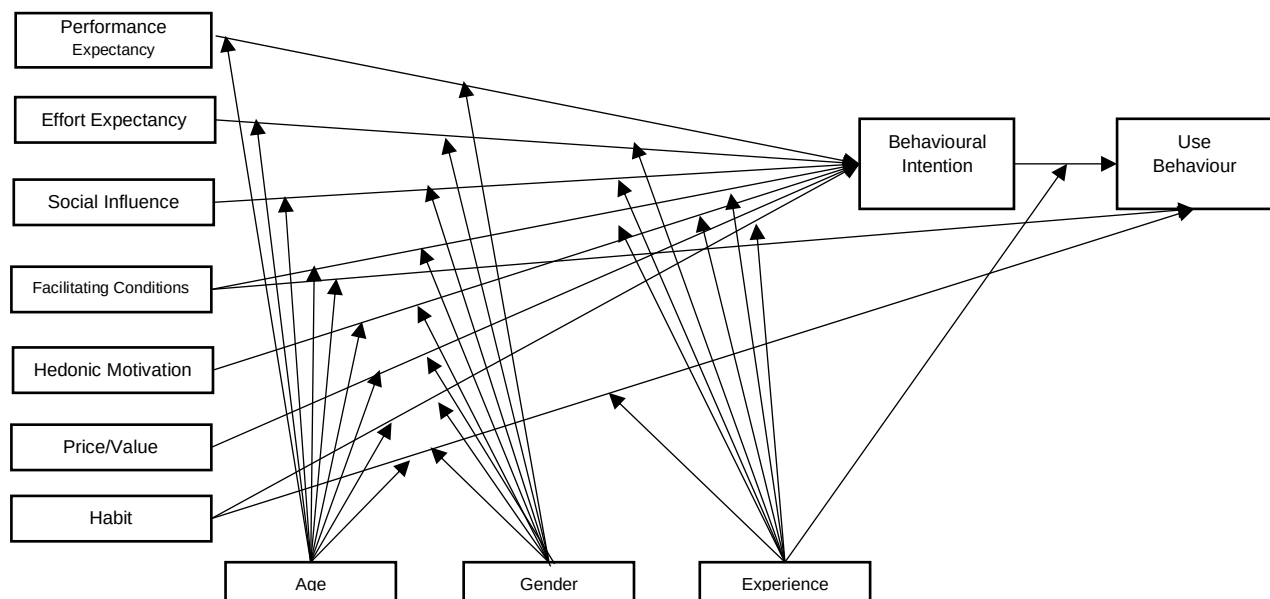


Figure 2-2 Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) (Venkatesh *et al.*, 2012)

UTAUT2 is considered the most comprehensive theory in understanding technology adoption and use. Hedonic motivation is regarded as the most crucial theoretical addition to the UTAUT2 model, adding a much-needed affective element to its primarily cognitive predecessor (UTAUT). The new model switched the focus from organisational users' extrinsic motivation (as a dominant paradigm) to consumer technologies' intrinsic motivation (Tamilmani *et al.*, 2019).

According to UTAUT2, the seven constructs (exogenous variables) are theorised as influencing behavioural intention to use technology while facilitating conditions and habits that determine the behaviour of technology use. In addition, individual variables, namely age, gender, and experience, are presented to moderate different UTAUT2 relationships (see Figure 2-11 above). It is worth noting that, compared to the original UTAUT model, the voluntariness construct (as a moderator) was dropped to make UTAUT2 more suitable for consumer voluntary behaviour. UTAUT2 has been criticised for its complexity, caused by the multitude of constructs and moderators (often applied without moderators). However, that multitude of factors is considered an advantage, helping to deliver the highest explanatory power of all standard acceptance models and thus helping to support the technology development process. Hence, UTAUT2 has been applied in various technologies within the consumer market, whereas UTAUT is used within the organisational context.

Consequently, UTAUT2 became one of the most comprehensive theories for explaining consumers' acceptance and use of technology. For instance, in a recent systematic literature review and UTAUT2 evaluation, Tamilmani *et al.* (2021) showed that although UTAUT2 was just 10 years old, it had already had over 6,000 citations (more than 3,000 citations on Google Scholar alone) and was widely used in information and beyond, emphasising its predictive ability. Furthermore, their findings aligned with Venkatesh, Thong and Xu's (2016) review of UTAUT-

based studies (which proposed a multi-level framework for the acceptance and use of technology). They observed that while the UTAUT/UTAUT2 models have gained enormous popularity as extensively cited IS theories, they are seldom employed in their entirety, which limits their generalizability. For instance, researchers often exclude UTAUT2's moderators, thereby neglecting their effects. A meta-analysis of UTAUT2-based empirical research revealed that only 35% of studies included habit, and 41% incorporated price, frequently yielding inconsistent results. Conversely, Tamilmani *et al.* (2021) highlighted that incorporating new moderation mechanisms represents the second-most popular extension of UTAUT2. Their analysis identified 15 studies exploring the impact of new moderator variables, independently or in combination with existing UTAUT2 moderators (e.g., age, gender, and experience), on various relationships, including novel ones.

Based on the above, the current study supports the existing stream of research by including the UTAUT2 model and enriching it with personality traits as moderators. The comprehensive literature review highlights UTAUT2 as the most widely applied theory in the context of wearable technology. Notably, UTAUT2 incorporates key constructs validated by prior research on wearable technology, while its constructs and their antecedents align closely with the objectives of the current study. This is to understand and examine the influence of personality trait factors and the relevant variables on consumers' continued use intention and continued use behaviour with respect to their wearable technology devices.

This study considered recommendations when examining the above-mentioned points and built on the UTAUT2 theory. The study investigates factors influencing consumers' continued intention and behaviour regarding using technology (WFT/SW). Similarly, in their study, Tarhini *et al.* (2016) investigated the factors that may hinder or facilitate the acceptance and use of

internet banking in Lebanon. As they recommended, there is still room for improvement and future research could increase the applicability of UTAUT2 to a wide variety of technology contexts by including other predictors. Taking that into account, and in response to that call, this study added personality traits as moderators to investigate their influence on the UTAUT2 model's main factors and continuance use behaviour of this technology. (Note that personality traits have not yet been investigated as moderators; see Attig and Franke, 2019, p. 213).

Thus, the current thesis adopted a theoretical foundation for the proposed conceptual model to address this gap. Figure 3-1 in the next chapter depicts the research model. The research aims to understand and examine the relationship between performance expectancy, effort expectancy, societal pressure (originally social influence), facilitating conditions, perceived enjoyment and perceived device annoyance (typically treated as single-dimension hedonic motivation), price value and technology habit, and adds technology upgradability, continued use intention, and continued use behaviour with regard to WFT/SW.

Theoretical Background and Why UTAUT2

As mentioned previously in this chapter, the UTAUT2 model, although a well-established framework for studying technology continuance, is extended in this study by integrating additional constructs that address the unique dynamics of WFT. Although UTAUT2 covers essential factors (i.e., performance expectancy, effort expectancy, and social influence), constructs such as perceived enjoyment, perceived device annoyance, and technology upgradability have been incorporated to provide a more comprehensive understanding of long-term user engagement. These constructs were chosen because they address the evolving, experiential nature of WFT usage, which is influenced by user enjoyment, device-related frustrations, and the importance of technological updates. Although constructs such as technology upgradability have been explored in fields such as consumer electronics and cloud

computing, they have not been examined in the context of WFT, making this inclusion a novel contribution. This extended framework better captures the multifaceted factors influencing sustained use and offers a more holistic perspective on consumer engagement with wearable technology. Table 2-3 summarises the construct definitions and suggested operational definitions used in the current thesis.

Various theoretical models have been established to explore consumers' intentions and actual usage of technology. However, UTAUT2 is a comprehensive core model that captures the fundamental characteristics of intention to use WFT, such as hedonic motivation, technology perception, and automatic outside task behaviour, such as habit. Thus, the first reason for using UTAUT2 as a background to the research is the desire to examine its constructs closely, as they are believed to influence CUI and so CUB. Second, UTAUT2's theoretical approach makes it possible to investigate the moderator variables; thus, one of the main focuses of this study is to demonstrate the impressive power of user-specific personal characteristics on the relationships of humans with technology. The third and more general reason is the place and importance of UTAUT2 in consumer behaviour research. It is a valid and effective model to explain individuals' adoption behaviours.

Table 2–3 Summary of constructs used in the study

Construct	Model name/Alias	Definition	Operational definition	Origin
Performance expectancy	UTAUT/2/PU/utility/relative advantage	The degree to which an individual believes that using technology will help him or her attain gains in job performance.	Consumers will continue to use WFT/SW if it benefits them in performing certain activities, such as monitoring/tracking the user's physical functions, sending/receiving instant messages, making voice/video calls, watching live videos, and connecting to social media.	Venkatesh <i>et al.</i> (2003)
Effort expectancy	UTAUT/2/EOU/usability	The degree of ease associated with the use of technology.	Consumers will continue to use WFT/SW if it is easy to use without any complications (i.e., easy usage of wearable devices will attract more consumers to continue using them).	Venkatesh <i>et al.</i> (2003)
Societal pressure	Peer expectations/expected social conformity/norms	The amount of pressure from society members, who might be family, peers, and friends, to continue using the technology. Body image refers to a person's subjectively perceived physical self embedded in a mental construct.	WFT/SW users' feelings towards health behaviour and how the influence of these groups can have a considerable impact on their continuance use of technology and gaining a better body image to minimise social pressure.	Myers and Biocca (1992); Cho, Cheng and Hung (2009)

Facilitating conditions	UTAUT/2	The degree to which a user believes that current resources and infrastructure are present to support the use of the technology/system.	Users will continue to use WFT/SW based on their perceptions of the resources/infrastructure and support available to perform a behaviour.	Venkatesh <i>et al.</i> (2003)
Perceived enjoyment	Extended TAM/hedonic benefits/hedonic motivation/hedonic value	The extent to which the activity of using the computer is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated.	The perception degree of a user in sensing WFT/SW as pleasant, enjoyable, and fun-oriented.	Developed based on Davis <i>et al.</i> (1992)
Price value	UTAUT2	Users' cognitive trade-off between the perceived benefits of the applications and the monetary cost of using them.	Users will continue to use WFT/SW only when they have balanced the cognitive trade-off between the perceived benefits of using wearable technology and its monetary cost.	Venkatesh, Thong and Xu (2012)
Technology habit	UTAUT2	This is defined in two different ways. The first meaning relates to prior behaviour; the second is observed by an individual who believes that a behaviour is becoming automatic.	Users will continue to use WFT/SW based on their possession of knowledge, prior experience, and continuous usage of this kind of wearable technology.	Venkatesh, Thong and Xu (2012)

Device annoyance	-	Annoyance is defined as an unpleasant emotional reaction to subjective overexposure to a certain kind of media.	Consumers who are excessively exposed to several notifications and interruptions can stop using their WFT/SW, as annoyance may occur only after some usage and potentially even lessens the feeling of sovereignty/enjoyment.	Developed based on Hutter <i>et al.</i> (2013) and Siepmann and Kowalczyk (2021)
Continued use intentions	Continuance intention/use intention, UTAUT/2	Behavioural intention indicates actual usage behaviour and refers to people's perception of their own willingness to use services/products.	Users' intention and perception/willingness to continue using WFT/SW.	Kijsanayotin, Pannarunothai and Speedie (2009); Yang <i>et al.</i> (2016)
Continued use behaviour	UTAUT/2	The intention to continue using a service/device.	Users' behaviours toward their WFD/SWs as they continuously incorporate them into their daily routines rather than discontinuing their use in the future.	Venkatesh, Thong and Xu (2012)
Openness to technological innovativeness	Technology readiness/ Personal innovativeness	Represents an individual characteristic that reflects a willingness to try out any new technology.	Consumers who are open to technological innovation will be more curious about and willing to continue using their devices in the future.	Developed based on Agarwal and Karahanna (2000) and Devaraj <i>et al.</i> (2008)
Neuroticism	Five-Factor Model (FFM) of personality	Emotional instability is characterised by general insecurity and anxiousness. Thus, high scorers mostly experience confusion, panic, sadness and stress and have a high degree of depression.	Consumers with high neuroticism might criticise their wearables (e.g., SW) for failing to find compelling value, which, in turn, causes them to stop using their devices.	Developed based on John and Srivastava (1999) and Costa and McCrae (2008)

Conscientiousness in health	FFM	Health consciousness indicates individuals' awareness of their health conditions as well as their desire and readiness to be healthier; thus, highly conscientious users focus on achievements and self-discipline.	Consumers with high conscientiousness in health tend to have those behaviours that can motivate them to keep using their wearable fitness devices, offering them opportunities for further achievements.	Developed based on Cho, Park and Lee (2014) and Peltonen <i>et al.</i> (2020)
Technology upgradability	-	A strategy for extending the lifespan of products by integrating modular features or design flexibility, ensuring devices remain relevant over time.	The ability/tendency (of technological products/devices, i.e., SW) to be improved in functionality in a way that matches consumers' ever-changing lifestyle, including software programs that provide added enhancements over an earlier version or hardware devices that provide greater performance than an earlier model.	Developed based on Khan <i>et al.</i> (2018)

2.3 Context of the Research: Health and Fitness Wearable Devices

Although wearable devices help users make better and more informed decisions in different disciplines, the current thesis will focus on health and fitness wearable devices (non-medical) from the individuals' perspective (i.e., not businesses). Wearable fitness devices are more than just fitness gadgets; they are also motivational tools that could help improve PA (Lewis *et al.*, 2020). They can offer a customised experience based on the user's needs; thus, they can take several forms, such as wristbands, SWs, and gadgets that can be part of a garment (Sergueeva, Shaw and Lee, 2020). These WFTs are available in different sizes and have opened new ways to gather data from people and the environment on a large scale. Bunn *et al.* (2018) state that these types of wearable devices are mainly used to log users' daily activity accurately and monitor overall health and fitness. The devices may not be the ideal standard for measuring workouts. However, they can accurately track steps and inactive behaviour to an acceptable degree, causing improvements in PA metrics to result from their validity (Nelson *et al.*, 2016).

Al-Emran *et al.* (2020) contend that self-tracking technology, such as wearable devices, is used to measure and record numerous elements of our lifestyles. The device is typically worn, allowing users to track, trace, and monitor their fitness gains effortlessly (Lunney, Cunningham and Eastin, 2016). For example, wearable fitness devices trace PA, such as calories burned, the number of steps taken, distance travelled, heart pace throughout exercise/rest periods, and workout intensity. Individuals can also measure the outcome of exercises after a workout to motivate them further and check whether they have achieved their daily targets (Pizzo *et al.*, 2020). Moreover, one study found that the use of wearables in interventions resulted in a considerable increase in daily step count, overall energy expenditure, and moderate and vigorous exercise compared to the other groups studied (Brickwood *et al.*, 2019).

Although wearable devices are projected to be the next major wave in the IT industry and are increasingly used for accessing expert advice and consultation globally (Gilmore, 2016), their adoption has been slower than anticipated (Chang, Lee and Ji, 2016). In contrast, Kalantari (2017) predicts rapid growth driven by the perceived benefits of wearables, ongoing technological advancements, and growing consumer empowerment.

While prior studies (as mentioned in the above examples) highlight the positive impacts of wearable technology, further empirical research is needed to better understand the factors influencing its acceptance and continued use. This is especially relevant in light of Lewis et al.'s (2020) recommendation to examine how wearer characteristics influence both usage patterns and perceived value. Gaining such insights can help marketers develop more targeted, consumer-oriented strategies and support manufacturers in designing devices that foster long-term user engagement.

In summary, despite their potential to promote PA and improve long-term health, wearable fitness devices continue to face challenges such as declining usage and user abandonment. Accordingly, this study investigates the key drivers of continuance intention, focusing on SWs, one of the most advanced and widely adopted forms of wearable fitness technology.

Significance of WFT

Technology is constantly undergoing substantial evolution due to the emergence of billions of new interconnected "things" and their incorporation into our daily lives. Wearable technology adoption is, therefore, becoming more common in the form of health and fitness devices, according to a recent study (Zakariah, Hosany and Cappellini, 2021) on how consumers integrate self-tracking technologies into their daily routines.

These cutting-edge devices, such as SWs, fitness trackers, and smart fabrics, can gather rich contextual data and provide a personalised experience (Ometov *et al.*, 2021). The 2024 Deloitte consumer trends report, based on a survey of 1,000 digital consumers aged 18 to 75 in Ireland, reveals a significant increase in wearable ownership, with smartwatches rising from 50% to 67% over the past year. Additionally, more than half of respondents reported using their smartphones or smartwatches for in-person mobile payments, with 38% doing so regularly and 13% occasionally (Deloitte, 2024). Thus, the increasing attention to wearable technology development and commercialisation has created the need to understand the facilitators and barriers to consumers' continuance intention to use it and, consequently, its long-term adoption in order to achieve subsequent benefits.

The literature review suggests that consumers' evaluation of technology can impact their degree of adoption, as well as their underlying continuance intention and use of devices. Cheung *et al.* (2019) argued that the rise in IT has resulted in the development of mobile and easily communicable devices, which have become smarter and emerged as essential communication tools. WFT continues to be a tool of next-generation technology; therefore, consumers should continue using such technology to achieve the desired goals. In addition, initial indications recommended the great potential for this technology to develop further and create a multi-billion-dollar industry (Sultan, 2015). In particular, the SW market reached USD 57.3 billion in 2021 and was predicted to reach USD 132.9 billion by 2026. However, this market was dominated by a few producers (i.e., Apple, Samsung, Fitbit, and Garmin) that had a comfortable lead while other brands were gearing up (Costello, 2019). Thus, due to the strong competition among producers, customers' continued usage could be a vital tool for sustaining market position.

Technology adoption in the UK has seen substantial growth in recent years. According to Deloitte (2021), wearable device adoption reached a decade-high between July 2020 and July 2021, with Britons purchasing approximately 19.2 million devices, averaging 1.6 million new devices per month. This surge was largely influenced by the COVID-19 pandemic, which accelerated interest in at-home fitness and self-monitoring technologies. During this period, wearable ownership rose significantly, with 40% of UK consumers reporting the use of a smartwatch or fitness band. Increased household savings also enabled many individuals to invest in new technologies, particularly wearables (Houston, 2021). Similarly, Gartner (2021) reported that heightened attention to health monitoring during the pandemic was a key driver of growth in the wearables market.

The global wearables market demonstrated strong growth in 2024, driven by increasing consumer demand for affordable devices and a growing emphasis on health monitoring features. Recent projections from the International Data Corporation (IDC) estimate a 6.1% year-over-year increase in global shipments, reaching approximately 537.9 million units by year-end. The SW segment, in particular, was anticipated to grow by 9.9%, with average selling prices for these devices likely to increase by 5.7% during 2024, reflecting a trend towards more feature-rich, higher-value options in the wearables market. Apple, Xiaomi, Huawei, and Samsung continue to dominate, although regional brands such as Imagine Marketing (boAt) are gaining traction, especially in cost-sensitive markets (IDC, 2024) (see Table 2-4).

Table 2–4 Top 5 wearable device companies by shipment volume, market share, and year-over-year growth, Q1 2024 (shipments in millions)

Source: International Data Corporation (IDC), 2024

Company	1Q24 Shipments	1Q24 Market Share	1Q23 Shipments	1Q23 Market Share	Year-Over-Year Growth
1. Apple	20.6	18.2%	25.4	24.5%	-18.9%
2. Xiaomi	11.8	10.5%	8.2	7.9%	43.4%
3. Huawei	10.9	9.6%	6.3	6.1%	72.4%
4. Samsung	10.6	9.3%	9.4	9.0%	13.0%
5. Imagine Marketing	6.1	5.4%	6.4	6.2%	-4.8%
Others	53.1	46.9%	48.2	46.4%	10.1%
Total	113.1	100.0%	104.0	100.0%	8.8%

The latest forecast assumption from Gartner is that by 2028, it is anticipated that over 50% of SWs will incorporate non-invasive methods for diabetes monitoring. However, these methods are not expected to meet clinical-grade standards. In addition, by 2027, 30% of SWs are expected to feature on-device AI capabilities. Despite these advancements, consumer willingness to share specific health and wellness data remains low; only 30% of consumers are expected to provide such data in exchange for personalised AI and generative AI-driven outcomes through 2027. As SW providers continue to demonstrate the accuracy and reliability of non-invasive monitoring technologies, however, consumer confidence in these devices is likely to increase, encouraging more widespread adoption (Gartner, 2024).

From the other side, although wearable technologies are widely adopted, their effective application and continuance use face ongoing challenges. The IDC ascribed the market's sluggish growth to widespread adoption. Despite the pandemic benefitting the overall wearables market, IDC noted a fall in some items, such as smart wristbands: worldwide shipments of smart

wristbands declined in Q2 and Q3 2020 (see Figure 2-12) and by 17.8% in Q1 2021 (IDC, 2021). Even pre-pandemic figures indicate that fitness tracker sales declined by 18% in 2017, representing a 23% drop from their peak in 2016. For example, one of the market leaders, Fitbit, continued to lose active users, reporting a 31% decrease in year-on-year unit sales in 2020 (Fruhlinger, 2018; FitBit, 2020).

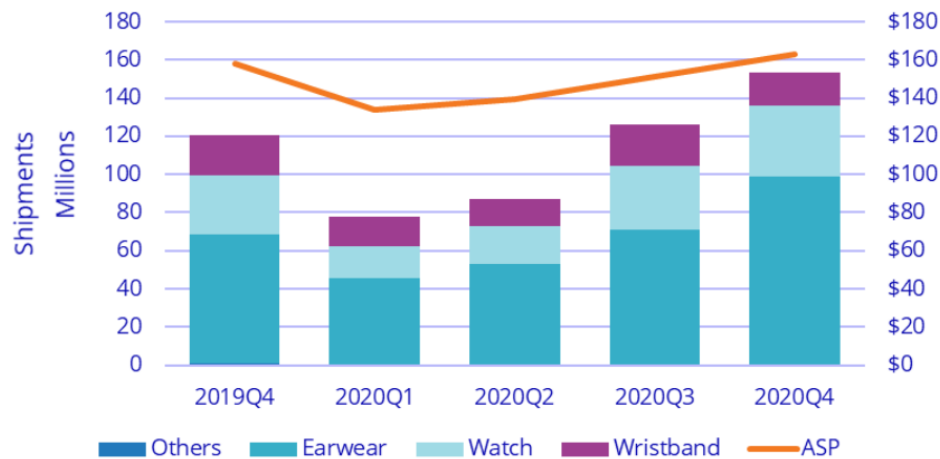


Figure 2-3 Worldwide wearables shipments by product type, 2020Q4
Source: International Data Corporation (IDC), 2021

Based on the above, further investigation is necessary to identify which factors influence the continued use of wearable technology, which is the focus of this thesis. More elaboration on smartwatches will be provided in the next section to offer examples of these devices.

2.3.1 Smartwatches (SW)

The increasing market penetration of smartwatches has altered the focus of both academics and practitioners, from studying initial adoption to examining continuance usage (e.g., Hong, Lin and Hsieh, 2017; Dehghani, Kim and Dangelico, 2018; Ogbanufe and Gerhart, 2018; Chuah, 2019).

The following section will elaborate on the definition and history of SWs and their relationship to PA in the context of wearable technology.

SW Definition and the Wearables Literature

After reviewing the literature, Table 2-5 below displays a detailed summary of studies on the definition of smartwatches. For instance, Benderlioğlu and Ata (2021, p.283) have defined smartwatches as “wearable technology devices in the form of a watch that is in contact with a smartphone and allows consumers to track their activities through sensors, transmitting the information”. Notably, SWs are one of the trendiest wearable technology devices in today's world despite being a relatively new product in its early diffusion stages in the international market (Chuah *et al.*, 2016). Consistent with research by Kim and Shin (2015) and Ernst and Ernst (2016), the adoption of smartwatches can be regarded as an especially important issue within the context of wearable technology.

Table 2–5 Summary of studies on smartwatch definitions

Author (Year)	Title	Journal title	Definition
Kim and Shin (2015)	An acceptance model for smartwatches: Implications for the adoption of future wearable technology	Internet Research	“Smartwatches serve mostly as satellite devices for amassing useful data from a paired smartphone via wireless Bluetooth connection and providing more convenient, faster, and substitutable access to information, especially as its information processing is less demanding and using a smartphone is sometimes impractical” (p. 528).
Cecchinato, Cox and Bird (2015)	Smartwatches: The good, the bad and the ugly?	Conference on Human Factors in Computing Systems—Proceedings	“A wrist-worn device with computational power that can connect to other devices via short-range wireless connectivity; provides alert notifications; collects personal data through a range of sensors and stores them; and has an integrated clock” (p. 2134).
Wu, Wu and Chang (2016)	Exploring consumers' intention to accept smartwatch	Computers in Human Behavior	“A smartwatch is a multi-purpose interactive tool rather than a mere timepiece or phone” (p. 385).
Choi and Kim (2016)	Is the smartwatch an IT product or a fashion product? A study on factors affecting the intention to use smartwatches	Computers in Human Behavior	“A smartwatch is a unique form of information technology in that its shape resembles an item that has been a close companion to us, humans, for many centuries, namely the wristwatch” (p. 777).

Chuah <i>et al.</i> (2016)	Wearable technologies: The role of usefulness and visibility in smartwatch adoption	Computers in Human Behavior	"A mini device that is worn like a traditional watch and allows for the installation and use of applications" (p. 277).
Hong <i>et al.</i> (2017)	The effect of consumer innovativeness on perceived value and continuance intention to use smartwatch	Computers in Human Behavior	"Devices that allow for the presentation of information in a manner that is simple and easier to access than smartphones" (p.265).
Hsiao (2017)	What drives smartwatch adoption intention? Comparing Apple and non-Apple watches	Library Hi Tech	"Smartwatch is a device that can connect with smartphones and receive a lot of information, such as time, text messages, schedules, and GPS data. While it can perform basic data and communications tasks, it is also capable of running mobile applications" (p. 186).
Dehghani <i>et al.</i> (2018)	Will smartwatches last? Factors contributing to the intention to keep using smart wearable technology	Telematics and Informatics	"A smartwatch is a multifunctional wrist-worn device that provides fast, convenient access to information and applications via a wireless/Bluetooth connection "(p. 481).
Nascimento, Oliveira and Tam (2018)	Wearable technology: What explains continuance intention in smartwatches?	Journal of Retailing and Consumer Services	"Smartwatch is a wrist-worn device with computational power that can connect to other devices via short-range wireless connectivity; provides alert notifications; collects personal data through a range of sensors and stores them; and has an integrated clock" (p. 157). Using the same definition as Cecchinato <i>et al.</i> (2015).

Krey <i>et al.</i> (2019)	How functional and emotional ads drive smartwatch adoption: The moderating role of consumer innovativeness and extraversion	Internet Research	“Smartwatches are small wearable computers worn like traditional watches on a user’s wrist. Smartwatches can run mobile apps and have features similar to those of smartphones. Examples: Apple Watch, LG G Watch, and Samsung Gear Live” (p. 589).
Bölen (2020)	Exploring the determinants of users’ continuance intention in smartwatches	Technology in Society	“Smartwatch is a type of wrist-worn device which has numerous functions that range from e-mailing to video recording” (p. 2).
Siepmann and Kowalczyk (2021)	Understanding continued smartwatch usage: The role of emotional as well as health and fitness factors	Electronic Markets	“Wearable devices which are equipped with a screen and sensors (e.g., accelerometers, IR sensors)” (p. 795).
A. Gupta <i>et al.</i> (2021)	Social comparison and continuance intention of smart fitness wearables: An extended expectation confirmation theory perspective	Behaviour and Information Technology	“A wrist-worn device with computational power, which can connect to other devices via short-range wireless connectivity; provides alert notifications; collects personal data through a range of sensors and stores them” (p. 1341).

Wrist-mounted devices (i.e., fitness bands and smartwatches) have evolved from basic timekeeping tools into sophisticated devices that have been commercially improved through hardware miniaturisation and further development to convert raw signals into real-time, understandable data. These enhancements helped move devices from being basic “smart pedometers” to include biometric sensing features (e.g., communicating with electronic devices and observing human activity and physiological signs) (Guk *et al.*, 2019). In the past 20 years, several industry leaders (i.e., Apple, Samsung, Google, Microsoft, Xiaomi, and Huawei) have made substantial investments in the wearable electronics industry. Consequently, the wearables market has grown considerably, as other significant electronic companies started to provide smartwatches (Samsung Galaxy Gear in 2013, followed by the Apple Watch in 2015).

Later, marketing teams endeavoured to encourage the adoption of such wristwatches worldwide. Despite the escalation of wearables in users' daily lives, however, marketers have had trouble positioning smartwatches (as one of the hybrid products that claim resources from various product classifications) in the market because they transcend traditional categories, emphasising the perceived utility of the devices (Nieroda, Mrad and Solomon, 2018).

Similar to smartphones, most wearable gadgets are versatile, interactive tools with numerous user-friendly functions, touch screens, and wireless communication (Dehghani, Kim and Dangelico, 2018). Likewise, Park, Son and Kim (2016) asserted that smartwatches are multi-category items seen as extensions of smartphones. Thus, several studies have tried to understand consumers' potential perceptions of SWs. For example, autonomous communication and screen format were found to be the most critical factors influencing the selection of smartwatches, but price and brand had no specific effect (Jung, Kim and Choi, 2016).

Fitness Wearable Devices/Smartwatches

Wearable technology (i.e., smartwatches) continuously monitors physiological parameters and daily activities, encouraging individuals to adopt a healthier lifestyle and resulting in reduced healthcare expenses. Thus, long-term technology (i.e., smartwatch) usage for personal fitness and health monitoring is highly desirable not only on the macro level for government and health insurance funds but also on the individual level for end-users (Siepmann and Kowalczyk, 2021). In addition, wearable devices can take several forms, such as wristbands, smartwatches, and gadgets that can be part of a garment (Sergueeva, Shaw and Lee, 2020). For this study, participants could use any of the most popular and up-to-date smartwatches, as these devices integrate the functionalities of other wearable technologies, such as fitness trackers.

2.4 Knowledge Gap

The majority of the previous studies in the IS and marketing fields that addressed the interaction between computers and humans mainly focused on one idea: technology as a force presented by brands or companies to consumers or users who should adopt, accept or use it passively. For instance, Hoyer *et al.* (2020) and Paul and Rosenbaum (2020) argued that technology shapes several characteristics of consumer behaviour. Another study shows that companies and organisations use data through individual traits to psychologically target and influence consumers' behaviours, including purchasing decisions (Stachl *et al.*, 2020). Notably, previous studies on wearable technology have mostly focused on general use or adoption-related issues, such as usefulness, trust, and privacy and security concerns (e.g., Chuah *et al.*, 2016; Wu, Wu and Chang, 2016). Other studies have examined further factors from different perspectives (e.g., Choi and Kim, 2016; Chuah *et al.*, 2016; Canhoto and Arp, 2017) and analysed the importance and use of wearable devices in well-being and health technology.

Nevertheless, studies remain scarce on consumer engagement and interaction with these technologies from a continuance perspective, meaning users' intention to continue/discontinue using such technology. Similarly, other research (Jin *et al.*, 2022) argued that few studies had taken a rigorous theoretical approach (e.g., by hypothesis formulation and testing) when investigating the underlying processes of the impact of wearable fitness devices on different consumers. The authors suggested that future studies could deliver a comprehensive theoretical framework of wearable fitness device consumers' behaviour to advance our understanding. Moreover, other researchers (Ridgers *et al.*, 2021) suggested that future research study the impact of wearable devices on PA levels and examine the critical factors for behaviour change. Another recent paper highlights a knowledge gap regarding how consumers interact with wearable technology and how that interaction may (or may not) lead to continuance intention to

use it (Ameen, Hosany and Tarhini, 2021). The authors suggested rethinking the consumer behaviour model when studying users' behaviour and marketing. For this reason, and as we live in a technology-oriented world with smart wearable products, a personalised perspective of consumers' continuance intention to use technology (WFT/SW) is needed to consider new ways to investigate their attitude and level of decision-making.

Researchers in different disciplines have studied consumers' adoption of wearable technologies, such as smartwatches and smart glasses, and applied various theories and methodologies. In addition, a growing body of literature shows that customers can perceive things differently due to their personality traits (Rupp *et al.*, 2018), which can significantly explain the attitude, continuance intention, and use of different technologies. However, surprisingly, those personality traits have been understudied in the WFT/SW context. More specifically, few researchers have examined the wearable device factors influencing individual attitudes and decision-making, building on personality traits theory from a long-term adoption perspective. For example, a recent study addressed how two personality traits, the need for touch and impulsiveness, could affect the use of online and mobile devices in omnichannel shopping (Rodríguez-Torrico, San José Cabezudo and San-Martín, 2017). Moreover, Rupp *et al.* (2018) argued that while wearable fitness devices can effectively motivate individuals to be active, many users abandon the technology shortly after purchase. The authors analysed various user profiles to explore continuance intention toward these devices and found that personality traits significantly influence perceived motivational resources, indirectly enhancing the desire to use them. However, their study was limited to capturing users' initial perceptions in a laboratory setting, which may not reflect long-term adoption, as these initial perceptions can evolve with extended access to the technology. To address these limitations, further research is needed to explore new approaches for investigating technology adoption (discussed in greater detail in subsequent chapters).

Consumers should constantly use wearable devices for the technology to be beneficial instead of abandoning them soon after purchase. According to Ferreira *et al.* (2021), if most people adopt wearables sustainably, the national health services could save billions of dollars. Therefore, long-term adoption is a critical concern that needs to be addressed to differentiate between the factors influencing wearable technology adoption and sustained use. Further, another recent study (Lewis *et al.*, 2020) encouraged further investigation into how a device's and its wearer's individuality can encourage long-term (continuance) use.

Based on the above, as the continuance intention to use wearable devices is expected to grow among consumers due to the popularity of wearable technologies, developing an innovative model that integrates a novel theoretical framework is needed to better understand this phenomenon. Although there has been much research on the adoption of wearable technology, little of the work has focused on continuance factors. Therefore, unlike other work, this study explores the factors affecting consumers' continuance intentions towards using IT (WFT/SW in this case) from the consumer perspective. This study further advances the technology adoption and continuance literature by exploring how personality traits moderate the relationship between continued use intention and continued use behaviour of WFTs. Notably, the role of personality traits as moderators in this context has yet to be investigated.

2.4.1 Gaps Highlighted in the Research

Based on the comprehensive review of the literature discussed above, Table 2-6 summarises the theoretical lenses used to study the CUB of technology, the factors that might influence it, and the role of personality traits (both general and user-specific characteristics). [Table 2-5](#) in the previous section (a detailed overview of smartwatch studies) shows that previous research on the intention to continue using wearable technology has primarily examined factors such as consumer innovativeness, perceived value, emotional and health motivations, and social comparison (Hong,

Lin and Hsieh, 2017; Dehghani, Kim and Dangelico, 2018; Nascimento, Oliveira and Tam, 2018; A. Gupta *et al.*, 2021; Siepmann and Kowalczyk, 2021). For instance, Hong, Lin and Hsieh (2017) and Dehghani, Kim and Dangelico (2018) explore the effects of consumer innovativeness and perceived value on sustained use, and A. Gupta *et al.* (2021) examine the role of social comparison. However, these studies rely on cross-sectional designs, which limits understanding of how user engagement evolves over time. Despite recommendations for longitudinal research to capture these dynamics, none has yet implemented this approach. The current study fills this gap using a longitudinal design to investigate how UTAUT2 constructs, moderated by personality traits, influence long-term engagement with wearable fitness devices. This framework not only expands the model theoretically but also provides a more nuanced, individualised perspective on continued use behaviour in relation to wearable technology. Thus, the current research study aims to address the following research gaps.

First, according to the literature on consumer IT adoption and use, much research has been done on technology adoption. However, little of the work has focused on continued use intention and continued use behaviour, specifically in a longitudinal setting (as the majority of empirical work has taken cross-sectional and/or experimental approaches).

This thesis, however, takes a unique longitudinal approach to investigate the dynamics of consumer intentions and technology use over time by understanding whether there are differences between technology adoption and post-adoption factors of WFT from the user's perspective, a topic that has not been extensively explored. Such a context (WFT), as an emerging revolution in this technological world, is considered one of the most novel and influential forms of IT due to its increasingly pervasive role in individuals' daily lives and offering numerous features that enhance users' health/well-being and efficiently motivate people to be active. However, the literature review demonstrates that users noticeably abandon their wearable

devices soon after purchase, losing all subsequent benefits that can only be achieved through continued use.

Research gap 1: A limited amount of research adopts a longitudinal approach to investigating how perceived predictors of continued use behaviour (CUB) evolve over time, examining differences between technology adoption and post-adoption (continued use) factors.

Second, previous research on technology continuance intention and use has predominantly relied on the TAM and UTAUT and their extensions. These models have been criticised for missing relevant factors, particularly the innovative nature of wearable technologies and their ability to provide a complex mix of utilitarian, affective, and social benefits. There is a notable scarcity of applications of the UTAUT2 model to CUB in the WFT/SW context, highlighting a gap that this research aims to address.

The primary purpose of this research is to leverage the explanatory power of the UTAUT2 model in the context of the CUB of WFT, and, as Venkatesh *et al.* (2003) emphasised that consumer decision-making on technology adoption varies across different contexts, this necessitates separate investigations for specific technologies. In addition, Venkatesh, Thong and Xu (2012) recommended extending the UTAUT2 model with relevant variables tailored to different technology contexts. Therefore, based on these recommendations, this study uses the UTAUT2 model as its theoretical foundation, extending it with relevant variables to better capture the unique aspects of wearable technologies. Technology upgradability (TUpG) is an appropriate construct yet to be assessed within the context of technology adoption and continuance use. From the technology usability perspective, users' decisions to continue or abandon their technology could be based on how they import/export and/or retrieve/lose their data from one technology version/generation to another.

Thus, this thesis introduces technology upgradability as a new exogenous mechanism, addressing a gap identified in the literature by Castanha, Pillai and Indrawati (2021), who noted the absence of this construct in prior research. By incorporating upgradability, this study extends the theoretical mechanisms of UTAUT2, providing a richer understanding of the factors influencing technology adoption and continuance use, particularly in the WFT context. It also refines the existing predictor, hedonic motivation, by splitting it into perceived enjoyment (PE_{nj}) and device annoyance (DA_{noy}).

Research gap 2: There is a lack of thorough empirical investigation into exploring CUB in WFT and utilising/extending the UTAUT2 model.

Finally, most studies implicitly presume that all consumers respond similarly to adopting and using technology, and thus neglect individual differences. However, a growing body of literature indicates that users' personality traits (PTs) can have a significant influence on their attitude and intention to continue using technology.

One of the reasons for PTs having received minimal attention in prior studies could be a lack of grounded theory to help researchers identify specific traits to explore inside the UTAUT2 model (Devaraj, Easley and Crant, 2008). Although previous studies have commonly used moderators such as gender, age, and experience, new moderating variables have not been integrated (Tamilmani *et al.*, 2021). By replacing the traditional moderators with PTs, this thesis responds to calls for further research to identify relevant factors that enhance the applicability of UTAUT2 to various technology use contexts. This integration allows for a more nuanced understanding of how PTs influence technology adoption and continuance use, offering significant theoretical contributions to the field. Therefore, personality traits (user-specific personal characteristics,

including openness to technological innovativeness, conscientiousness in health, and neuroticism) are proposed as moderators. These characteristics have yet to be assessed within the area of wearable technology in the context of continued IT usage.

Research gap 3: The role of PTs as moderators of the relationship between CUI and CUB in the context of WFT remains unexplored despite the importance of individual psychological factors in technology use.

By doing so, the current thesis responds to theoretically and managerially related gaps (see Table 2-6). It contributes to the theory by providing an empirical investigation of consumers' continued use intention and behaviour regarding WFTs (for more details, see the previous chapter, section [1.3](#)). To this end, the research employs questionnaires asking consumers who have recently started using WFTs about their intention to continue using their devices, in order to understand those users' behaviours and decision-making levels. Regarding the research [methodology](#), this study uses a [quantitative method](#) and a [longitudinal study](#) was carried out to examine the research model, wherein a survey includes those constructs involved in the conceptual model. A justification for the methodological choice and details of the research processes employed are presented at each study stage. This approach ensures that the rationale behind selecting specific research methods is transparent, demonstrating the alignment between the research objectives and the methodological design. It also highlights how each stage contributes to a systematic examination of the factors influencing technology's continued use, providing a coherent framework that supports the study's validity and relevance in the context of WFT adoption and continued use behaviour.

Table 2–6 Prominent theoretical lenses used in wearable technology adoption and continuance use research

	Study	Main theory/model	Technology/context	Moderators	Functional factors	Hedonic factors	Research design	Key findings
1	Adapa <i>et al.</i> (2018)	TAM UTAUT	SW AR Smt Glass	-	Functionality	-	n=25 (USA), laddering technique	AR Smt Glass, look and feel is the most-mentioned factor for adoption. SW, availability of fitness apps is the deciding factor.
2	Canhoto and Arp (2017)	-	H&F WD	-	Utilitarian benefits	Hedonic benefits	n=20 (Germany), focus group	Adoption intention, technology features that signal a device's ability to satisfy utilitarian and hedonic needs are crucial. Sustained use, device portability and resilience are important.
3	Chae (2009)	TAM	Other WDs	Technology innovation, fashion innovation	Usefulness EOU	-	n=815 (South Korea), SEM	Consumers with high technology and fashion innovation perceive smart clothes as easy to use and useful.
4	Choi and Kim (2016)	TAM	SW	-	Usefulness EOU	Enjoyment	n=562 (South Korea), SEM	Intention to use both utilitarian and non-utilitarian factors. Fashion attributes, an individual's desire for uniqueness.
5	Chuah <i>et al.</i> (2016)	TAM	SW	-	Usefulness EOU	-	n=226 (Malaysia), SEM	Adoption intention, perceived usefulness and visibility
6	Dehghani <i>et al.</i> (2018)	TAM UTAUT	SW	-	Usefulness EOU	-	n=326 (USA), ethnography	Continuance intention, perceived usefulness, EOU, enabling technologies, functionality, compatibility, fashionology, healthtology, and complementary goods

	Study	Main theory/model	Technology/context	Moderators	Functional factors	Hedonic factors	Research design	Key findings
7	Gao <i>et al.</i> (2015)	UTAUT2	H&F WD	Product type	Performance expectancy	Hedonic motivation	n=462 (China), SEM	Adoption intention, product type (fitness or medical devices). Factors from technology acceptance, health behaviour, and privacy-context influence adoption decision. Effects vary across groups (fitness and medical devices users).
8	Hong, Lin and Hsieh (2017)	TAM DOI theory	SW	-	Utilitarian value	Hedonic value	n=276 (Taiwan), SEM	Wearable types (fitness vs. medical), continuance intention, value perceptions (hedonic and utilitarian), influenced by consumer innovativeness.
9	Hsiao (2017)	TTF DOI theory	SW	-	Relative advantage	-	n=341 (Taiwan), SEM	Relative advantage strongest impact on adoption intention. Antecedents of Apple SWs and non-Apple SWs have an impact on the relationships.
10	Hwang <i>et al.</i> (2016)	TAM	Other WDs	-	Usefulness EOU Comfort	-	n=720 (USA), SEM	Perceived compatibility and comfort determine the usefulness, EOU, and performance risk of smart clothing. Perceived performance risk, aesthetic attributes, and environmental concerns significantly affect consumers' attitudes towards smart clothing.
11	Jeong <i>et al.</i> (2017)	DOI theory	WD	-	Relative advantage	-	n=312 (South Korea), SEM	Perceived attributes (relative advantage, social image, aesthetics, and novelty) of wearable devices; information processing has a stronger effect than product processing on these attributes.

	Study	Main theory/model	Technology/context	Moderators	Functional factors	Hedonic factors	Research design	Key findings
12	Kim (2016)	TAM	SW	-	Usefulness EOU	Affective quality	n=200 (East Asia), SEM	Adoption process: a round screen reduces perceived controllability, but utilitarian quality still has an impact on adoption. Non-utilitarian quality: a round screen is more effective than a square screen in promoting these qualities.
13	Kim and Shin (2015)	TAM	SW	-	Usefulness EOU	-	n=363 (South Korea), SEM	Perceived usefulness, affective quality and relative advantage. Perceived EOU, mobility and availability. User attitude and adoption intention, devices' subcultural appeal and cost.
14	Kwee-Meier <i>et al.</i> (2016)	TAM UTAUT	Other WDs	-	Usefulness	-	n=2,086 (Germany), SPSS	Intention to use, wearable location system, expected usefulness, trust, social influence, privacy concern, and perceived security risk. Mostly determined by passengers' age and need for safety.
15	Nascimento, Oliveira and Tam (2018)	ECM	SW	Habit	Usefulness	Enjoyment	n=574 (USA), SEM	Continuance intention, user satisfaction (driven by perceived usefulness and enjoyment) and habit (also a moderator between satisfaction and continuance intention).
16	Rauschnabel (2018)	U&G theory	AR Smt Glass	-	Life efficiency	Enjoyment	n=206 (USA), SEM	Intention to use in private, consumers' life efficiency, enjoyment, and desired enhancement of reality. Intention to use in public, wearable comfort, socialising, and self-expression.

	Study	Main theory/model	Technology/context	Moderators	Functional factors	Hedonic factors	Research design	Key findings
17	Rauschnabel and Ro (2016)	TAM DOI theory	AR Smt Glass	Self- presentation benefits	Functional benefits EOU	-	n=201 (Germany), regression and mediation analyses	Adoption intention, functional benefits, EOU, individual differences variables, brand attitudes, and social norms.
18	Rauschnabel <i>et al.</i> (2015)	BIG 5 personality traits	AR Smt Glass	Openness Neuroticism Extraversion	Functional benefits	-	n=146 (Germany), SEM	Adoption intention, potential for high functional benefits and social conformity. Strength of these effects is moderated by consumers' individual personality.
19	Reyes-Mercado (2018)	UTAUT	H&F WD	-	Performance expectancy	-	n=363 (Mexico), SEM and fsQCA	Current users follow a streamlined path to adoption. Non-adopters follow a number of paths to intention to use through performance expectancy, effort expectancy or facilitating conditions.
20	tom Dieck and Jung, (2018)	TAM	Other WDs	-	Usefulness Alternative convenience, EOU, Instructions, Costs of effort	-	n=5 (Ireland), focus group, thematic analysis	Tourists' acceptance of mobile AR, information and system quality, costs of use, recommendations and personal innovativeness, risk, and facilitating conditions.
21	Turhan (2013)	TAM TPB	Other WDs	-	Usefulness	-	n=1,412 (Turkey), SEM	Attitude towards using smart bras and t-shirts, and perceived usefulness is influenced by EOU.
22	Wu, Wu and Chang (2016)	TAM DOI theory UTAUT	SW	Gender Age	Relative advantage EOU	Enjoyment	n=212 (Taiwan), SEM	Attitude, relative advantage, and enjoyment. Gender has no significant effect on smartwatch acceptance.

	Study	Main theory/model	Technology/context	Moderators	Functional factors	Hedonic factors	Research design	Key findings
23	Yang <i>et al.</i> (2016)	-	WD	-	Usefulness Functionality	Enjoyment	n=375 (South Korea), SEM	Adoption intention, perceived benefits (usefulness, enjoyment, and social image) have a greater impact than perceived risks (performance, financial). Perceived usefulness is driven by functionality and compatibility. Perceived enjoyment and social image, influenced by visual attractiveness.
24	Krey <i>et al.</i> (2019)	TAM ELM Schema incongruity theory	SW	Personal innovativeness Extraversion	Usefulness EOU	Enjoyment	n=999 (Malaysia), PLS-SEM	Ad strategies model, includes value drivers, attitude, and adoption intention. Personal innovativeness and extraversion serve as moderators.
25	Sergueeva, Shaw and Lee (2020)	UTAUT2	WD	-	Performance expectancy	-	n=277 (US-based residents), PLS	Managing personal health, consumer expectations; health consciousness; personalisation–privacy paradox.
26	Farivar, Abouzahra and Ghasemaghahi (2020)	-	WD	Subjective well-being	-	-	n=44 (US and Canada), PLS	Adoption intention, complexity and cognitive age.
27	Talukder <i>et al.</i> (2020)	UTAUT2	Other WDs	-	Performance expectancy	Hedonic motivation	n=325 (China), SEM	Behavioural intention, adoption decision, effort expectancy, technology anxiety, self-actualisation, functional congruence, among elderly people.
28	Siepmann and Kowalczyk (2021)	ECM SDT	SW		Usefulness	Enjoyment	n=335 (Germany), SEM	Continuance intention, ECM extent with emotional, health and fitness factors, device annoyance, goal pursuit motivation and self-quantification behaviour.

	Study	Main theory/model	Technology/context	Moderators	Functional factors	Hedonic factors	Research design	Key findings
29	Kamble, Desai and Abhang (2021)	TAM AGT	WD	Goal orientation	Usefulness EOU	-	n=324 (India), SEM	Acceptance by generation Z, intention to use, motivational affordances, self-monitoring, rewards, social comparison, performance and mastery goals, attitude and subjective norms.
30	Attié and Meyer-Waarden (2022)	TAM DOI theory U&G privacy calculus	SCO	Innovativeness Privacy concerns	Usefulness EOU	-	n=702 (France), SEM	Intention to use, real use (longitudinal study), adoption stages, acceptance and usage of smart connected objects, well-being and social image.
31	Rahman <i>et al.</i> (2022)	UTAUT2 TPB	WD	-	Performance expectancy	Hedonic motivation	n=318 (Bangladesh), SEM	Behavioural intention, adoption, intention to recommend, effort expectancy, social influence, price value, habit and attitude.
32	Asimakopoulos, Asimakopoulos and Spillers (2017)	SDT	FT	-	-	-	n=34 users (Spain)	Mobile healthcare; user engagement, user experience, motivation, health technology factors, self-efficacy, mHealth heuristics, JawBone and Fitbit.
33	A. Gupta <i>et al.</i> (2021)	ECM/SCM	SW/FT	-	Usefulness	-	n=684 users (India), SEM	Smart fitness wearables; continuance intention; expectation confirmation model; confirmation, satisfaction, perceived health outcomes, social comparison.
34	Park (2020)	WD	ECM/TAM/ Flow state	-	Usefulness EOU	Enjoyment	n=1,380 users (Korea)	Continued intention, perceived cost, flow state, satisfaction.
35	Bölen (2020)	ECM	SW	-	Usefulness	-	n=348 actual users (Turkey)	Continuance, individual mobility, perceived aesthetics, habit.

	Study	Main theory/model	Technology/context	Moderators	Functional factors	Hedonic factors	Research design	Key findings
36	Current study	UTAUT2	WFD/SW	Personality traits (technology user-specific characteristics)	Performance expectancy	Enjoyment	267-331 users	Performance expectancy, effort expectancy, societal pressure, facilitating conditions, perceived enjoyment, price value, technology habit, perceived device annoyance, technology upgradability, consumers' continued usage intention and continuance use behaviour with wearable technology.

Notes: AGT = achievement goal theory; AR = augmented reality; AR Smt Glass = augmented reality smart glass; DOI theory = Diffusion of Innovations theory; ECM = expectation-confirmation model; ELM = Elaboration Likelihood Model; EOU = ease of use; fsQCA = fuzzy-set qualitative comparative analysis; FT = fitness tracker; H&F WD = health and fitness wearable device; Other WDs = other wearable devices; PLS = partial least squares; PLS-SEM = partial least squares structural equation modelling; SCM = social comparison model; SCO = smart connected objects; SDT = Self-Determination Theory; SEM = structural equation modelling; SPSS = Statistical Package for the Social Sciences; SW = smartwatch; TAM = Technology Acceptance Model; TPB = Theory of Planned Behaviour; TTF = task-technology fit; U&G theory = uses and gratification theory; UTAUT = Unified Theory of Acceptance and Use of Technology; UTAUT2 = Unified Theory of Acceptance and Use of Technology 2; WD = wearable device (in general); WFD = wearable fitness device.

Chapter 3: Research Hypotheses and Conceptual Framework

This chapter focuses on the development of the hypotheses developed to investigate the relationships among the study's key variables. Drawing from empirical evidence and grounded in established theoretical foundations, the chapter begins by examining the following predictors: performance expectancy, effort expectancy, societal pressure (adapted from the concept of social influence), perceived enjoyment, perceived device annoyance (both dimensions of hedonic motivation), facilitating conditions, technology habit, price value, and technology upgradability. The chapter further explores the mediating role of continued use intention in these relationships and introduces hypotheses regarding the moderating effects of specific personality traits. To provide a cohesive overview, the chapter presents a conceptual framework, visually mapping the interactions between predictors, mediator, and moderators. This ensures clarity and precision while reflecting the multifaceted nature of the variables studied.

3.1 Conceptual Model Development

The primary purpose of the study is to develop an integrated model designed to explain and predict user continued intention and continued use behaviour toward wearable technologies. This phenomenon has, to date, been largely overlooked in IT research, particularly in longitudinal contexts. Most empirical studies have relied on cross-sectional or experimental designs (i.e., Hong, Lin and Hsieh, 2017; Dehghani, Kim and Dangelico, 2018; Nascimento, Oliveira and Tam, 2018; Gupta *et al.*, 2021; Siepmann and Kowalczyk, 2021), constraining our understanding of evolving user engagement. Unlike the aforementioned studies, my thesis employs a longitudinal approach to capture a comprehensive sense of the dynamics of continued use over time.

As previously highlighted in Chapter 1, the current research reveals three critical gaps in understanding CUB for WFT. Firstly, longitudinal studies examining evolving predictors of CUB over time remain scarce, limiting insights into differences between adoption and continued use.

Secondly, few empirical investigations have utilised or extended the UTAUT2 model in WFT contexts. Finally, the moderating role of PTs in the relationship between CUI and CUB is unexplored despite the relevance of the former to technology use. To fill the gaps identified in the literature, the study further extends UTAUT2 to examine the determinants of individual continued use intention and behaviour toward WFT/SW by introducing new moderators in the model.

After considering the literature review and the factors mentioned, the theoretical framework guiding this study is illustrated in Figure 3-1 to understand consumers' continued use behaviour towards WFT as the dependent variable (DV). Drawing on previous research in related sectors (details provided under each variable), the main factors of the extended UTAUT2 model: performance expectancy, effort expectancy, societal pressure (regarding body image), perceived enjoyment, perceived device annoyance, facilitating conditions, technology habit, price value, and technology upgradability, are considered the independent variables (IV). Users' CUI mediates these nine main constructs (IVs) and CUB (DV). Moreover, consumers' psychological traits (both general personality and technology user-specific characteristics) moderate the relationship between CUI and CUB in the conceptual model. More elaboration in the next section.

Model Specification

This study extends the UTAUT2 to develop an integrated model for examining continued use behaviour (CUB) in the context of WFT, specifically smartwatches. UTAUT2 serves as a robust foundation for understanding post-adoption technology use, yet it requires contextual adaptations to better capture consumer dynamics in the WFT domain. Accordingly, the final

theoretical model retains core UTAUT2 constructs while also incorporating conceptual extensions grounded in the relevant literature.

The following constructs from UTAUT2 are retained in their original form due to their continued relevance to post-adoption behaviour: performance expectancy (PerExp), effort expectancy (EffExp), facilitating conditions (FCons), price value (PValu) and technology habit (TechH). However, the original construct of social influence is adapted and reconceptualised as societal pressure (SotPrss) to better capture contemporary norms related to body image and social comparison, which are particularly important in the context of fitness technology. This modified construct reflects subjective norms as measured by individuals' perceptions of societal expectations and their motivation to comply with them (Bandura, 2004).

The original hedonic motivation construct is split into two distinct emotional dimensions: **p**erceived enjoyment (PEnj), adapted from Venkatesh and Bala (2008) and Yang *et al.* (2016), captures positive emotional engagement with the device. In contrast, perceived device annoyance (DAnoy), developed based on Hutter *et al.* (2013) and Siepmann and Kowalczyk (2021), reflects negative emotional responses such as frustration caused by intrusive notifications, tracking fatigue, or design limitations. In addition, a new construct, technology upgradability (TUpG), is introduced to capture consumers' expectations regarding a device's ability to be updated or adapted over time. This construct, adapted from Pae and Hyun (2006), is informed by literature on technology lifecycle perception, device modularity, and sustainable innovation in consumer electronics. Continued use intention (CUI) acts as a mediating construct between the independent variables and the dependent variable, continued use behaviour (CUB).

To account for individual differences, three personality traits from the Five Factor Model (FFM) are included as moderators of the CUI → CUB relationship: (1) openness to technological

innovativeness (OTTI), adapted from Yang (2005), reflects an individual's tendency to seek out and embrace novel ideas, values, and behaviours; (2) conscientiousness in health (CinH), adapted from Michaelidou and Hassan (2008), represents the tendency to be goal-directed, dependable, and deliberate in health-related decisions; (3) and neuroticism (Neu), adapted from John and Srivastava (1999), captures a disposition toward worry, self-consciousness, and the experience of negative emotions. These traits were selected based on their theoretical associations with technology engagement and health-related behaviours, offering deeper insight into how personality may influence continued interaction with WFT. The rationale for selecting CinH, OTTI, and Neu and excluding other traits is detailed in Chapter 3 under [Relevance of CinH, OTTI, and Neu](#).

The final conceptual model was operationalised and tested using Structural Equation Modelling (SEM). Each latent construct was measured reflectively using multiple observed indicators adapted from established scales. Confirmatory Factor Analysis (CFA) was first employed to assess the reliability and validity of the measurement model. Direct structural paths were then specified from all independent variables to CUI and from CUI to CUB. Moderating effects of personality traits were tested using interaction terms to explore their influence on the CUI → CUB path. This SEM model specification enabled an integrated assessment of both measurement and structural components, supporting a robust examination of the study's theoretical framework (see below Figure 3-1). The specific hypotheses are discussed in the following section.

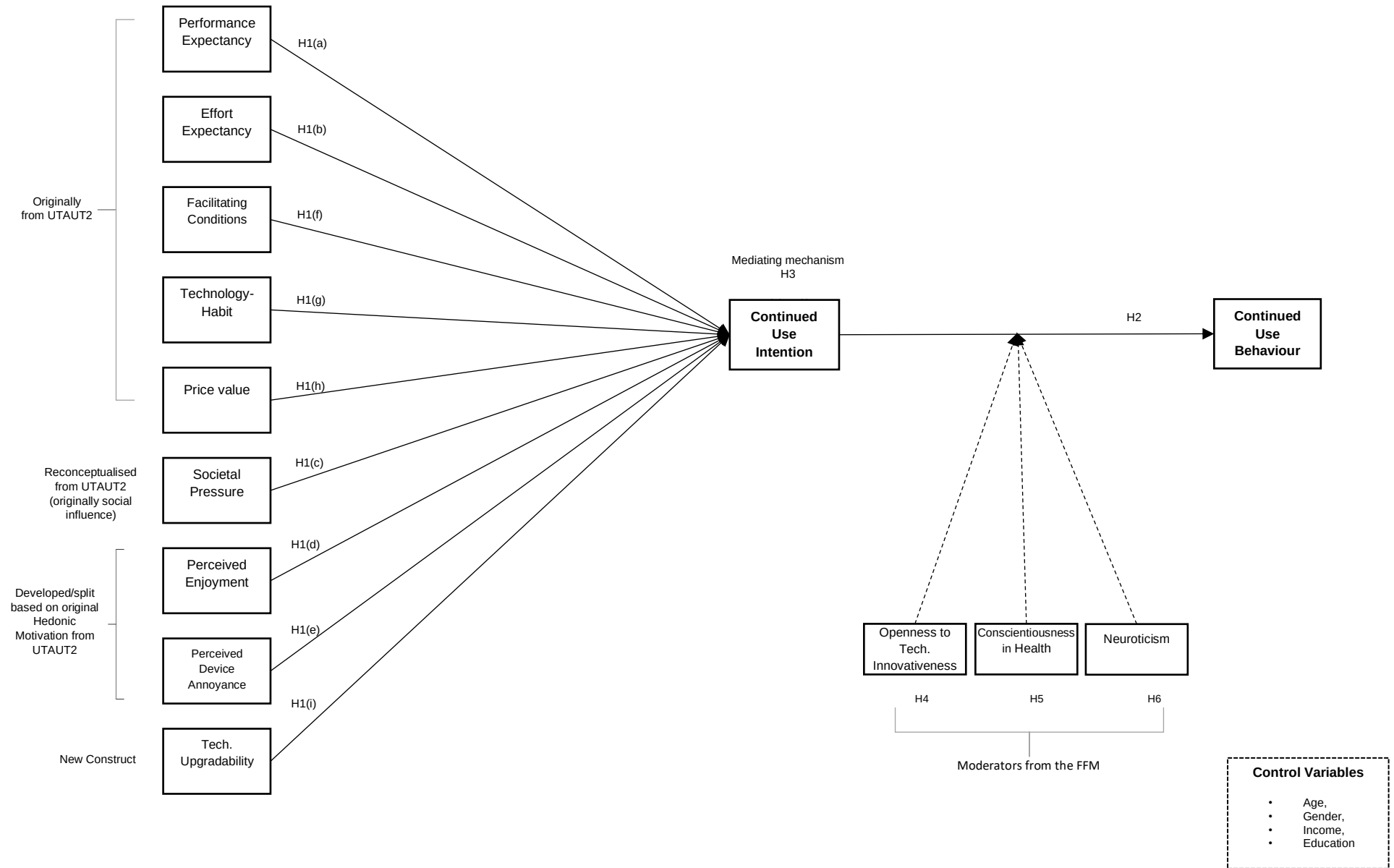


Figure 3-1 Demonstrates the changes made to the original UTAUT2 model

3.1.1 Direct Hypotheses

a) Theoretical Underpinning

The present study employs UTAUT2 (Venkatesh, Thong and Xu, 2012) as its conceptual framework to reinforce the validity of the proposed model in the context of WFT continuance use. As depicted in Figure 3-1, the conceptual model suggests performance expectancy H1(a), effort expectancy H1(b), societal pressure H1(c), facilitating conditions H1(f), technology habit H1(g) and price value H1(h). All these, along with extended constructs that are not in the original in Venkatesh, Thong and Xu (2012), split "hedonic motivation" into two concepts: perceived enjoyment H1(d) and perceived device annoyance H1(e) and add a new exogenous construct: technology upgradability H1(i) as the core driver of continued use intention and behaviour.

b) Relationship Between Perceived Factors and Continued Use Intention

Performance Expectancy (PerExp) → Continued Use Intention

Performance expectancy was presented by Venkatesh *et al.* (2003) and defined as "the degree to which an individual believes that using the system/technology will help a person to attain gains in job performance" (p. 447). This variable contains another five sub-constructs: extrinsic motivation, perceived usefulness (TAM/TAM2), outcome expectations, relative advantage, and job fit. According to the literature, PerExp under each of these five constructs is the most significant predictor of intention (Venkatesh *et al.*, 2003). It refers to the usefulness of technology when it is being adopted for specific purposes. Users are more driven to adopt technology when it is more advantageous and effective in their everyday life (Davis, 1989; Alalwan, Dwivedi and Williams, 2016).

The influence of PerExp on behavioural intention (BI) to use WFTs has been widely studied and confirmed in the literature. For example, Lu, Yu and Liu (2009) validated PerExp as a direct determinant of users' BI, identifying it as the strongest factor in their study of mobile data services

in China. Similarly, Gao *et al.* (2015) confirmed the positive relationship between PerExp and BI in the context of medical devices. Alam *et al.* (2022) demonstrated that PerExp has a significant impact on mobile health (mHealth) adoption in developing countries, highlighting its universal relevance. Moreover, Molavi, Ghosh and Strebler (2020) explored PerExp in the context of wearable health trackers as part of corporate wellness programmes in the US, showing its role in enhancing engagement with such technologies. This underscores that WFTs can be integrated into social and professional networks by aligning their perceived usefulness with the specific needs of the users, such as improving health monitoring, enabling connectivity, and fostering goal achievement within these environments.

Talukder *et al.* (2020) identified a positive relationship among key variables in the adoption of wearable healthcare technology (WHT) among the elderly. Similarly, Rahman *et al.* (2022) demonstrated that behavioural intention significantly influences teenagers' adoption of wearable technologies. In addition, Sergueeva, Shaw and Lee (2020) highlighted that performance expectancy strongly affects both the intention to use and the actual use of wearable technology devices. Reyes-Mercado (2018) further reinforced this finding by demonstrating the influence of performance expectancy on wearable fitness device adoption in Mexico, applicable to both adopters and non-adopters. Moreover, Oc and Toker's (2022) findings showed that PerExp is a critical factor in the behavioural intention to use sports technologies.

From the above argument, as PerExp has already been used to predict behavioural intention in the research mentioned earlier, the current study follows in those researchers' footsteps and also focuses on this determinant, according to the relevant applications regarding IT (i.e.,

WFT/SW). Therefore, to demonstrate the effect of PerExp on continued use intention towards WFT, the following hypothesis postulates:

H1(a) Performance expectancy has a positive and significant impact on CUI.

Effort Expectancy (EffExp) → Continued Use Intention

Venkatesh *et al.* (2003) introduced effort expectancy as a major indicator of adoption intention in the UTAUT model. It is one of the main independent constructs and can be divided into three sub-facets: perceived ease of use (TAM/TAM2), complexity, and ease of use. EffExp is defined as "the degree of ease associated with an individual use of a system or technology" (Venkatesh, Thong and Xu, 2012, P. 159).

Similar to performance expectancy, the influence of effort expectancy on behavioural intention to use WFT has also been widely studied and confirmed in the literature. WFT devices should be supported by a user-friendly interface and learner guidance that users can easily accept and use. For instance, easy access to personal data is a major motivator for WFT use (Canhoto and Arp, 2017; Jarrahi, Gafinowitz and Shin, 2018). Conversely, users will stop using their WFT (such as the Fitbit One) if they are unable to interact with the device comfortably (e.g., through lack of expertise to interpret the data or having too complex a device) (Clawson *et al.*, 2015; Lazar *et al.*, 2015; Seiler and Hüttermann, 2015; Randriambelonoro, Chen and Pu, 2017). Further, Naglis and Bhatiasavi's 2019 study showed that users seem to find wearables simple to use if they have the chance to try them out or monitor how they are used in their surroundings.

EffExp, in the context of wearable technology, evaluates the ease with which users interact with and operate these devices. When technology is perceived as intuitive and easy to use, it enhances user satisfaction while providing benefits in accomplishing specific activities

(Venkatesh, Thong and Xu, 2012). It is crucial to assess whether current users perceive WFT/SW as user-friendly and straightforward to learn, as this perception significantly influences their long-term adoption and sustained usage decisions. Many earlier studies endorse a positive relationship between EffExp and intention to use. For example, Alalwan *et al.* (2018) found a highly significant correlation between EffExp and BI towards mobile banking. In addition, Wei *et al.* (2021) observed a positive impact of EffExp among men on adoption behaviour towards mobile payment. Likewise, Molavi, Ghosh and Strebler (2020) tested EffExp in their study on wearable health trackers as part of a corporate wellness programme in the US. In other work, Reyes-Mercado (2018) and Kim and Shin (2015) pointed out that EffExp has high net effects on the use and intention to use for adopters of health and fitness wearable devices. Consistent with the last set of findings, Oc and Toker (2022) demonstrated that EffExp is critical for behavioural intention to use sports technologies. Surprisingly, however, Talukder *et al.* (2020) found no noteworthy relationship among these variables in WHT for the elderly. Similarly, Rahman *et al.*'s (2022) study of teenagers found that effort expectancy towards wearable technologies did not significantly influence behavioural intention.

In accordance with the empirical and theoretical arguments, the current study attempts to better understand these contradictory results in the current context of WFT continuance use. As EffExp has already been used to predict behavioural intention in the research mentioned earlier, drawing on their research, the current study also focuses on this determinant. According to the relevant applications regarding IT (i.e., WFT/SW), this study proposes a second hypothesis:

H1(b). Effort expectancy has a positive and significant impact on CUI.

Societal Pressure (SotPrss) → Continued Use Intention

Social influence, social factors and subjective norms collectively highlight the role of societal pressure in shaping individual behaviours. Social influence refers to how others' expectations affect thoughts, feelings, and actions, while subjective norms emphasise the perceived pressure from significant others to adopt specific behaviours. Similarly, constructs like social factors and body images highlight how societal expectations and group dynamics compel individuals to align their behaviour with perceived norms. These interconnected constructs illustrate that societal pressure often drives individuals to conform to acceptable or valued behaviours in their social circles. The following provides a detailed explanation of each, emphasising why the concept of societal pressure is replacing them. Societal pressure refers to the amount of pressure from society members, who include family, peers, and friends, to continue using technology (Cho, Cheng and Hung, 2009). For instance, users who perceive that friends/relatives are discussing/using WFT/SW may feel left out/unable to fit in, which, in turn, increases their intention to adopt WFT/SW and conform to their key referents. In other words, in the context of IT continuance use, users are likely to develop positive intentions towards IT continuance use if they believe that their key referent others will approve of their continued IT usage but negative intentions if they expect disapproval from their referents. Therefore, an examination of societal pressure, particularly the role of subjective norms, is required to analyse the continuance use of technology, as it is considered one of the dimensions of subjective norms (i.e., social influence).

Social influence is defined by Venkatesh, Thong and Xu (2012) as "the extent to which an individual perceives those important others (e.g., family and friends) believe they should use a particular technology" (p. 159). Additionally, Venkatesh *et al.* (2003) also demonstrated that the social influence construct has similarities to other constructs, such as subjective norms (TRA,

TAM2, TPB/DTPB, and Combined TAM and TPB (C-TAM-TPB)), social factors (MPCU), and image (IDT).

Social factors are described as “The individual’s internalisation of the reference group’s subjective culture and specific interpersonal agreements that the individual has made with others in specific social situations” (Thompson, Higgins and Howell, 1991, p. 126.) From the consumer viewpoint, people influence one another’s consumption and shopping habits, whether through a compliment, a recommendation, or simply by sharing a very positive or negative experience. Peers are not the only source of social influence on decision-making that can be recognised; purchase decisions are also influenced by the environment and trusted people. Therefore, individuals prefer to focus on and implement other people’s opinions in their daily lives in order to feel socially accepted (Benderlioğlu and Ata, 2021).

Building relationships and maintaining social connections are essential for individuals, as these interactions foster optimal psychological functioning and support the need for social bonds (Ryan, Deci and Grolnick, 1995). Today’s consumers participate in complex and extensive networks that are increasingly digital, creating dynamic ecosystems of interconnected individuals. WFT, particularly smartwatches, facilitates these networks by enhancing users’ capacity for social engagement and information-sharing. These devices integrate seamlessly into digital ecosystems, supporting a range of interactions, such as monitoring health metrics, participating in shared fitness goals, and enabling social comparisons through online platforms (Verhoef *et al.*, 2017).

Smartwatches extend beyond mere transactional use; they connect individuals not only with their own data but also with those of others in a virtual community, fostering an environment for real-time feedback and collective health motivation (Attig and Franke, 2019). This connectivity

through wearables contributes to a sense of belonging and interaction within users' social networks, encouraging continued use as a way to maintain both physical health and social engagement. Thus, wearables become embedded within users' social frameworks, integrating individual health goals with collective experiences that reinforce ongoing engagement.

A recent systematic review by Padyab and Habibipour (2021) explores some of the main social issues that could be among the adoption barriers to wearable technologies (i.e., over-reliance on technology and social pressure). Their interviews found that many users believe that over-reliance on wearable technology has invaded their social lives and affected personal communication, which has led to a loss of human interference. Another study examining Fitbit's impact on PA motivation found that forcing people into competition or involvement reduces their self-determined motivation and sense of autonomy (Kerner and Goodyear, 2017). Similarly, Goodyear, Kerner and Quennerstedt (2019) argue that unhealthy competition between a group of users (e.g., adolescents) who are getting involved in wearable devices' shared activities might bring peer pressure that leads to guilty feelings. In contrast, social prestige refers to how much a product is considered stylish, which is determined by its cost. The various wearable devices have different functionalities, affecting their price. Therefore, the more expensive the device, the more stylish it will be (Anderson and Lee, 2008; Chuah *et al.*, 2016), while people strive to show possessing such elegant commodities to express identity and social status.

Adapa *et al.* (2018) argued that adoption issues and barriers might differ according to the different application domains in wearables. Therefore, research has recommended that future studies examine the effects of barriers to technology adoption on social issues (Padyab and Habibipour, 2021). Furthermore, both Canhoto and Arp (2017) and Yousaf, Mishra and Gupta (2021) advised future investigation into the role of image and social influence in the continued use intentions of users of wearable devices and the part played by social influence (as a latent

construct was not included in their model), respectively. Likewise, Siepmann and Kowalczyk (2021) claimed that fulfilling the three psychological needs, competence, autonomy, and relatedness (originally proposed by Deci and Ryan, 2012), is crucial. In contrast, smartwatches address the need for relatedness because they allow individuals to interact and connect with family members and companions. Therefore, the authors recommended highlighting the social component of smartwatches.

Subjective Norm (SN) In the IT adoption/continuance intention literature, subjective norms, as in the TRA proposed by Fishbein and Ajzen (1975), are manipulated as social influence variables. The theorists defined a subjective norm as "the person's perception that most important people think he should or should not perform the behaviour in question" (Fishbein and Ajzen, 1975, p. 302). Moreover, it refers to the perceived social pressure to perform a particular behaviour or not (Ajzen, 1991, p. 188). A social norm demonstrates how people's perceptions and the wishes of others they care about can have an impact on them. In accordance with social norms, individuals are prone to undertaking particular behaviours to obtain acceptance within their circle of influence, considering both interpersonal and external environmental influences (Bhattacharjee, 2001; Al-Debei, Al-Lozi and Papazafeiropoulou, 2013).

Many researchers have demonstrated that subjective norms directly affect customers' adoption (e.g., internet banking; see Marakarkandy, Yajnik and Dasgupta, 2017; Yoon and Lim, 2020). Likewise, SNs are more important, whether prior to or in the early stages of innovation adoption, when users have limited direct experience in developing their attitudes (Tan and Teo, 2000). Similarly, the TPB suggests that SNs affect a person's psychological state, which leads to behavioural intention (Ajzen, 1985). It is linked to intention since people frequently act based on what they believe others should do. Venkatesh and Davis (2000) suggested that SNs could directly affect behavioural intention. Equally, Tarhini, Hone and Liu's (2014) empirical study

confirmed that SNs positively influence behavioural intention. Furthermore, a range of studies, for instance, on social networking (Al-Debei, Al-Lozi and Papazafeiropoulou, 2013; Yoon, Jeong and Rolland, 2015) and online gaming (Chang, Liu and Chen, 2014), show that SNs have a significant impact on continuous intention and behaviour.

In contrast, other studies have not found evidence of such a relationship. For instance, an earlier study reported that social norms do not significantly predict users' satisfaction or intention to continue using IT, particularly health apps (Yan *et al.*, 2021). Their findings indicate that social influences may still have an impact on technology usage but may not always be consciously recognised. Therefore, the researchers called for investigations of specific aspects, such as body image and social pressure.

Societal Pressure (SotPrss) and Body Image Societal pressure, like social pressure, is the amount of pressure to use technology that comes from society members, who are family, peers, and friends in this study (Cho, Cheng and Hung, 2009). With growing pressure from society, a greater number of calls for conformity and rational argument/persuasion from family, peers and friends are moving technology users towards using such devices and looking after their health (body image). As a result, whether users continue to use a WFT device would, at least partially, depend on their peers' behaviour and the pressure from their family members/friends because of their attitude towards the technology. That is, users are likely to be influenced by society members using health monitoring/tracking gadgets. This is because if most of society continuously uses a particular wearable device, an individual user may feel pressured to follow suit.

Body Image refers to a person's subjectively perceived physical self embedded in a mental construct (Myers and Biocca, 1992). According to the most widely recognised body image

theory, people with poor body image are concerned about how others perceive them. They avoid public venues where their bodies are exposed to other people, such as swimming pools and gyms (Thompson and Chad, 2002). Furthermore, the current wearable technology user's family, friends, and co-workers/peers represent possible influences and pressure to obtain a better body image, which, in turn, could be achieved by the sustained use of their wearable devices. Yim and Park's (2019) study revealed the important role of consumers' perceived body image in their evaluation and intention to adopt AR technology. Thus, the current study defines societal pressure in relation to body image as WFT/SW users' feelings towards health behaviour and how the influence of these groups will have a considerable impact on their continuance use of technology and obtaining a better body image to minimise social pressure.

From the above discussion, in response to these calls and in line with the latter study, the current thesis **replaces** the original UTAUT2's social influence antecedent with "societal pressure" (regarding body image in the WFT/SW context) and formulated the following hypothesis:

H1(c) Societal pressure has a positive and significant impact on CUI.

Perceived Enjoyment (PE_{nj}) → Continued Use Intention

Perceived enjoyment is conceptualised as a hedonic value (Beh *et al.*, 2021). As Davis *et al.* (1992) found in their study, perceived enjoyment significantly affects the intended use of new technology. Following Venkatesh (2000) and Davis *et al.* (1992), in this study, the researcher considers perceived enjoyment an important user belief that can lead to successful continuous use of a system/IT. It is defined as "the extent to which the activity of using the computer is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated" (Davis *et al.*, 1992, p. 113). Perceived enjoyment, originally drawn from TAM3, is presented in different contexts. For instance, it has been used extensively in studies on IT

adoption, such as in the smartphone context (Chtourou and Souiden, 2010). Similarly, in the TAM model, perceived enjoyment has a direct impact on satisfaction and usage intention (Agrebi and Jallais, 2015). It has also been found to affect perceived usefulness and jointly affects behavioural intention in banking (Yoon and Lim, 2020) and activities such as video calling (Zhou and Feng, 2017). In their work, Oyibo and Vassileva (2020) found that perceived enjoyment relates to layout and colour scheme in the case of websites.

Studies in IT/IS and consumer behaviour have theorised that various constructs related to hedonic motivation (e.g., enjoyment) are important in consumer product and/or technology use. After Venkatesh, Thong and Xu (2012) integrated hedonic motivation to complement UTAUT's strongest predictor, emphasising utility, more recent researchers used UTAUT2 to study hedonic technologies (Gao, Li and Luo, 2015; Molavi, Ghosh and Strebler, 2020). Hedonic motivation reflects the feelings of pleasure and enjoyment experienced while using these technologies. i.e., digital platforms (Kuriakose and Nagasubramaniyan, 2024). Therefore, developing UTAUT2 seems to be a rational approach to studying the continuance use of disruptive technologies such as WFT/SW. This model is still in existence and is recommended in the literature as one of the most influential theories of human behaviour.

Furthermore, according to Self-Determination Theory, extrinsic motivation describes the behaviour driven by external achievements and rewards (Deci and Ryan, 1985). In contrast, intrinsic motivation refers to internal rewards, such as pleasure and satisfaction from an activity. Prior studies have considered perceived enjoyment as a critical intrinsic and hedonic motivation, adding to the extrinsic motivation for adopting IT products/services (Venkatesh, 2000). Enjoyment belongs to intrinsic motivations and arises when all three basic psychological needs (competence, autonomy, and relatedness) are satisfied by the activity performed (Ryan *et al.*, 2006). Within the research field of wearable technology adoption, Choi and Kim (2016) found a

strong positive effect of perceived enjoyment on the attitude towards using smartwatches. Krey *et al.* (2019) demonstrated that expected enjoyment, indirectly over attitude, enhances the intention to adopt a smartwatch.

Previous studies have indicated perceived enjoyment or playfulness as a powerful predictor of WFT adoption (Rheingans, Cikit and Ernst, 2016; Randriambelonoro, Chen and Pu, 2017). The enjoyment or excitement obtained from using a wearable device influences individuals' intention to use the gadget. This provides a hint that when determining whether or not to utilise these devices, people should consider the pleasure-bringing qualities of the technology (Gimpe, Nißen and Görlitz, 2013; Gao, Li and Luo, 2015). Likewise, previous research empirically confirmed the saliency of the enjoyment concept in explaining IT continuance use (Thong, Hong and Tam, 2006) as it is particularly crucial in the case of hedonic IT.

From the points considered above, perceived enjoyment as a construct becomes an important determinant explaining consumers' adoption, and, eventually, continued use intention, which needs to be studied. Users could continue to use a wearable fitness device due to the “enjoyment” factor. Therefore, this study hypothesises the following:

H1(d). Perceived enjoyment has a positive and significant impact on CUI.

Perceived Device Annoyance (DAnoy) → Continued Use Intention

Research on IT usage has focused primarily on cognition-oriented rational models. However, Ortiz de Guinea and Markus (2009) argued that the continuance use of IT is also shaped by emotive concepts, such as perceived annoyance (perceived device annoyance in this study). Thus, another device-related factor that has been identified as important for the use of WFT is a distraction from the focal activity (Kim, 2014; Randriambelonoro *et al.*, 2015; Coorevits and

Coenen, 2016), which has also been identified as an important barrier to continuous WFT use (Siepmann and Kowalczyk, 2021). It is also a novel construct, suggested as an emotional (negative) factor or driver which captures the feeling of being bothered by notifications from the WFT/SW (subjective overexposure). Thereby, in this study, the researcher integrates device annoyance within the UTAUT2 model and hypothesises that,

H1(e). Perceived device annoyance has a negative and significant impact on CUI.

Facilitating Conditions (FCons) → Continued Use Intention

Facilitating conditions are defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh *et al.*, 2003, p. 447). Three variables were integrated from the available models tested in the literature: "Perceived behavioural control (TPB; combined TAM-TPB)"; "Facilitating conditions (MPCU)"; and "Compatibility (IDT)". Facilitating conditions also refers to "consumers' perceptions of the resources and support available to perform a behaviour" (Venkatesh, Thong and Xu, 2012, p. 159). Such a construct has not been widely investigated in the individual/group user context because, originally, this factor was developed and examined for organisational users' adoption of technology. For instance, various studies have confirmed the importance of FCons on the behavioural intention of users across multiple contexts, such as m-commerce (Tarhini *et al.*, 2019), m-learning (Chao, 2019; Mojarro Aliaño *et al.*, 2019), e-banking (Farah, Hasni and Abbas, 2018), and healthcare (Quaosar, Hoque and Bao, 2018).

In comparison, Hoque and Sorwar (2017) found that FCons are not a significant predictor in determining m-health services adoption by the elderly in developing countries such as Bangladesh, and Talukder *et al.* (2020) found similar findings in relation to WHT use by the

elderly. Dhir, Kaur and Rajala (2018) also confirmed that FCons had no significant influence on users' intentions to photo-tag on social networking sites. A systematic review and meta-analysis conducted by Chiu, Oh and Cho (2021) showed that although UTAUT2 has been used as a fundamental model of consumer wearable technology adoption (i.e., smartwatches and wearable healthcare devices), several factors, such as facilitating conditions, are not always significantly related to the adoption intention regarding wearable fitness devices. Hence, it is essential to determine the effects of FCons using UTAUT2 in the WFT/SW context to verify this contradiction.

Some wearable devices may have a complex user-application interface, while others may show an easier use. Thus, FCons have a significant effect on consumers' intention to use wearable technology devices, which is consistent with other studies on the adoption of wearable technology such as smartwatches among Chinese consumers (Talukder *et al.*, 2019) and Indian IT professionals (Kranthi and Asraar Ahmed, 2018), fitness trackers (Reyes-Mercado, 2018), and smart wearable gadgets (Li *et al.*, 2019).

The current study defines FCons as the infrastructure, resources (internet connectivity, device requirements), and physical conditions required to use any WFT device. Thus, in line with the findings in the literature, the current study suggests that users who perceive having more control over the external conditions that enable or constrain their IT usage are more likely to continue using the technology. Similarly, this study deems that an increase in FCons influences an increase in continued intention to use WFT/SW.

The above discussion resulted in the following hypothesis:

H1(f). Facilitating conditions have a positive and significant impact on CUI.

Technology Habit (TechH) → Continued Use Intention

Physical Activity and Technology Habits

Physical activity (PA) refers to a set of attitudes, beliefs, practices, and behaviours that have been socially formed. The term has been defined as "any bodily movement produced by skeletal muscles that requires energy expenditure, referring to all movement, including during leisure time, for transport to get to and from places, or as part of a person's work or domestic activities" (World Health Organization: WHO, 2024). PA includes informal activities such as exercising, playing, walking, running, and dancing, and formal activities such as practising, physical training and contending within specified rules in competitions and fixed environments (Girginov *et al.*, 2020). Participants can create mutually close social relationships and confirm their sense of self by acquiring recognition and social status in formal and informal PA forms. Their interest in PA and sports is heavily influenced by their own social status, recognition, and identities.

Wearable fitness devices that track PA in real time have increased immensely in popularity in recent years as more individuals have welcomed them. The devices can improve users' PA levels and foster healthy living habits due to their superior portability and user-friendly interface (Bietz *et al.*, 2016). These wearables have numerous benefits that have a positive impact on users' PA levels. These advantages include goal setting, workout tracking, step-counting, stair-counting, or social features. In addition, they are known to improve several health outcomes, such as reducing heart disease and diabetes and lowering the wearer's BMI (Giddens, Leidner and Gonzalez, 2017). For instance, a study by Cheng Chia, Anderson and McLean (2019) employed content analysis to examine how fitness trackers reduce sedentary behaviour and align with PA guidelines. These devices thus offer a promising avenue for implementing PA interventions that are both cost-effective and accessible to a broad population.

Research consistently demonstrates that WFTs (e.g., pedometers and Fitbits) have a positive impact on the duration and frequency of moderate-to-vigorous physical activities, contributing to healthier and more active lifestyles (Pellegrini *et al.*, 2012; Butryn *et al.*, 2016; Jakicic *et al.*, 2016). These devices also promote goal-oriented behaviours, encouraging users to engage in structured activities to achieve specific objectives (Kolt *et al.*, 2012; Glynn *et al.*, 2014; Jarrahi, Gafinowitz and Shin, 2018).

However, a dependence on the subjective perceptions of small participant samples is a major flaw in the existing studies (Piwek *et al.*, 2016). Wearable fitness devices are designed to provide users with cognitive feedback on their bodily functions and PA and offer opportunities for social interactions. For these reasons, this study will extend the current understanding of the role of fitness devices in increasing users' sustained use of wearable technology, enhancing users' health and well-being, and efficiently motivating people to be active.

In comparison, physical inactivity poses a significant global public health risk (La Barbera and Ajzen, 2024). Wearable devices, increasingly integrated into daily routines, offer promising solutions by encouraging regular PA (Ridgers *et al.*, 2017). However, their long-term effectiveness in sustaining health behaviours, such as regular exercise, remains inconsistent, with mixed findings on user adherence and behaviour change (Brickwood *et al.*, 2019). Understanding why some users successfully alter their habits while others do not highlight the need for deeper insights into systematic behaviour changes driven by wearables.

Technology Habit (TechH) Habit is one of the three constructs introduced in the UTAUT2 model by Venkatesh, Thong and Xu (2012) and is instrumental in explaining technology use. It is defined both as a reflection of prior behaviour and as the extent to which an individual perceives a behaviour to have become automatic. This dual conceptualisation captures the cognitive and

behavioural dimensions of habitual usage, making it essential for understanding user engagement over time. Studies such as those by Lin, Wang and Hsu (2017), Nascimento, Oliveira and Tam (2018), and Bölen (2020) define a habit as an automatic behavioural tendency resulting from repeated actions, emphasising its role in promoting unconscious, familiar patterns of technology use.

Research has consistently demonstrated the critical role of habit in predicting behavioural intention and use behaviours. For example, Van Winkle *et al.* (2019) highlighted that technology habits significantly influence the intention to use mobile devices in leisure settings (festivals), underlining the importance of incorporating this construct into models of technology engagement. Limayem *et al.* (2007) showed that habit moderates the effect of BI on actual behaviour. This finding was further reinforced by Schomakers *et al.* (2022), who demonstrated the pivotal role of habit in shaping use intentions in mHealth care apps. Similarly, Liu *et al.* (2023) identified a significant positive association between habit and BI for mHealth services (all are technological applications). These collective findings show the critical role of habit in contexts such as WFT, in which accessibility and integration into daily routines are paramount.

To align with this specificity, the current study refines the construct from "habit" to "**technology habit**", ensuring a precise focus on habitual behaviours tied to WFT usage. This distinction underscores the unique interplay between users' technological engagement and continuance intentions. This change ensures alignment with studies that emphasise how habits formed through repeated interactions with technology, such as WFT, differ from general behavioural habits by incorporating both cognitive and device-specific dimensions (Venkatesh, Thong and Xu, 2012; Van Winkle *et al.*, 2019). Defining habit in this setting as "technology habit" better captures the automaticity of user engagement with technological devices, addressing nuances

such as habitual usage patterns and their impact on continuance intentions in the context of digital tools (Limayem *et al.*, 2007; Liu *et al.*, 2023).

Incorporating technology habits into the model enhances its ability to bridge deliberate decision-making and automatic behaviours. This aligns with UTAUT2's advancements and addresses the need to analyse sustained WFT adoption. By capturing both intentional and habitual dimensions of user behaviour, the model provides a comprehensive framework for understanding the continued use of wearable technologies.

Therefore, the following hypothesis is posited:

H1(g). Technology habit has a positive and significant impact on CUI.

Price Value (PValu) → Continued Use Intention

Venkatesh, Thong and Xu (2012) argued that personal users often tolerate extra monetary charges compared to organisation employees; therefore, cost and pricing value may significantly impact consumers' use of technology. Dodds, Monroe and Grewal (1991) define the actual price as “an objective external characteristic of a product that consumers perceive as a stimulus” (p. 308). Further, perceived device value is individuals' total evaluation of a product's usefulness based on their perception of what they get (e.g., benefits) and what they have paid (e.g., costs) (Kalantari, 2017).

According to Venkatesh, Thong and Xu (2012), price value is “the consumers' cognitive trade-off between the perceived benefits of the applications and the monetary cost for using them” (p. 161), whereby a relationship exists between price value and consumers' intention to use technology. Also, when the advantage of using a technology is greater than the associated monetary costs and price value, the price value will have a positive influence on intention since

the technology is regarded as a bargain (Chen *et al.*, 2021), so PValu, in this case, is considered constructive (Kranthi and Asraar Ahmed, 2018).

The literature indicates that perceived price value, that is, advantages minus expenses, encourages positive intention to use wearables (Clawson *et al.*, 2015; Canhoto and Arp, 2017). Equally, Gualtieri, Rosenbluth and Phillips (2016) found that the perceived value of a wearable device is positively related to its acceptance and use. Moreover, the price can substantially influence consumers' technology use through pricing structure. For example, Basoglu, Ok and Daim (2017) uncovered that price was one of the factors (product characteristics) influencing consumers' adoption of smart glasses. It also moderates the relationship between satisfaction and continuance intention (Hidayat-ur-Rehman *et al.*, 2020). Further, PValu was found to have a significant impact on smartwatch adoption among South Koreans (Kim and Shin, 2015; Jung *et al.*, 2016; Yang *et al.*, 2016) and French users (Mani and Chouk, 2017). Conversely, other studies have incorporated the cost construct in their investigation and shown a negative effect of cost on individuals' decision to use fitness wearables (Gualtieri, Rosenbluth and Phillips, 2016).

As a consequence, in order to gain further insights into the literature, price value is included as a predictor of the CUI of technology. Based on this rationale, the following hypothesis is proposed:

H1(h) Price value has a positive and significant impact on CUI.

Technology Upgradability (TUpG) → Continued Use Intention

A comprehensive review of the literature revealed that the term “upgradability” has been used in different contexts, such as economic, environmental, cloud computing and consumer electronics

settings (see Table 3-1). However, such a construct relevant to the current study has yet to be assessed within user technology adoption and continuance use context.

Upgradability has appeared in management science in relation to high-technology markets. For instance, Pae and Hyun (2006) attempted to demonstrate the importance of switching costs in the success of corporate technology advancement strategies. They argued that shifting to a different technology may seem appealing to consumers. Moreover, switching costs influence the effectiveness of technological upgrades, which encourages users to commit to incumbent technology. Existing technology can be upgraded in steps by upgrading individual modules instead of revamping the entire product, lowering switching costs when undergoing modular upgrades rather than an entire technological transition. Upgrading technology enables users to transition seamlessly to newer, more advanced technological offerings. Manufacturers respond by developing a broader range of compatible products, aligning with a standardized technological framework facilitated by upgrades while also allowing users to apply their skills across different brands. Consequently, a complete shift to new technology incurs higher consumer switching costs compared to upgrading the existing technology.

Technology upgradability has been used in a transformative technology context (Schmidt *et al.*, 2019), which investigated the benefit of upgradability in terms of maintaining receivers' immunity against spoofing. The role of the upgradable architecture of cloud computing in data centre architecture (Csernai *et al.*, 2013) and software upgradability in IoT has been visible in the literature (Yaqoob *et al.*, 2017). In addition, another study on consumer electronics evaluated the economic and environmental implications of modular upgradability (Agrawal, Atasu and Ülkü, 2016) and its role in environmental impact as a green design strategy. Likewise, in the economics literature, various studies have explored product design upgrade strategies for a circular economy and sustainability (van Loon, Diener and Harris, 2021) and in the case of

toothbrush circularity (Vimal *et al.*, 2021). Khan *et al.* (2018) assessed and summarised the available literature on product upgradability, recognising upgradability as a crucial strategy for extending product lifespans within Product–Service Systems, benefitting both sustainability and consumer satisfaction. They also highlighted the challenges of implementation, such as design constraints, costs, and consumer awareness, while advocating for its integration into circular economy-focused business models.

Khan *et al.* (2018) define upgradability as a strategy for extending the lifespan of products by integrating modular features or design flexibility, ensuring devices remain relevant over time. Building on the latter definition, the current study defines upgradability as "the ability/tendency of technological products/devices, i.e., SWs, to be improved in functionality in a way that matches users' ever-changing lifestyle, including a software program that provides added enhancements over an earlier version or a hardware device that provides greater performance than an earlier model". Therefore, the current study will contribute to the literature on consumer technology adoption by adding the upgradability construct to its proposed model.

From the technology usability perspective, consumers' decisions to continue/abandon their technology could be based on how they import/export and/or retrieve/lose their data from one technology version/generation to another, despite being within the same brand or a different one. Thus, the current study includes upgradability as another determinate in the proposed conceptual model, as the following hypothesis warrants investigation:

H1(i). Technology upgradability has a positive and significant impact on CUI.

Table 3–1 Upgradability in different contexts

Author(s)	Title	Year	Keywords	Journal title	Context	Key argument(s)
Mehra, Rajput and Paul (2022)	Determinants of adoption of latest version smartphones: Theory and evidence	2022	Smartphones; Android; OS version; Behavioral intention; Adoption UTAUT; DOI; TAM; Structural modelling; Perceived usefulness	Technological Forecasting and Social Change	Smartphones	The study examined the factors influencing consumers to buy the newest/latest version of Android-based smartphones.
Vimal et al. (2022)	Circular function deployment: A novel mathematical model to identify design factors for circular economy	2021	Quality function deployment; Circular product design; Circular economy; Circular function deployment; Circularity metrics; Product circularity score	Environment, Development and Sustainability	Product design/economy	The study assessed a toothbrush's circularity metrics (upgradability and adaptability) as a case product.
van Loon, Diener and Harris (2021)	Circular products and business models and environmental impact reductions: Current knowledge and knowledge gaps	2021	Circular economy; Environmental impact; Life-cycle assessment; Rebound effects; Renewable energy; Sustainability	Journal of Cleaner Production	Life-cycle assessment /economy	The research studied product design strategies for a circular economy (e.g., upgradability).
Schmidt et al. (2019)	Software-defined radio GNSS instrumentation for spoofing mitigation: A review and a case study	2019	Terms—Global navigation satellite systems (GNSS); Global positioning system (GPS); Instrumentation review; Interference mitigation; Software-defined radio (SDR)	IEEE Transactions on Instrumentation and Measurement	Transformative technology/software	How (receiver) upgradability is an important advantage for maintaining their immunity against spoofing.

Khan et al. (2018)	Review on upgradability—A product lifetime extension strategy in the context of product–service systems	2018	Circular economy; Life cycle; Product lifetime extension; Product service systems; Remanufacturing; Upgradability	Journal of Cleaner Production	Product–service systems/economy	The paper aimed to identify and summarise the product upgradability available in the literature.
Yaqoob et al. (2017)	The rise of ransomware and emerging security challenges in the Internet of Things	2017	Authentication; Internet of Things; Ransomware; Security; Trust	Computer Networks	Security concerns in IoT	The paper presented the ransomware attacks and security concerns in the IoT, highlighting the lack of upgradability of security software.
Agrawal, Atasu and Ülkü (2016)	Modular upgradability in consumer electronics: Economic and environmental implications	2016	Consumer electronics; Industrial ecology; Modularity; Product design; Sustainable consumption; Upgradability	Journal of Industrial Ecology	Consumer electronics/economy	The study investigated the limited adoption of modular upgradability in consumer electronics.
Agrawal and Ülkü (2013)	The role of modular upgradability as a green design strategy	2013	Modularity; Green product design; Sustainability; New product development; Sustainable operations	Manufacturing and Service Operations Management	Manufacturing and firms' development	The study investigated the role of modular upgradability in the environmental impact of some product categories.

Csernai et al. (2013)	Incrementally upgradable data centre architecture using hyperbolic tessellations	2013	Cloud computing; Data centre; Distributed operation; Greedy routing; Hyperbolic tessellation; Incremental upgrade	Computer Networks	Cloud computing	The research examined the role of upgradable architecture in data centre architecture.
Pae and Hyun (2006)	Technology advancement strategy on patronage decisions: The role of switching costs in high-technology markets	2006	Preannouncement; Switching costs; Technology compatibility; Technology patronage; Upgradability	Omega: The International Journal of Management Science	Switching costs	The paper attempted to demonstrate the importance of switching costs in the success of corporate technology advancement strategies—technology upgradability, complementary technology and compatibility promotion.

c) Relationship Between Continued Use Intention and Continued Use Behaviour (CUI → CUB)

An individual's behavioural intention can be equated to self-instruction, which allows that person to perform a specific behaviour (Triandis, 1989). Ajzen (1991) emphasised the importance of intentions in capturing the motivational factors that drive behaviour. Thus, behavioural intention indicates actual usage behaviour (Kijisanayotin, Pannarunothai and Speedie, 2009). Likewise, Yang *et al.* (2016) highlighted that behavioural intention refers to people's perception of their willingness to use services/products. Several empirical studies conducted in various IT usage contexts have demonstrated that users' intention to use IT is the most influential factor in shaping their IT usage behaviour (Bhattacharjee and Lin, 2015). Furthermore, most current research on IT continuance maintains theoretical continuity with the IT adoption literature, emphasising that IT continuance use is primarily driven by continued use intention. Numerous empirical investigations have extensively validated the positive relationship between continuance behavioural intention and actual use, drawing on foundational theories from social psychology (Bhattacharjee, 2001; Thong, Hong and Tam, 2006). In addition, Bhattacharjee (2001) suggests that when individuals first adopt technology, they develop psychological motives that influence their desire to continue using it. Consequently, the market share of any IT company is largely determined by the number of early adopters and continuous users. Moreover, continuous users play a critical role in ensuring the long-term feasibility of a technology (Eriksson and Nilsson, 2007).

The growing market diffusion of wearable fitness devices, and smartwatches in particular, has shifted the attention of both practitioners and academics from initial adoption to investigating factors that lead to continuance usage (for a review, see, for example, Hong, Lin and Hsieh, 2017; Dehghani, Kim and Dangelico, 2018). Previous research shows that wearable devices allow individuals to take charge of their health and be active. However, users should adopt and sustain

the use of these wearables to achieve their targets rather than abandoning them soon after purchase. Beyond this, researchers have debated that technology adoption factors vary from those for sustained use. For instance, Canhoto and Arp (2017) observed that elements that signify a device's potential to collect activity data are critical for adoption. The device's mobility and durability, on the other hand, are crucial for long-term use.

In the current study, this generalised relationship should also remain true. In other words, once consumers have developed an intention to continue using an IT device (in this case, a wearable fitness device/SW), it is quite likely that they will continue using it in the future. In the following, this research study sheds light on how technology use is expected to change over time and whether users are still using their WFT/SW, which is investigated in the longitudinal design. Thus, this study posits the following hypothesis:

H2. Continued use intention has a positive and significant impact on CUB.

3.1.2 Mediating Role of Continued Use Intentions (CUI)

Perception of factors drives consumers' intention to adopt innovations such as wearable fitness devices and smartwatches, which, in turn, influences their long-term use behaviour. The relationship between these factors and continued use behaviour suggests that continued use intention mediates this relationship. In other words, CUI is the key mechanism that explains how and why these factors lead to the continued use of wearable fitness devices. This understanding forms the basis for the hypothesis that CUI mediates the relationship between perception factors and CUB.

H3(a) Continued use intention mediates the relationship between performance expectancy and CUB.

H3(b) Continued use intention mediates the relationship between effort expectancy and CUB.

H3(c) Continued use intention mediates the relationship between societal pressure and CUB.

H3(d) Continued use intention mediates the relationship between perceived enjoyment and CUB.

H3(e) Continued use intention mediates the relationship between perceived device annoyance and CUB.

H3(f) Continued use intention mediates the relationship between facilitating conditions and CUB.

H3(g) Continued use intention mediates the relationship between technology habit and CUB.

H3(h) Continued use intention mediates the relationship between price value and CUB.

H3(i) Continued use intention mediates the relationship between technology upgradability and CUB.

3.1.3 Moderating Hypotheses

In the following, the researcher sheds light on the role of personality dimensions in continuance use intention by examining the personality traits model. This section discusses the personality-related individual difference variables (user-specific personal characteristics) that the researcher proposes to play a role in the adoption and continued usage of wearable technology. Figure 3-1 shows that the assumed effect is summarised in the conceptual framework. The researcher presumes that consumers' psychological traits (both general personality and technology user-specific characteristics) are moderators between extended UTAUT2's main factors (performance expectancy, effort expectancy, societal pressure (regarding body image), perceived enjoyment, perceived device annoyance, facilitating conditions, technology habit, technology upgradability and price value) and consumers' continued use intention and continued use behaviour of wearable technology.

In summary, the primary focus is on moderating variables, including personality traits (i.e., user-specific personal characteristics) in the context of wearable fitness devices. Thus, the following section will elaborate on the proposed moderators in hypothesising the relationships between the extended UTAUT2.

Personality Traits Model

Understanding personality can be achieved through several lenses, and one of the most popular is the Big Five Personality Inventory (Terracciano and Costa, 2004). Personality refers to an individual's stable, consistent, and distinct set of mental and emotional characteristics. Personality is "all attributes, qualities, and characteristics that distinguish individuals' behaviour, thoughts, and feelings" (Gerard and Sanjay, 2015, p. 283).

Although numerous traits have been revealed in personality research, the Five-Factor Model of personality, also called the Big Five (Goldberg, 1990; Costa and McCrae, 1992), was extensively

applied to identify the most important dimensions of personality. The FFM explains and measures human personality due to mainly biologically determined "basic tendencies" and can be described by five superordinate constructs: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (McCrae and Costa, 1987; Costa and McCrae, 1992). Questionnaires such as the Big Five Inventory (BFI) (John *et al.*, 1991) were conventionally used to determine a user's personality.

In the next section, the researcher will elaborate on the model and its relationship to technology adoption and continued use, highlighting relevant literature. This will be followed by a thorough explanation of the rationale behind choosing **specific personality traits** while omitting others deemed less relevant to the study context.

Relationship Between Personality Traits and Technology Adoption, CUI, and CUB

Continued use of wearable technology may rely upon individual characteristics, such as personality traits, as one of the influential factors. As stated above, personality is "all attributes, qualities, and characteristics that distinguish individuals' behaviour, thoughts, and feelings" (Gerard and Sanjay, 2015, p. 283). Kajonius and Johnson (2018) further termed personality traits "consistencies in affect, thinking, and behaviour that tend to be stable across situations and timespans, developing predictably throughout life" (p. 127).

As referred to above, the FFM, developed by Goldberg (1990) and Costa and McCrae (1992), is widely recognised as the most comprehensive framework for identifying personality traits. It is often regarded as the state-of-the-art personality measurement model. It explains and measures human personality through biologically influenced "basic tendencies": Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism—collectively known as the Big

Five (McCrae and Costa, 1987; Costa and McCrae, 1992). Traditional tools such as the BFI are commonly employed to assess these traits (John *et al.*, 1991).

Research work by Deci, Olafsen, and Ryan (2017) identified that Gordon Allport, an early pioneer, developed the personality trait model. It is considered the most empirically supported framework, with decades of study to support it. It is a widely used personality test model in scientific research, whereby all the factors determine human personality, psyche, and temperament. According to John and Srivastava (1999), the study of personality is conceptualised from various theoretical perspectives. Only the most recent construct of the Big Five has succeeded in defining clear domains while facilitating the grouping of variables, resulting in agreement on defining basic personality traits. The description of the five personality traits is summarised in Table 3-2 and further elaborated below.

Table 3–2 Five personality traits of the FFM (Costa and McCrea, 1992)

Factor	Description
Agreeableness (friendly/compassionate vs. challenging/callous)	Pro-social attitudes towards others, including traits such as trust and tendermindedness.
Conscientiousness (efficient/organised vs. extravagant/careless)	Impulse control behaviours that help with a goal and task completion, such as planning, organising, and delaying gratification.
Extraversion (outgoing/energetic vs. solitary/reserved)	Sociability and an energetic approach to the world.
Neuroticism (sensitive/nervous vs. resilient/confident)	The contrast in emotional stability includes feelings such as anxiety and sadness.
Openness (inventive/curious vs. consistent/cautious)	The extent to which an individual's mind and experiences are complex and original.

The five factors of personality are each described by six aspects, which are sets of interconnected traits called facets/sub-traits. The aspects are as follows: Openness to experience (fantasy, aesthetics, feelings, actions, ideas, and values); Conscientiousness (competence, order,

dutifulness, achievement-striving, self-discipline, and deliberation); Extraversion (warmth, gregariousness, assertiveness, activity, excitement-seeking, and positive emotions); Agreeableness (straightforwardness, altruism, trust, compliance, modesty, and tendermindedness); and Neuroticism or emotional instability (anxiety, anger, depression, self-consciousness, impulsiveness, and vulnerability). Both Lakhal and Khechine (2017) and Bano, Shah and Ali (2019) have presented definitions of the five personality factors as well as some examples of correlated personality traits (see Table 3-3) as outlined by John and Srivastava (1999).

Table 3–3 Descriptions of the Big Five Factors of Personality Traits (John and Srivastava, 1999)

Some traits characterising a student with a high score	Five factors of personality	Some traits characterising a student with a low score
Worried, nervous, emotional, maladjusted, hypochondriac	Neuroticism	Calm, relaxed, phlegmatic, robust, secure, satisfied
	Could identify students prone to psychological distress, unrealistic ideas, needs or excessive desires and inappropriate coping strategies.	
Sociable, active, talkative, open to others, optimistic, fun-loving, affectionate	Extraversion	Reserved, sober, undemonstrative, remote, task-oriented, discreet, quiet
	Assesses the quantity and the intensity of interpersonal interaction, the level of activity, the need for stimulation and the ability to have fun.	
Curious, eclectic, creative, original, imaginative, unconventional	Openness to experience	Conformist, realistic, exclusive, poorly developed sense of art
	Assesses proactive research and ability to appreciate experiences, tolerate uncertainty and explore.	
Compassionate, easy-going, confident, helpful, indulgent, gullible, frank	Agreeableness	Cynical, rude, defiant, uncooperative, vindictive, ruthless, irritable, manipulative
	Assesses the quality of interpersonal orientation of the student along a continuum, from compassion to antagonism, in ideas, feelings and actions.	
Organised, reliable, hardworking, disciplined, punctual, meticulous, careful, ambitious, persevering	Conscientiousness	Aimless, unreliable, lazy, careless, lax, careless, indecisive, hedonistic
	Assesses the degree of organisation, perseverance, and motivation in the behaviour of a student who is oriented towards a goal. Compares a reliable and meticulous student to another that is nonchalant and neglectful.	

Personality Traits in Previous Studies

The Five-Factor Model of personality has been extensively studied and validated in the scientific literature, making it the most widely accepted framework in sociological and behavioural sciences for describing personality. It has become widely applicable and acceptable to numerous research studies of human personality and its influence on different human endeavours. As a result, scholars have recently discovered strong links between personal characteristics, product preferences and buying decisions that have long been analysed (Buettner, 2017), including e-satisfaction and repurchase intention (Mansourimoayyed *et al.*, 2020). Moreover, Selden and Goodie (2018) reviewed the effects of the FFM of personality traits on social network analysis, network structures, and perceptions of structure. Similarly, the study of human personality has become notably important with an impact on many elements of consumer behaviour towards social media activities/platforms for sustainable fashion (Salem and Alanadoly, 2021), its impact on word of mouth (Adamopoulos, Ghose and Todri, 2018), academic success (Nofle and Robins, 2007), online academic self-efficacy in Moodle (Rivers, 2021), online gamified surveys (Triantoro *et al.*, 2020), cybersecurity (McBride, Carter and Warkentin, 2012), and even smoking (Malouff, Thorsteinsson and Schutte, 2006).

Furthermore, other studies have concluded that personality might influence technology skills (Carlos Barrera, 2021), smartphone usage (Peltonen *et al.*, 2020; Stachl *et al.*, 2020), and e-government portal use (Venkatesh, Sykes and Venkatraman, 2014). Recent research has examined how personality traits affect technology adoption, especially among engineers, for innovation and technology development (Williamson, Lounsbury and Han, 2013) and agricultural production decisions (Ali, Bowen and Deininger, 2020). Further examples of the role of personality traits are found in life aspirations and well-being (Visser and Pozzebon, 2013), the adoption of Google Glass wearables (Rauschnabel, Brem and Ivens, 2015), the motivational costs of wearing

activity trackers in actual users (Attig and Franke, 2019), and the perceptions of trust, usability, and motivational impact on wearable fitness devices (Rupp *et al.*, 2018).

Recent literature proposes a deeper relationship between personality traits and wearable tracker usage, as smartwatches are increasingly integral to daily life (Attig and Franke, 2019). Smartwatches enhance users' health and well-being and improve people's ability to connect with their preferred features. Thus, it is recommended that users continue using wearables that embrace those features. Therefore, understanding the influence of personality traits on smartwatch continuance intention and usage patterns is essential, as these traits may significantly shape how and why individuals remain engaged with wearable technology.

However, after many years of research conducted to understand how wearable devices are adopted, the question remains unanswered regarding the relationship between someone's personality and how that individual uses wearables, that is, smartwatches, in order to predict actual and continued future use. Several conceptualised psychological measures are proposed for assessing personality. Here, the Big Five personality traits model is applied to investigate how different traits are manifested in SW adoption and usage. Unlike other work, this study explores the factors affecting consumers' continuance intentions, from the user perspective, towards using wearable technology. It also goes beyond and contributes to the technology adoption literature by understanding how personality traits moderate the relationship between the CUI and CUB of WFTs. It is further noted that personality traits have not yet been investigated as moderators of the proposed related wearable device features and have not previously been tested together (Attig and Franke, 2019, p. 213).

Based on the above, users perceive things differently due to their personality traits. It has also been highlighted that "personality traits are often one of the fundamental theories explaining the

characteristics affecting users' subsequent behaviour" (Ngai, Tao and Moon, 2015, p. 34). Thus, personality traits can be significant in explaining the continuance use of different technologies (Mansourimoayyed *et al.*, 2020) and, therefore, it is critical that theoretical and analytical efforts emphasise the importance of these ubiquitous technologies. Hence, this research aims to identify the variation in personality traits (Rivers, 2021) that could influence users' continued use intention and continued use behaviour toward wearable fitness devices.

3.1.4 Study Moderators

The technology continuance issue has attracted great attention in the IS research field (Chang and Zhu, 2012; Oghuma *et al.*, 2016; Bölen, 2020; Marinković, Đorđević and Kalinić, 2020; Tsai, Lee and Ruangkanjanases, 2020; Chen, Chan and Hashim, 2023). Despite this, the role of personality traits as moderators remains underexplored, representing a critical gap in understanding individual differences in continued use behaviours. To address this, this research study integrates three specific personality traits as moderators: Openness to Technological Innovativeness (OTTI), Conscientiousness in Health (CinH), and Neuroticism (Neu), selected for their contextual relevance to WFT continuance use. The research strategically omits agreeableness and extraversion by prioritising internal psychological traits over external social factors. However, social factors are still acknowledged, particularly societal pressure (as a predictor), which aligns with the social influence dimension of subjective norms. This targeted approach ensures a focused investigation into health-oriented, sustained technology use while avoiding an overly broad scope that could dilute the study's contributions and practical relevance.

Relevance of OTTI, CinH, and Neu

The following text elaborates on the selected personality-related individual variables that the researcher assumes play a role regarding the continuance use of WFT. Research indicates that OTTI is a vital personality trait for this study, representing goal-oriented individuals who are socially

connected and adaptable to innovation and change (Ismail *et al.*, 2023). Unlike extraversion or agreeableness, openness uniquely captures both the social and cognitive dimensions critical for understanding the continuance use of WFT. Research shows that individuals with a high degree of openness are more likely to adopt and sustain the use of novel technologies, including mHealth apps and non-Apple smartwatches (Hsiao, 2017), which aligns closely with the current thesis context. By the same token, CinH has a significant influence on health-related behaviour and promotes the continued use of health technologies, such as fitness apps (Hong, 2011; Alshawmar, Tulu and Hall-Phillips, 2022). Individuals with higher health consciousness (HC) are more aware of their health conditions and motivated to adopt healthier lifestyles (Cho, Park and Lee, 2014). They actively seek health-preserving information (Rodgers *et al.*, 2007), track their health status (Dutta-Bergman, 2004), and engage in fitness activities (Kraft and Goodell, 1993), leading to adherence to behaviours such as regular exercise (Rupp *et al.*, 2018).

Finally, **Neu** is a pivotal moderator in this study due to its profound impact on technology use and stress management behaviours (Barnett *et al.*, 2015), and is characterised by emotional instability, anxiety, and a tendency towards negative emotions (Terracciano and Costa, 2004). Neurotic individuals are particularly susceptible to stress and heightened emotional reactivity. They often perceive environmental threats, leading to disengagement and inconsistent usage patterns (Costa and McCrae, 2008; Fang *et al.*, 2015). In the context of WFT, devices equipped with health-monitoring features, such as heart rate and blood pressure tracking, can support stress management and act as motivational tools for health monitoring (Soto and Tackett, 2016; Sergueeva, Shaw and Lee, 2020). However, the paradoxical nature of neuroticism becomes evident, as heightened emotional responses may also hinder sustained engagement (Rupp *et al.*, 2018). For example, studies have shown that neuroticism has a negative impact on the adoption of smart glasses, demonstrating the broader challenges in technology usage among neurotic

individuals (Rauschnabel, Brem and Ivens, 2015). Therefore, this thesis focuses on neuroticism to explore how such anxieties influence WFT adoption and whether their effects diminish or amplify with continued use.

Lower Lever of Relevance of Agreeableness and Extraversion

Conversely, agreeableness and extraversion are less relevant. For instance, **agreeableness**, marked by traits such as cooperation and altruism (Costa and McCrae, 1992), primarily influences social interactions rather than individual, goal-driven behaviours, while being relevant to social technologies such as social media (Ross *et al.*, 2009). However, its predictive power for personal health-focused devices such as WFTs is limited, making it less applicable to this study, which focuses on continued engagement with technology driven by personal goals rather than social dynamics. Similarly, **extraversion**, which encompasses sociability, assertiveness, and a preference for external stimulation, has stronger associations with socially interactive technologies than with health-monitoring systems such as WFTs (Landers and Lounsbury, 2006). Although extraverts may engage with technology for its social connectivity features, this trait does not align strongly with the intrinsic, health-oriented motivations that drive continued WFT use.

In summary

As elaborated above, IS academics have recently begun focusing on ICT usage and personality-related issues, as individual differences related to tendencies to display consistent patterns of feelings, thoughts, and actions referred to as personality traits (Costa and McCrae, 1992). Taking all these factors into account and reinforcing previous studies, this approach ensures that the research is relevant and grounded in established literature, enhancing the validity and applicability of the findings and contributing valuable insights to both academia and industry. Thus, the researcher concludes and expects that **OTTI** reflects an openness to novel and evolving technology, which is critical for engaging with WFTs that require adaptability to updates and

innovations. **CinH** emphasises self-discipline and health-focused goals that align with the long-term health management objectives of WFT users. **Neu** is included for its role in emotional reactivity and stress management, factors influencing reliance on wearable technologies for monitoring and self-regulation. Conversely, agreeableness and extraversion are deliberately excluded as moderators due to their limited relevance to the specific context of WFT continuance use.

The next section will elaborate on the selection of CinH, OTTI, and Neu by demonstrating their stronger theoretical and empirical alignment with the study's objectives while justifying the exclusion of agreeableness and extraversion through a detailed discussion of their lesser relevance to WFT's continued use behaviour. This ensures that the model is both theoretically sound and contextually aligned with the study's objectives to explore sustained user engagement with wearable technologies. Figure 3-1 above demonstrates the proposed study hypotheses: openness to technological innovativeness (H4), conscientiousness in health (H5), and neuroticism (H6) are associated with the UTAUT2 model constructs (the section below elaborates on the development of the hypotheses).

The Moderating Role of Openness to Technological Innovativeness (OTTI)

Openness to Experience is considered a broad dimension of individual differences, encompassing both structural and motivational aspects. According to McCrae and Costa, "Openness is seen in the breadth, depth, and permeability of consciousness, and in the recurrent need to enlarge and examine experience" (McCrae, 1992, p. 2). Further, openness means the desire of an individual to show new or unusual ideas, opinions, viewpoints, and experiences. Hence, openness to experience reflects individuals who are highly goal-oriented, socially engaged, and full of energy. They are particularly receptive to new ideas, innovative approaches, and any form of change, embracing them enthusiastically (Ismail *et al.*, 2023). In addition, people with high scores are usually imaginative and intellectual (Alshawmar, Tulu and Hall-Phillips, 2022).

Various research work has been conducted in this regard, revealing that both low and high levels of openness may benefit people depending on the task (Tomiatti *et al.*, 2012). For instance, high scorers of openness to using innovative technology are usually more conscious of getting inspired or receiving new information and are eager to experience new things and features. Being curious and adventurous might also increase their device usage behaviour. Equally, studies have found that individuals who score high in openness to experience tend to adopt, actively use, and continue using various mHealth apps over the long term, including self-management apps for managing hypertension (Breil *et al.*, 2019). Another study revealed that this personality trait had the strongest relationship with students' creativity in design and technology (Ismail *et al.*, 2023), which confirms users' desire to achieve useful activities that provide significant results, such as a new job or higher income (Alshawmar, Tulu and Hall-Phillips, 2022). Thus, this thesis posits that those who score high for this trait are more likely to continue using their technological devices compared to low scorers, who are usually uncomfortable with changing their daily routines and might be cautious about using their wearables.

The personality traits of open individuals include being open to innovative ideas or adventures and being willing to try something new. Since WFT/SWs are a type of innovative technology, it is proposed that consumers with the **OTTI** trait will be more curious about and willing to continue using their devices. Thus, this current study explores the relationship between personality characteristics and consumers' continuance use of WFT/SW, leading to the following research hypothesis:

H4. Openness to technological innovativeness moderates positively the relationship between continued use intention and continued use behaviour of WFT.

The Moderating Role of Conscientiousness in Health (CinH)

As referred to above, Conscientiousness, one of the Big Five personality traits, is described by six facets/sub-traits: competence, order, dutifulness, achievement-striving, self-discipline, and deliberation (Costa and McCrae, 1992). These are known as impulse control behaviours that help with goal and task completion, such as planning and organising. Conscientiousness is generally characterised by various activities, such as being well-structured and persistent. It is also considered the tendency to be active in scheduling ahead and being goal-oriented with a strong sense of purpose. The conscientiousness factor has appeared under task interest and willingness to accomplish (John and Srivastava, 1999). Further, it has previously been found that persistent, achievement-oriented, and dedicated individuals are more likely to become involved with useful and productive new technologies (Howell and Higgins, 1990; Rogers, 2003). Thus, conscientious individuals are generally efficient and tend to search for different means to use technologies to improve their level of performance (McCrae and Costa, 1991).

Prior research on personality and internet usage suggests that conscientious individuals are more likely to use the internet for productive purposes rather than unproductive ones. Landers and Lounsbury (2006) found that conscientious people dedicate less time to online leisure activities and focus instead on work-related tasks. This indicates a strong correlation between conscientiousness and goal-oriented internet use, highlighting the influence of personality traits on digital behaviour.

Several other studies have investigated the role of conscientious personality traits within different IS contexts. For example, understanding e-government portal use in rural India (Venkatesh, Sykes and Venkatraman, 2014), word of mouth on social media platforms (Adamopoulos, Ghose and Todri, 2018), acceptance and use of desktop videoconferencing in higher education (Lakhal and Khechine, 2017), the acceptance, actual use, and achievement in Moodle on a Japanese university course in higher education (Rivers, 2021), student creativity in a functional project (Ismail *et al.*, 2023), gamified surveys (Triantoro *et al.*, 2020), continued use of fitness apps (Alshawmar, Tulu and Hall-Phillips, 2022), use of social network sites (Mouakket and Sun, 2020), and instant messaging (Wang, Ngai and Wei, 2012).

Previous research suggests that HC can influence health behaviour (Hong, 2011), contributing to the sustained use of technology. HC indicates individuals' awareness of their health conditions as well as their desire and motivation to be healthier (Cho, Park and Lee, 2014). It is considered a predictor of both health behaviour and attitude (Gould, 1988; Iversen and Kraft, 2006; Michaelidou and Hassan, 2008). Individuals with high HC are more likely to track and record their health status (Dutta-Bergman, 2004) and to get involved in nutrition, stress management, and fitness activities (Kraft and Goodell, 1993; Newsom *et al.*, 2005). They are also more inclined to pursue information and implement strategies that could improve or preserve their health and have a better quality of

life (Rodgers *et al.*, 2007). For instance, highly conscientious people adhere to healthy behaviours, such as not smoking and actively engaging in health, exercise, and diet programmes. They mostly get appropriate medicine with proper health check-ups because it benefits their physical and overall health and well-being (Rupp *et al.*, 2018). In addition, higher conscientiousness in health is linked to a lower risk of obesity. Even those (with high conscientiousness) who are already obese have a higher probability of becoming non-obese within five years, as shown in a meta-analysis study (Jokela *et al.*, 2013). The findings suggest that conscientiousness may be the only broad-level personality feature in the personality trait model that is constantly obesity-related across populations.

Hence, WFT devices offer features that help individuals enhance or maintain their health, access valuable health information, and track their health status over time. Lee and Lee (2018) argue that wearable healthcare devices equipped with health-focused capabilities foster the development of healthy habits by enabling users to monitor and control their functions. By continuously tracking activity, these devices encourage healthier lifestyles, particularly by promoting positive changes in exercise routines. That is relevant to highly conscientious users who focus on achievements and self-discipline, which motivates them consistently to use wearable fitness devices integrated with mobile technology that fosters new tech habits (Peltonen *et al.*, 2020).

In contrast, individuals with low conscientiousness scores tend to be impulsive and spontaneous, showing less interest in using wearable device features due to perceived carelessness. Highly conscientious individuals who find technology useful generally maintain a positive attitude towards its continued use, viewing it as a means for further achievement. Similarly, health-conscious individuals are strongly motivated to improve their performance levels and find WFT beneficial.

From the aforementioned, within the WFT context, individuals with high HC have better knowledge and clearer health and fitness goals. Thus, they will better judge WFT devices. In the case of individuals with higher HC, the effect of CUI on CUB is likely to be magnified. Therefore, the following hypothesis was established:

H5. Conscientiousness in health positively moderates the relationship between continued use intention and continued use behaviour of WFT.

The Moderating Role of Neuroticism (Neu)

Neuroticism is recognised as a core personality trait and is characterised by emotional instability and a predisposition towards negative experiences, such as depression and anxiety (Costa and McCrae, 2008). Neurotic individuals often perceive potential threats in their environment, leading to heightened states of confusion and panic; thus, they are less often approached for friendship or advice due to their emotional instability and negative outlook (Fang *et al.*, 2015). These tendencies make them more vulnerable to stress and sadness as their psychological defences are easily triggered. Research suggests that WFT could play a vital role in helping such individuals manage their stress-related habits (Soto and Tackett, 2016). For instance, the continuous monitoring of vital signs, such as heart rate, glucose levels, and blood pressure, provided by wearable devices may serve as a motivational tool for users to stay engaged with the technology (Sergueeva, Shaw and Lee, 2020).

However, neurotic individuals often exhibit a paradoxical relationship with technology. While these devices could support stress management, heightened emotional reactivity may discourage consistent use. This underscores the importance of addressing factors influencing continued use, particularly among neurotic users, to maximise the benefits of WFTs and encourage sustained engagement (Rupp *et al.*, 2018). Moreover, as these computing devices ([see Section 1.4](#)) are often integrated into the IoT ecosystem, they collect and share sensitive personal data with smartphones and other platforms. Such data-sharing capabilities could have a further impact on users' willingness to continue using these devices, particularly for those with intensified concerns about privacy and trust. Addressing these challenges is crucial for leveraging WFTs to manage stress and promote long-term health benefits.

For example, Rauschnabel *et al.* (2015) hypothesised that personality could affect users' perception and intention to adopt smart glasses. They drew on the Big Five personality traits to

analyse the direct effects of neuroticism on consumers' awareness of Google glasses and their moderating effect on consumers' adoption intention. Their results indicate that neurotic users are less likely to adopt smart glasses. Another study validated one of the technology models for safety enhancement in the context of wearable locating systems, such as passengers' bracelets. Their investigation in the event of an evacuation is associated with high stress levels. Therefore, the scholars considered high neuroticism to be the inability to deal with this situation and even the thought of it. Hence, people with high levels of neuroticism presumably evaluate the means of support in the event of a disaster higher than others (Kwee-Meier, Bützler and Schlick, 2016).

Accordingly, the researcher posits that individuals with a high degree of neuroticism might be the type of users who criticise their wearables (i.e., SWs) for failing to find compelling values, which causes them to abandon using their devices. Therefore, the following hypothesis was established:

H6. Neuroticism moderates negatively the relationship between users' continued use intention and continuance use behaviour of WFT.

3.2 Conceptual Framework

The hypotheses developed in this chapter are grounded in the UTAUT2 (Venkatesh, Thong and Xu, 2012) and the proposed personality traits model (Goldberg, 1990; Costa and McCrae (1992)). These theoretical foundations guided the development and testing of the conceptual framework, as illustrated in Figure 3-1. The next chapter details the research methodology employed in this study.

Chapter 4: Research Methodology

This research study aims to investigate the factors associated with consumers' continuance use of WFTs and examine the moderating effects of users' psychological traits (both general personality and technology user-specific characteristics) on their continued use intention and continued use behaviour. This chapter aims to discuss the methodology used to test the hypotheses developed in the preceding chapter, which describes the study's theoretical framework.

The epistemological and ontological assumptions underpinning various research designs have a significant influence on their suitability for addressing social issues. The appropriateness of a design is closely aligned with the research question, as the philosophical foundations shape the study's knowledge requirements and steer the methodological direction. By aligning the research design with the inquiry's aims, scholars ensure that the selected approach is effective in supporting the generation of meaningful and relevant insights. Thus, this chapter addresses these challenges and comprehensively outlines the research methodology employed by this study by addressing the research philosophy, approach, design, data collection methods, and sampling. The chapter presents a detailed explanation of the procedures followed to design the instruments and the strategies implemented to ensure their validity and reliability. The pilot study of the survey instrument is also included in this chapter, with a broad explanation of the data collection and analysis procedures and the participants' demographic information. The last section presents the ethical considerations observed by the researcher.

4.1 Research Philosophy

The research onion, a model established by Saunders, Lewis and Thornhill (2019), offers a systematic framework for understanding the various stages and components of the research process. The model contains multiple layers, each representing a different aspect of the research

process, from the most general and broadest to the most specific and detailed (Figure 4-1 shows the research design decisions taken for this PhD thesis). The research onion model helps researchers navigate the difficulties of the research process and make well-informed decisions at each stage. The layers are as follows: philosophical assumptions, research approach, methodological choice, research strategy, time horizon, and techniques and procedures (elaborated upon in the next sections).

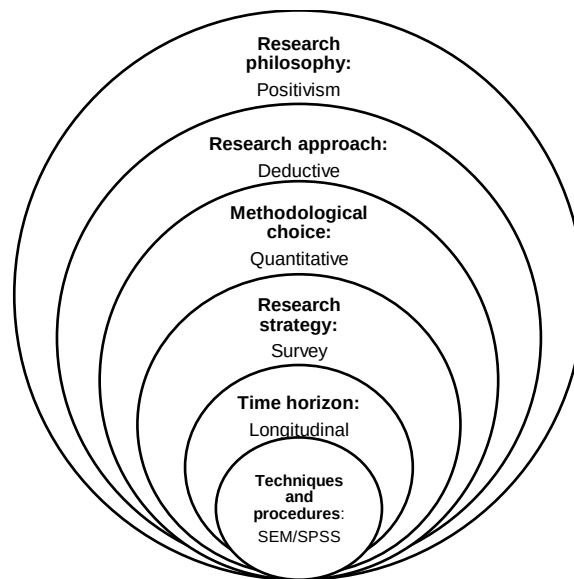


Figure 4-1 Research design diagram, adapted from Saunders, Lewis and Thornhill (2019)

Research philosophy refers to the underlying beliefs, assumptions, and principles that guide researchers in conducting research. Saunders, Lewis and Thornhill (2019) define it as a "system of beliefs and assumptions about the development of knowledge" (p. 130). Different research philosophies shape the researcher's worldview and influence the overall research design, data collection methods, and data analysis approaches. Therefore, philosophical assumptions play an important role in the way scientific research is conducted.

Each stage of the research process requires researchers to make various assumptions about the potential realities they may encounter. For example, the ontological (the nature of reality and

existence), epistemological (the approach to human knowledge-generation), and axiological (the role of the researcher's values and ethics within the research process) assumptions (Saunders, Lewis and Thornhill, 2019).

Ontology and epistemology are fundamental concepts in research that help shape the researcher's understanding of reality and knowledge. The choice of ontological and epistemological positions has significant implications for the research process. For example, for Saunders, Lewis and Thornhill (2019), "Ontology is concerned with the nature of reality" (p. 133), and it can be objective or subjective. According to an objective ontology, reality is single, constant, and independent of social actors. On the other hand, a subjective ontology holds that reality varies for every individual and is predicated on how social actors interpret and perceive it (Saunders, Lewis and Thornhill, 2019).

Epistemology is the study of knowledge, including what constitutes valid and acceptable knowledge and how we can communicate it to others (Saunders, Lewis and Thornhill, 2019). It concerns "what is regarded as appropriate knowledge about the social world" (Bell, Bryman and Harley, 2011, p. 27). It raises questions like, "How do we know what we know? What is the relationship between the researcher (the knower) and what is known?" (Kasim and Antwi, 2015). It could also be based on objectivism, whereby knowledge is realised as objective and quantifiable (Johnson and Duberley, 2000). According to objective epistemology, knowledge is acquired through experiences and by paying attention to quantifiable facts (Saunders, Lewis and Thornhill, 2019). Conversely, subjective epistemology contends that there are various ways to acquire knowledge and that knowledge is based on interpretations (Walsham, 1993). It seeks to understand a phenomenon by examining its meanings (Bryman, 2016). Therefore, researchers should consider their ontological and epistemological assumptions in order to ensure coherence and alignment with their research objectives and questions.

Within the business and management discipline, researchers can adopt various epistemological approaches, including interpretivism, critical realism, positivism, pragmatism, and postmodernism (Saunders, Lewis and Thornhill, 2019). These approaches are presented below.

Interpretivism is a research approach that emphasises understanding social phenomena through individuals' subjective experiences and interpretations (Bryman, 2016). It contrasts with positivism, which seeks objective, quantifiable knowledge. Ontologically, interpretivists acknowledge that individuals from diverse cultural backgrounds construct unique meanings of social reality. To understand these subjective interpretations, researchers often employ qualitative research methods to gather rich, in-depth data (Saunders, Lewis and Thornhill, 2019). The data analysis is usually based on coding using thematic, discourse, and textual analysis (Bryman, 2016). This approach allows researchers to acquire insights into the experiences and perspectives of individuals within their specific contexts. In the realm of business and management research, interpretivists seek to comprehend organisations through the eyes of various stakeholder groups. Epistemologically, interpretivists seek to understand organisations and social worlds by interpreting narratives, language, culture, and history. This approach aims to develop new understandings and worldviews (Saunders, Lewis and Thornhill, 2019). The axiology is value-laden; for example, the researcher is engaged in the data collection process and aims to understand the participants' perspectives and interpretations of the research phenomenon and the factors influencing their opinions (Kaplan and Maxwell, 2005).

In contrast with interpretivism, **realism** takes a scientific approach to knowledge development. It is predicated on the assumption that an external reality exists and is unrelated to social actors. The axiology of realism suggests a value-laden research process whereby personal views, experiences, and cultural backgrounds influence the researcher (Saunders, Lewis and Thornhill,

2019). There are two types of realism: direct and critical (Saunders, Lewis and Thornhill, 2019). Firstly, **direct realism** (naïve realism) assumes that the world is stable and unchanging; it portrays reality as being reflected in people's perceptions and does not consider the underlying mechanisms driving a social phenomenon (Hartwig, 2011).

On the other hand, **critical realism** acknowledges the existence of an external reality (reality is partially understood by what people perceive) that is not directly observable (Bryman, 2016). It recognises the influence of social and historical contexts on reality and explores the critical relationship between social structures and individual actions (Guba and Lincoln, 1994). Critical realist researchers typically employ mixed methods, combining qualitative and quantitative approaches to gain a comprehensive understanding of social phenomena.

In contrast, **positivism** is grounded in the epistemological belief that knowledge can be derived from observable and measurable phenomena, emphasising objectivity and quantification (Bryman, 2016). As a research philosophy, it was developed in the 19th century by Auguste Comte, a French philosopher and sociologist (Kasim and Antwi, 2015). Comte advocated for an objective and scientific approach to understanding social phenomena, emphasising empirical observation, measurement, and verification (Bryman, 2016). He argued that the methods of the natural sciences should be employed to study society to uncover general laws and principles governing human behaviour (Johnson and Duberley, 2000).

Over time, other prominent social scientists contributed to the development of positivism as a research paradigm, leading to its widespread influence across disciplines such as economics, political science, and sociology. It also influenced other fields, including psychology and the natural sciences, by emphasising the study of observable phenomena, quantification, and causal relationships. Positivism refers to the "philosophical stance of the natural scientist and entails

working with an observable social reality to produce law-like generalisations" (Saunders, Lewis and Thornhill, 2019, p. 144). The positivist philosophy "asserts that social phenomena and their meanings exist independent of social actors" (Bryman, 2012, p. 3).

Ontologically, positivists adhere to the principle of universalism, perceiving social entities to be as real as natural phenomena; in other words, reality is single and stable (Hudson and Ozanne, 1988). Consequently, this paradigm requires an existing theory in order to develop hypotheses, which can then be tested and confirmed to generate further development of the theory (Saunders, Lewis and Thornhill, 2019). From an epistemological standpoint, positivism emphasises empirical knowledge acquisition through observable and measurable phenomena. Positivist researchers aim to uncover cause-and-effect relationships by relying on quantifiable data and scientific methods, adhering to the principle that knowledge must be verifiable and objective (Crotty, 1998). Axiologically, positivism maintains a value-neutral stance, advocating that the researcher's personal beliefs or biases should not influence the research process, emphasising the role of scientific rigour and neutrality in generating knowledge (Saunders, Lewis and Thornhill, 2019).

The positivist philosophy suggests using quantitative research methods for data collection and analysis. Data collection often relies on surveys and questionnaires using large, randomly selected samples (Easterby, Thorpe and Jackson, 2020). Typical of such research is the demonstration of causality between variables and using confirmed or rejected hypotheses (Johnson and Duberley, 2000). In order to obtain objective, quantifiable data, researchers must also use rigorous scale measurements from large samples. Conclusions can then be drawn from empirical investigations, not subjective interpretations, and the results can be generalised and based on observable phenomena, resulting in theory development (Saunders, Lewis and Thornhill, 2019). With regard to axiology, positivist researchers adopt a value-free perspective and try to remain neutral, independent, and detached from their research and data. Hence, the focus is on collecting

measurable and quantifiable data that can be statistically analysed (Saunders, Lewis and Thornhill, 2019).

The next philosophical stance to be considered is **pragmatism**, which embraces both objectivism and subjectivism and strives for coherence between facts and values. Ontologically, pragmatists perceive reality as shaped by the practical outcomes of ideas. Epistemologically, they prioritise theories and knowledge that prove effective in achieving desired outcomes, emphasising actionable research that addresses real-world problems and informs future practice. Axiologically, pragmatism adopts a value-driven approach, recognising that the researcher's beliefs and uncertainties often fuel research. This philosophy places the research problem and question at the forefront, advocating for multiple methods to collect credible and relevant data that adequately address the inquiry (Saunders, Lewis and Thornhill, 2019).

The last philosophical stance to be presented here is **postmodernism**, which offers a more critical examination of positivism and objectivism than does interpretivism. It is historically intertwined with the intellectual framework of poststructuralism. It emerged during the late 20th century and is closely linked to the works of French philosophers such as Jean-François Lyotard, Jacques Derrida, Michel Foucault, Gilles Deleuze, Félix Guattari, and Jean Baudrillard (Saunders, Lewis and Thornhill, 2019). From an ontological perspective, postmodernists highlight the central role of language in constructing the social world. They argue that because language is inherently incomplete and limited, it is impossible to describe the social world in a universally "correct" or "true" way (Foucault, 2012). Epistemologically, postmodernism is sceptical of grand narratives and universal knowledge claims, advocating for recognising localised, context-specific knowledge (Bryman, 2016). Postmodernists aim to challenge and deconstruct power dynamics that uphold dominant realities by dissecting these constructs and exposing the inconsistencies within widely accepted truths. This approach critically examines and destabilises established frameworks of

thought and knowledge, prompting alternative ways of understanding and interpreting reality (Derrida, 2016). Axiologically, postmodernists differ from interpretivists by embracing a value-laden approach to research. They focus on a deep exploration of the complexities of the social world, emphasising that power dynamics between the researcher and the subjects inevitably influence the research process (Calás and Smircich, 1997).

4.1.1 The Research Philosophy in this Study

Given that the positivist philosophical approach emphasises a scientific and objective process of knowledge development, it is the most relevant philosophy for this study. This relevance is informed by the research phenomenon being examined, the development of hypotheses, and the quantitative methods chosen for data collection. A subjective ontology and interpretive epistemological approach would not align with the nature of this research, as these approaches focus on qualitative data and subjective interpretation (e.g., through interviews), which are less suited to investigating the structured hypotheses and measurable constructs central to this study.

Furthermore, the realist paradigm incorporates the values and perceptions of the researcher into the research process (Bryman, 2012). While mixed methods research, which often aligns with realism, offers the advantage of combining qualitative and quantitative data to provide a comprehensive perspective, it was not deemed suitable for this study. This decision stems from the study's focus on testing specific hypotheses through structured, measurable constructs rather than exploring contextual insights or subjective experiences in depth, which would typically require mixed methods. Hence, the chosen approach aligns better with the study's objectives and methodology. Moreover, the investigation employs a non-directive approach, minimising researcher interference. By focusing on objective and quantifiable data, the realist paradigm,

typically involving the integration of the researcher's perceptions and subjective interpretations, was deemed less appropriate for the study's aims and methodology.

The research study takes a positivist epistemological position, as it aims to investigate the factors associated with consumers' continued use of WFTs and to examine the moderating effects of consumers' psychological traits (both general personality and technology user-specific characteristics) on user continued use intention and continued use behaviour. Maintaining a positivist research philosophy involves identifying hypotheses that can be developed and adapted based on prior theories that can be tested in a given environment (Saunders, Lewis and Thornhill, 2019).

In this context, the “social actors” refer to **users** who adopt and continue to use WFTs, focusing particularly on their behaviours and perceptions related to the technology. From an epistemological standpoint, this positivist study investigates the phenomenon of consumers' continued use of WFTs by relying on measurable, objective data to draw conclusions. This approach avoids subjective interpretations and emphasises observable and quantifiable facts. Axiologically, the current research study is based on capturing the respondents' views (users) as expressed in their responses rather than the researcher personally interacting with them. Hence, the data to be collected were free from the researcher's personal values.

4.2 Research Approach

The second layer of the research onion (as shown in Figure 4-1), which is always determined by the philosophical doctrine selected, is the research approach. In business and management research, whether the research is based on theory building or theory testing depends on the research approach adopted by the researcher. There are three approaches: deductive, inductive, and abductive (Saunders, Lewis and Thornhill, 2019).

The positivist philosophical position generally supports the deductive approach, which involves falsifying or verifying theory through a series of hypotheses or propositions based on the existing literature. In other words, the research starts with a theory, then hypotheses are developed, and finally, they are empirically tested (Ketokivi and Mantere, 2010). To test the hypotheses formed, quantitative data (usually from larger samples, allowing for generalisation) are collected and analysed with the aid of a precision methodology for testing causal interactions (Gill and Johnson, 2010). The results of the analysis are checked for consistency within the premises of a logical argument (that has been compared with existing theories), and conclusions are then drawn based on premises regarding acceptance or rejection of the hypotheses based on whether the theory has been corroborated or falsified (Saunders, Lewis and Thornhill, 2019).

An inductive approach is most likely to be supported by the interpretive philosophical position, which is used in research aiming to understand individuals' meanings and perspectives. In contrast to the deductive method, the inductive approach is based on the notion of theory generation and building. It is more flexible and is not concerned with generalisation. In addition, the role of the researcher is not seen to be independent of the research process (Ketokivi and Mantere, 2010). Considering the context surrounding the social phenomena under investigation, the researcher collects qualitative data from small samples to explore a phenomenon and identify themes and patterns to formulate a theory (Saunders, Lewis and Thornhill, 2019).

The third research approach is abductive, mostly supported by critical realist, pragmatist, and postmodernist philosophical positions. It combines both inductive and deductive approaches, which are conceptually different (see Table 4-1) and still used in conjunction with business and marketing research (Saunders, Lewis and Thornhill, 2019). Deductive and inductive approaches are not mutually exclusive; therefore, researchers may use a combination of both depending on their research objectives and the nature of the research phenomenon. Thus, the abductive

approach serves as a foundation for both developing new theories (theory generation) and modifying existing ones (Saunders, Lewis and Thornhill, 2019). This approach involves the researcher collecting data to identify phenomena or themes, incorporating them into a conceptual framework, and subsequently testing this framework through further data collection (Saunders, Lewis and Thornhill, 2019).

Table 4–1 Key differences between deductive and inductive approaches in research (Bryman, 2016)

	Deductive Approach	Inductive Approach
<i>Purpose</i>	To test existing theories or hypotheses	To generate new theories or hypotheses
<i>Logic</i>	Moves from the general to the specific	Moves from the specific to the general
<i>Process</i>	Starts with a theory or hypothesis	Starts with observations or data
<i>Data Analysis</i>	Begins with predefined variables and theories	Uses coding and categorisation of qualitative data
<i>Research</i>	Emphasises objectivity and controlled environments	Acknowledges subjectivity and real-world conditions
<i>Sample</i>	Often involves large and representative samples	May involve smaller and more purposeful samples
<i>Generalisability</i>	Seeks to generalise findings to a larger population	May not prioritise generalisability, focuses on context-specific understanding
<i>Theory Development</i>	Tests and refines existing theories	Builds new theories based on observed patterns

The methodology implemented in the current research is that of a positivist philosophical approach that was utilised to investigate the factors influencing consumers' continued use of WFTs. Furthermore, the current study also sought to examine the moderating effects of psychological traits on continued use intentions and behaviours, prioritising empirical measurement over in-depth exploration of the phenomenon. Based on that, the current research developed hypotheses based on existing theories, the testing and analysis of which were carried out using quantitative data collected via an online survey from a large sample of consumers. Therefore, this study adopted a deductive approach, which seemed the most suitable for this PhD research phenomenon.

4.3 Research Design

The research design is a detailed framework that outlines the systematic actions and strategies necessary to achieve the research objectives in the most effective way. It encompasses both a written statement and a structured set of activities to ensure the research process is logical, coherent, and aligned with its goals (Easterby-Smith, Thorpe and Jackson, 2015). It refers to the overall plan/strategy that researchers develop to address their research question(s) through a framework for collecting and analysing data in a structured manner. This type of logical plan clearly states those objectives derived from the research question(s), the source(s) of the data to be collected, and the method of analysing the collected data. Specifically, getting from “here” to “there” where “here” is an initial set of research questions and “there” is a set of answers (Yin, 2018).

The research design also takes into account the ethical concerns that are required to be addressed during the collection of the data, as well as any limitations that may arise during the process of researching a phenomenon. It is generally defined based on its own characteristics and the purpose to be fulfilled by the study. More specifically, in the field of business and management, several research designs are commonly employed to investigate various phenomena and address the research question(s). Some of the most common research designs are exploratory, explanatory, and descriptive (Saunders, Lewis and Thornhill, 2019).

An **exploratory** research design is used when the researcher’s main purpose is to gain a preliminary understanding of a particular research phenomenon or to explore new areas, examining a research problem with limited prior knowledge or theory. It often employs qualitative methods such as focus groups or interviews to collect rich and in-depth data. Thus, it generally asks open questions, which are likely to begin with “How” or “What”. Exploratory research has both advantages and drawbacks. Its flexibility is a considerable advantage, allowing the researcher to adapt and redirect the study as new data and insights emerge (Saunders, Lewis and Thornhill,

2019). However, this flexibility can also pose challenges, such as the research process becoming time-consuming (Jain, 2021). Conducting thorough literature reviews, interviews, and focus group discussions to gather diverse perspectives often requires substantial effort and time. While the comprehensive nature of exploratory research is valuable, the potential for protracted timelines might be seen as a drawback, particularly in contexts in which timely results are critical (Casula, Rangarajan and Shields, 2021). Thus, the trade-off between depth and efficiency must be carefully managed.

An **explanatory** research design primarily explains established cause-and-effect relationships between variables. Thus, it is also known as a causal research design and mainly includes experimental methods to test causal relationships (Ghauri, Grønhaug and Strange, 2010), utilising questions that are asked during data collection that generally begin with “How” or “Why” (Saunders, Lewis and Thornhill, 2019).

A **descriptive** research design aims to provide a detailed and accurate description of a phenomenon or population (persons, events, or situations) for answering the research question(s) beginning with or including: “Where”, “What”, “When”, “Who”, or “How”. Therefore, it involves observing, documenting, and summarising characteristics, attitudes, or behaviours without attempting to establish relationships or manipulate variables. It can sometimes be applied as a follow-up to or an extension of exploratory research or as part of explanatory research (Saunders, Lewis and Thornhill, 2019). This type of research design is constructed on existing theories by employing predefined variables from the literature to test the relationships between the variables. In this type of research design, data are generally collected using research instruments, common methods being observation, as well as case studies or questionnaires (Iacobucci and Churchill, 2018). Based on these, the choice of a specific research design depends on the research question(s), the context, and the resources available.

This study employed a descriptive research approach, using questionnaires for data collection. It was more suitable than an exploratory design, which typically relies on qualitative methods such as interviews or focus groups to gain deeper insights. Further, although both descriptive and explanatory designs can be applied to test hypotheses, an explanatory design pays particular attention to cause-and-effect relationships using experiments. Since the present research study aims to examine direct, mediating, and moderating relationships among the mediator and the dependent variables rather than identifying cause-and-effect relationships, a descriptive research design is the most appropriate for this study.

The research model was assessed in a longitudinal setting, which is further detailed in a later subsection on [longitudinal design](#). As shown in Figure 4-2, data were collected at two points in time. At time 1 (T1), data on UTAUT2 factors and personality traits were gathered. Six months later, at time 2 (T2), the same participants were asked to complete the same questionnaire.

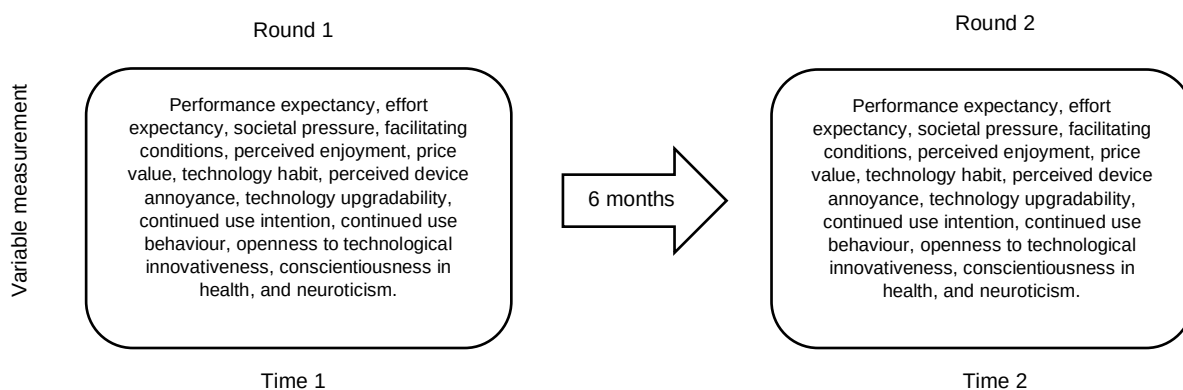


Figure 4-2 Data were collected at two different points in time.

A research design could also be classified as being quantitative, qualitative, or utilising mixed methods (representing a combination of qualitative and quantitative research methods).

Quantitative research methods involve the collection of numerical data, which are analysed statistically to arrive at the study findings (Punch, 2013). The qualitative research approach is usually associated with the interpretivist philosophy and interviews or observations as data collection methods. In contrast, quantitative research methods are usually associated with the positivist philosophical approach, using numerical data collection approaches such as experiments and questionnaires. Quantitative research is used within the deductive approach, which focuses on testing various relationships between operationalised variables that are analysed statistically (Saunders, Lewis and Thornhill, 2019).

This PhD thesis aims to study the factors associated with consumers' continued use of WFTs and examine the moderating effects of users' psychological traits on their continued use intentions and continued use behaviour. The study builds on UTAUT2 to predict the relationships between the different variables. Therefore, the present research adopted a positivist philosophical approach and employed a quantitative research design that was deemed the most suitable for investigating the topic and testing the hypotheses.

This section describes the quantitative study objectives and the data collection process used to accomplish them in accordance with the deductive approach and quantitative research design defined above.

4.3.1 Quantitative Study Objectives

This study was designed to test the hypotheses formulated in the conceptual framework. The objectives are as follows:

1. To conduct an empirical investigation of the relationships between various latent constructs vis-à-vis perceived predictors, consumers' continued use intention toward wearable fitness devices and continued use behaviour (CUB).

2. To test the mediating effect of consumers' continued use intention toward wearable fitness devices between perceived predictors and CUB.
3. To test the moderating effects of personality traits (user-specific personal characteristics) on the relationship between consumers' continued use intention and continued use behaviour toward wearable fitness devices.

4.3.2 Longitudinal Design

Longitudinal research is frequently used in the social sciences to explore life events throughout generations or lifetimes and, more importantly, describe patterns of change. They help social scientists differentiate short- and long-term phenomena by providing distinctive insights, compared to other research types that fail to deliver such understanding. For example, cross-sectional studies are static and may be used to analyse several variables at a given instance, without providing information regarding the influence of time on the variables measured. As a result, they are less useful for investigating cause-and-effect relationships (unlike longitudinal designs, the primary purpose of which is to explain causal relationships) (Caruana *et al.*, 2015).

Longitudinal research is often used in social-personality and clinical psychology to examine developmental trends across a lifespan and to investigate rapid fluctuations in thoughts, emotions, and behaviours from moment to moment. Gayle and Lambert (2019) suggest that most worldwide descriptions of longitudinal social science data refer to "any data that have a temporal (i.e., time) dimension", whereby data are collected from the same units on several occasions.

Longitudinal studies are mostly observational in nature; however, they may also be experimental, which can take several forms: (I) prospective, (II) retrospective, or (III) repeated cross-sectional studies (Szajna, 1996). They follow certain individuals over prolonged periods of time in order to collect data qualitatively and/or quantitatively on any combination of exposures and outcomes

without applying any external influence (Caruana *et al.*, 2015). A longitudinal design can also, for example, be used to evaluate and compare various business and branding aspects by using surveys to gather feedback from both regular and new customers, focusing on areas such as market trends, brand awareness, and product feedback. At the same time, the design allows for examining the robustness and generalisability of hypothesised models across multiple technologies and IT usage contexts (Bhattacharjee and Premkumar, 2004).

Performing longitudinal studies with surveys is obvious and applicable to almost any discipline. For instance, Magsamen-Conrad and Dillon (2020) performed a longitudinal investigation to study how mobile technology diffuses across the lifespan within a multi-generational population. Jeong *et al.* (2017) examined how college students wear smartwatches and what factors affect their behaviours by analysing a longitudinal activity dataset. Another researcher conducted a longitudinal study to analyse herd behaviour in technology adoption and the impact it has on decision-making (Sun, 2013). Another example is one in which researchers used a laboratory study to examine initial perceptions of trust, usability, and motivational affordances. Their results are limited because they only measured users' initial perceptions in their study; however, these are expected to change over time as individuals gain more experience with a device through extended access to the technology (Rupp *et al.*, 2018). Furthermore, a longitudinal examination is recommended in previous studies to clarify further factors influencing consumers' technology adoption and to obtain more information about how users develop attitudes towards wearable devices over time (Kalantari, 2017).

As such, longitudinal designs can be carried out over time to assess consumers' long-term adoption repeatedly. These behaviours are dynamic and subject to change, which may lead users to discontinue their use of wearable devices/SWs (in this case). Although several researchers have suggested examining this relationship longitudinally (e.g., Rupp *et al.*, 2018), the current thesis will add methodological strengths in an attempt to address some of the limitations of previous studies

(e.g., Talukder *et al.*, 2020) and provide a more comprehensive research approach that allows an understanding of the direction and degree of change over time.

In summary, conducting a longitudinal study is straightforward and relevant to nearly any discipline. Researchers can measure and compare consumer aspects through a longitudinal study by deploying surveys. As a result, it is critical to utilise a longitudinal study to understand users' CUI and CUB regarding IT over time. Therefore, this thesis employs a longitudinal design, as people's perceptions of IT (in this case, WFT/SW) evolve over time. Appropriate statistical tests were employed to analyse the quantitative longitudinal data, which were collected prospectively by designing a panel of subjects and gathering data at two or more distinct time points to track and compare changes. The following section provides a detailed discussion of the sampling procedure and data collection methods used in this study.

4.3.3 Sampling Procedure and Sampling Units

Sampling involves selecting a specific segment or subset of a population to represent the whole for the purpose of investigation. Thus, sampling is a crucial part of every piece of research, as it allows the researcher to collect data from a particular part of the population (Saunders, Lewis and Thornhill, 2019). A sample that echoes the population correctly is known as a representative sample (Bryman, 2012). There are two main sampling techniques: probability and non-probability, under which many sub techniques are classified.

As Saunders, Lewis and Thornhill (2019) described, **probability sampling**, also known as random sampling, uses a random selection method. In other words, every individual has a fair chance of being chosen to participate in a particular study (M. M. Rahman *et al.*, 2022). Conversely, **non-probability sampling** is primarily associated with qualitative research designs and refers to a non-

random selection technique. As a result, not all groups in the population have an equal chance of taking part in the study (Sekaran and Bougie, 2016). Specifically, the likelihood of any individual being chosen from the population is unknown. Consequently, the findings from such methods cannot typically be generalised to the entire population. Non-probability sampling includes several types, such as convenience, purposive, quota, and snowball sampling (Saunders, Lewis and Thornhill, 2019), which are outlined below.

Convenience sampling is a non-probability sampling method. It is concerned with collecting data from conveniently available people, is cost-effective, and saves time. Nevertheless, some shortcomings of using this method pertain to generalisation. In particular, business, sociology, and social psychology research relies heavily on the convenience sampling technique. Purposive sampling is another non-probability sampling method. It focuses on selecting participants who meet specific criteria relevant to the research objectives, ensuring targeted and meaningful data collection. Quota sampling aims to represent particular subgroups within the population by selecting a predetermined number of participants from each group. This method ensures proportional representation but does not involve random selection (Sekaran and Bougie, 2016). Snowball sampling is particularly effective for reaching hidden or hard-to-access populations, such as marginalised groups or individuals in sensitive contexts. In this method, the earlier participants recruit others from their networks, creating a "snowball effect". Although these methods provide practical advantages, their results often lack generalisability, emphasising the importance of a clear rationale for their application in the research design (Babbie, 2020).

Stratified random sampling is a technique used in research to ensure that specific subgroups within a population are represented accurately in the sample. This method involves dividing the population into distinct strata, or groups, based on shared characteristics, such as age, gender, income, or education level. Once the population is stratified, participants are randomly selected

from each subgroup, ensuring that each stratum is proportionately represented in the final sample (Easterby-Smith, Thorpe and Jackson, 2015). This approach is particularly effective when the research aims to explore differences or patterns across distinct subgroups, improving the robustness and validity of the findings (Babbie, 2020). Thus, the approach improves population coverage by giving researchers control over subgroups, ensuring each is adequately represented (M. M. Rahman *et al.*, 2022).

The current research study investigates factors influencing users' long-term engagement with technological devices and how psychological traits moderate this continued use intention and behaviour. It presents several hypotheses regarding the relationships between perceived predictors, consumers' continued use intention (CUI) and the subsequent continued use behaviour (CUB) of WFT. The researcher initially conducted a short **pre-screening survey** to recruit a large pool of participants (633 in total) to ensure the desired sample size and eligibility for the main study, as outlined in the [pilot study](#) subsection below. The pre-screening targeted experienced users meeting specific criteria, including age, approval rate, and the number of prior submissions. Only participants who fulfilled these selection requirements were allowed to proceed, without imposing any location-based restrictions. Participants also received a nominal compensation for completing the survey.

The eligibility criteria stated that participants be at least 18 years old and have owned or used a wearable fitness device, such as a smartwatch, for more than three weeks (this is consistent with the focus of the study mentioned earlier). These criteria ensured the selection of a relevant and representative participant group aligned with the research objectives. Therefore, to collect data, a stratified random sampling method was performed based on the criteria specified, and then participants from that sample were randomly selected. The researcher recruited participants through the Prolific platform (a survey distribution tool) using a custom allowlist. Those specific

participants who met the main study criteria were randomly selected and then invited to complete a survey form (administered by Qualtrics).

Study Setting

Adoption behaviours vary across generations, as each generation experiences a unique mix of anxieties when it comes to adoption and continued use decisions. These factors include psychological, technological, physical, and social influences (Magsamen-Conrad *et al.*, 2015). However, consumers within a generational cohort tend to share similar values, expectations, and behaviours (Parment, 2013). For example, Gen Y (millennials/born between 1981 and 1996) and Gen Z (post-millennials/born between 1997 and 2010) (Dimock, 2019) are considerably more accustomed to adopting new technology at a faster rate than older people (Freestone and Mitchell, 2004). Their consumption habits set them apart from earlier generations (Ng *et al.*, 2019).

Moreover, Gen Y and Gen Z have been using cell phones and other technology devices since childhood for various purposes (McMahon and Pospisil, 2005). In their daily use of smart devices, such as wearables, they expect seamless and reliable performance, free from issues such as security flaws, bugs, slow speeds, or battery/power problems. Members of these generations are also heavy technology users (Bergh *et al.*, 2011), dedicating time to physical fitness and sports to track and monitor real-time health data, as well as to share their lifestyle information with peers and friends through technology platforms (Nayak *et al.*, 2022).

As a consequence of the above, the two generations (Gen Y and Gen Z) encompass the largest pool of WFT users. They are technology enthusiasts and known for their rapid adoption of and adaptation to new technologies (Seemiller and Grace, 2019). They possess extensive knowledge of new devices and technologies and are naturally familiar with technology products and devices. Therefore, they are acknowledged as important segments for wearable technology that warrant investigations into their intentions to continue using WFD/SWs (Talukder *et al.*, 2019). Therefore,

only users aged 18 to 60, comprising “young consumers” (Gen Y and Gen Z), were included in this research study.

Materials and Apparatus

Wearable devices can take several forms, such as wristbands, smartwatches, and gadgets that can be part of a garment (Sergueeva, Shaw and Lee, 2020). Therefore, the participants could use any of the most popular and up-to-date wearable fitness devices/smartwatches.

4.4 Research Strategy: Survey

The research strategy is an important part of the research methodology, as it concerns the tools and resources that improve the research process. Further, it is determined by the research philosophy and the methods selected for data collection and analysis (Denzin and Lincoln, 2006). Certain data collection and analysis methods are used in specific research designs. For instance, qualitative research often employs methods such as interviews, focus groups, and case studies, which are integral to gathering in-depth insights (Bryman, 2016). However, in quantitative research, methods such as experiments, surveys, and statistical analysis are typically employed (Saunders, Lewis and Thornhill, 2019).

For this research study, a positivist philosophy was paired with a quantitative research design, as surveys were selected as the primary data collection strategy. It is important to note that questionnaires are a specific method within the broader survey strategy, helping gather measurable data from participants (Bryman, 2016).

In research, a survey serves as a widely used strategy for data collection, aiming to gather information systematically from a large sample of participants. Surveys are often associated with quantitative methods, focusing on examining relationships between variables or describing specific population characteristics (Saunders, Lewis and Thornhill, 2019). Within the survey strategy,

questionnaires and structured interviews are common methods for collecting data. The primary distinction between questionnaires and structured interviews lies in their administration: interviews require the presence of an interviewer, whereas questionnaires allow participants to complete them independently (Bryman, 2016). Surveys are particularly valued for their efficiency in collecting large volumes of data relatively quickly compared to other strategies, such as experiments or observational studies. However, one potential drawback of surveys is that participants may provide inaccurate information, attempt to give socially desirable or "correct" answers or misunderstand certain questions (Bryman, 2016).

To address the research problem, this study employed a **quantitative** approach, using surveys as the data collection method. The model developed for this research is grounded in the UTAUT2 theory, which serves as the basis for testing the hypotheses. Given the nature of the study and the need for empirical evaluation, a **survey-based** approach was deemed the most suitable for gathering data and analysing patterns in consumer behaviour over time. This methodology allows for the systematic measurement of variables and the assessment of causal relationships, aligning with the study's goals to provide insight into the continuance use of WFTs.

Longitudinal Data Collection Approach

The section below elaborates on how the questionnaire was utilised to collect data longitudinally from current users of existing WFT/SW. Longitudinal designs involve collecting data from the same individuals or over an extended period. This design enables researchers to examine changes, trends, and patterns over time, providing insights into causal relationships and developmental processes (Creswell, 2009). This means that from a time-horizon perspective, the research model was assessed in a longitudinal setting. As shown in Figure 4-2 above, data were collected at two points: T1 (as explained in the previous section) and T2 (six months after the first round).

4.5 Data Collection

This section gives a detailed description of the questionnaire used to gather the data required for the study. The measurement scales for the various variables are discussed in the [conceptual framework](#) (Chapter 3), and the pilot study was carried out before the main data collection procedure.

Questionnaire Design

This study utilised a self-completion questionnaire, also known as a self-administered questionnaire, defined by Bryman (2016) as a method whereby respondents independently answer questions by completing the questionnaire themselves; this approach allows participants to provide their responses autonomously. Self-completion questionnaires have several benefits over structured interviews, including being quicker and less expensive to administer, as well as allowing the collection of responses from geographically dispersed samples. In the past, before the rise of electronic methods, postal service or mail was traditionally often used to distribute these questionnaires. In addition, many questionnaires can be mailed (both offline and online). According to Bryman (2016), using questionnaires can eliminate the influence of interviewer characteristics, such as gender, social background, and ethnicity, which may otherwise affect participants' responses. In addition, questionnaires are not subject to interviewer variability, whereby the order of the questions may vary. Furthermore, participants can complete the questionnaire at their convenience.

For this study, an **online social questionnaire** was conducted using Qualtrics and Prolific, as suggested by Bryman (2012). To reduce the effects of common method bias (CMB), the researcher followed the recommendations in Podsakoff *et al.* (2003) and Kock (2015), which included ensuring anonymity and encouraging honest responses. The survey questionnaire was divided into five sections, which are detailed below.

In the **first section**, the questionnaire (see [Appendix D](#)) briefly introduced the study with a detailed description, stating its objectives and providing statements regarding the maintenance of anonymity of participants' personal data; participation consent statements were also provided. Two screening questions followed this in the **second section**, in which the participants were asked whether they have/own a WFT device and how long they had owned it (the questions are elaborated in the questionnaire administration section below).

The **third section** contained statements related to the variables of interest (i.e., performance expectancy, effort expectancy, societal pressure, perceived enjoyment, perceived device annoyance, facilitating conditions, technology habit, price value, technology upgradability continued use intention, and continued use behaviour). In addition, a few attention-checking questions (e.g., "Please select Strongly agree for this sentence"; "Please select Strongly disagree"; and other similar questions) were randomly inserted in between the various statements on the study variables in order to ensure that only high-quality responses from attentive participants were recorded (Izogo *et al.*, 2022). Likewise, respondents were asked about their personality characteristics in the **fourth section**.

In the **fifth** and final section, demographic and socioeconomic status information about the participants, such as their age, gender, education level, and household income, were recorded. These were further used as control variables during the data analysis. In addition to the WFT/SW brand, WFT/SW possession duration, physical fitness level, and physical activity frequency (these three questions were asked at the beginning of the survey, after the screener validation questions) were recorded. Finally, the questionnaire ended with a note thanking the respondents for participating.

Measurements

All the constructs were measured using established multi-item scales adopted from previous studies, as shown in Table 4-2. However, the wording of the items for each construct was modified to fit the respective context of wearable fitness devices. A five-point Likert scale was employed for all scale items, enabling participants to indicate their level of agreement or disagreement with the statements, ranging from 1 (Strongly disagree) to 5 (Strongly agree). The choice of a five-point Likert scale is well supported in the literature, particularly in studies on technology adoption, as it balances simplicity and effectiveness in capturing participant responses. In his seminal work “A Technique for the Measurement of Attitudes”, Rensis Likert (1932) originally proposed a five-point response format as a standardised method for measuring attitudes and opinions (Schrum *et al.*, 2023). This scale simplifies the process for respondents to interpret and respond to the measurement while maintaining sufficient variability in the data for meaningful analysis (Attié and Meyer-Waarden, 2022). Its fully labelled format enhances the scale's clarity, making it easier for both researchers and respondents to interpret and understand (Weijters, Cabooter and Schillewaert, 2010). Furthermore, its widespread use in empirical research indicates that it is effective in assessing the quality of research measures and ensuring reliable and meaningful data collection (Salleh and Othman, 2019). The construct measurement scales included in the conceptual framework are discussed below.

Variables from UTAUT2 Theory and Other Variables

To operationalise the variables of the UTAUT2 model, the researcher borrowed items from previous studies (please note that some items were dropped or modified from Venkatesh, Thong and Xu's (2012) original research to better fit the context of the present study). Thus, existing measures were utilised to assess the UTAUT2 constructs.

Performance expectancy was measured using a four-item scale: I find the WFT useful in my daily life; Using WFT helps accomplish things more quickly; Using WFT improves the quality of my daily health/fitness activities; and Using WFT devices can provide the data/information I need. These items were adapted from Venkatesh *et al.* (2003), Venkatesh, Thong and Xu (2012), Gao, Li and Luo (2015), Zhu *et al.* (2022) and M. S. Rahman *et al.* (2022).

Effort expectancy was measured using a five-item scale: I can learn how to use new electronic devices (i.e., smartwatches) very quickly; I find WFT devices easy to use; I think it is easy to get hold of the data provided by WFT; I think I can make good use of WFT and the data provided; and It is easy for me to become skilful at using WFT devices. These items were adapted from Venkatesh *et al.* (2003), Venkatesh, Thong and Xu (2012), Gao, Li and Luo (2015), Zhu *et al.* (2022) and M. S. Rahman *et al.* (2022).

Facilitating conditions was measured using a five-item scale: I have the resources necessary to use WFT; I have the knowledge necessary to use WFT; WFT is compatible with other technologies I use; I can get help from others when I have difficulties using WFT devices; and Guidance will be available to me in using WFT devices (i.e., user manual, website, forums, live chats...etc.). These items were adapted from Venkatesh *et al.* (2003) and Venkatesh, Thong and Xu (2012).

Societal pressure, a kind of subjective norm, consists of four items relating to the perceived pressure from society members which are based on a scale by earlier researchers (Morris, Venkatesh and Ackerman, 2005), with appropriate modifications to examine WFT/SW adoption.

Societal pressure was measured using a four-item scale: My family members think that I should use the chosen WFT device to enhance my body image; My peers think that I should use the chosen WFT device to enhance my body image; My friends think that I should use the chosen

WFT device to enhance my body image; and As a whole, the use of the chosen WFT device is a trend which I will follow. These items were adapted from Morris, Venkatesh and Ackerman (2005).

Perceived enjoyment was measured using a four-item scale: Using WFT devices is truly fun; Using WFT devices is enjoyable; Using WFT gives me pleasure; and Using WFT makes me feel good. These items were adapted from Venkatesh and Bala (2008) and Yang *et al.* (2016).

Price value was measured using a four-item scale: It enables me to use WFT devices at a reasonable price; WFT devices are a good investment compared to the price paid for them; At the current price, WFT devices provide a good value/performance ratio; and Affordable, and I am willing to pay the current price given its features. These items were adapted from Venkatesh, Thong and Xu (2012).

Technology habit was measured using a four-item scale: The use of WFT devices has become a habit for me; I am addicted to using WFT devices; I must use WFT devices (Without them, I feel uncomfortable); and Using WFT devices has become natural to me (i.e., completely without thinking). These items were adapted from Venkatesh, Thong and Xu (2012).

Device annoyance was measured using a three-item scale (responding to I think it is disturbing if...): ...my WFT asks me to exercise (i.e., nudges, time to stand up, etc.); ...my WFT sends me motivational messages (i.e., badges, exercise rings closed); and ...my WFT informs me about my friends' sports activities (i.e., Nike run club). These items were adapted and developed based on Hutter *et al.* (2013) and Siepmann and Kowalczyk (2021).

Technology upgradability was measured using a four-item scale: WFT/SW devices have continuously been upgraded; WFT/SW devices will continuously be upgraded in the future; WFT/SW will improve its functionality (software program) while adding enhancements over an

earlier version; and WFT/SW will improve its functionality (hardware device) while providing greater performance than an earlier model. These items were adapted from Pae and Hyun (2006).

Consumers' Continued Use Intention and Continued Use Behaviour of WFT

Continued use intention was measured using a five-item scale: I intend to use WFT in the future; I always intend to use WFT at every opportunity in my daily life; I plan to increase my use of WFT frequently; I would like to use WFT whenever possible to achieve my fitness goals; and Considering my current mindset, I am more likely to use WFT further. These items were adapted from Venkatesh, Thong and Xu (2012).

Continued use behaviour was measured using a five-item scale: I intend to continue using these WFTs in the future; I will keep using WFT in my daily life as regularly as I do now; In the future, I will use this WFT more often; If I could, I would like to continue using this WFT as it positively impacted my daily activities; and Overall, I will continue using WFT than use any alternative means. These items were adapted from Venkatesh, Thong and Xu (2012).

Personality Traits

Similarly, the modified personality traits constructs were assessed by well-established measures from technology user-specific personal characteristics and applied psychology literature. For instance, the Five Factors Model of personality was measured using the NEO-Five Factor Inventory (Costa and McCrae, 1992). This well-validated measure assesses (1) openness to experience (the tendency to seek and be receptive to novel ideas, values, and behaviours), (2) conscientiousness (the tendency to be goal-directed, dependable, and premeditative), and (3) neuroticism (the tendency to worry, be self-conscious, and feel negative emotions). All the items were measured on a 5-point Likert scale ranging from 1 (Strongly disagree) to 5 (Strongly agree). Based on these measurements, some modifications were made to control the length of the three instruments.

Openness to technology innovativeness was measured using a five-item scale: I like to be around unconventional people who dare to try new things; I am curious about how things work; I like to experiment with new ways of doing things; I like to search for information about new products or technologies; and I often seek out information about new products. These items were adapted from Yang (2005).

Conscientiousness in health was measured using a four-item scale: I am very self-conscious about my health; I am alert to changes in my health; I like to experiment with new ways of doing things; and I take responsibility for the state of my health. These items were adapted from Michaelidou and Hassan (2008).

Neuroticism was measured using a three-item scale: I am easily worried about things; I am easily disturbed; and I get upset easily. These items were adapted from John and Srivastava (1999).

The rationale for focusing on the three personality-related individual variables selected and the decision to exclude agreeableness and extraversion were discussed in detail in Chapter 3, specifically in the section titled [Relevance of CinH, OTTI, and Neu](#).

Table 4–2 Measurement items

Construct/Variable	Measurement items	Item source
Performance expectancy (PerExp)	PerExp1 I find the WFT useful in my daily life. PerExp2 Using WFT helps accomplish things more quickly. PerExp3 Using WFT improves the quality of my daily health/fitness activities. PerExp4 Using WFT devices can provide the data/information I need.	Adapted and modified from “effort expectancy” in
Effort expectancy (EffExp)	EffExp1: I can learn how to use new electronic devices (i.e., smartwatches) very quickly. EffExp2 I find WFT devices easy to use. EffExp3 I think it is easy to get hold of the data provided by WFT. EffExp4 I think I can make good use of WFT and the data provided. EffExp5 It is easy for me to become skilful at using WFT devices.	Venkatesh <i>et al.</i> (2003), Venkatesh, Thong and Xu (2012), Gao, Li and Luo (2015), Zhu <i>et al.</i> (2022), and M. S. Rahman <i>et al.</i> (2022)
Facilitating conditions (FCons)	FCons1 I have the resources necessary to use WFT. FCons2 I have the knowledge necessary to use WFT. FCons3 WFT is compatible with other technologies I use. FCons4 I can get help from others when I have difficulties using WFT devices. FCons5 Guidance will be available to me in using WFT devices (i.e., user manual, website, forums, live chats...etc.).	Venkatesh <i>et al.</i> (2003) and Venkatesh, Thong and Xu (2012)
Societal pressure (SotPrss)	SotPrss1 My family members think that I should use the chosen WFT device to enhance my body image. SotPrss2 My peers think that I should use the chosen WFT device to enhance my body image. SotPrss3 My friends think that I should use the chosen WFT device to enhance my body image. SotPrss4 As a whole, the use of the chosen WFT device is a trend which I will follow.	Morris, Venkatesh and Ackerman (2005)
Perceived enjoyment (PEnj)	PEnj1 Using WFT devices is truly fun. PEnj2 Using WFT devices is enjoyable. PEnj3 Using WFT gives me pleasure. PEnj4 Using WFT makes me feel good.	Venkatesh and Bala (2008) and Yang <i>et al.</i> (2016)

Construct/Variable	Measurement items	Item source
Price value (PValu)	PValu1 It enables me to use WFT devices at a reasonable price. PValu2 WFT devices are a good investment compared to the price paid for them. PValu3 At the current price, WFT devices provide a good value/performance ratio. PValu4 Affordable, and I am willing to pay the current price given its features.	Venkatesh, Thong and Xu (2012)
Technology habit (TechH)	TechH1 The use of WFT devices has become a habit for me. TechH2 I am addicted to using WFT devices. TechH3 I must use WFT devices (Without them, I feel uncomfortable). TechH4 Using WFT devices has become natural to me (i.e., completely without thinking).	Venkatesh, Thong and Xu (2012)
Device annoyance (DAnoy)	I think it is disturbing if... DAnoy1 ...my WFT asks me to exercise (i.e., nudges, time to stand up, etc.). DAnoy2 ...my WFT sends me motivational messages (i.e., badges, exercise rings closed). DAnoy3 ...my WFT informs me about my friends' sports activities (i.e., Nike run club).	Developed based on Hutter <i>et al.</i> (2013) and Siepmann and Kowalczyk (2021)
Continued use intention (CUI)	CUI1 I intend to use WFT in the future. CUI2 I always intend to use WFT at every opportunity in my daily life. CUI3 I plan to increase my use of WFT frequently. CUI4 I would like to use WFT whenever possible to achieve my fitness goals. CUI5 Considering my current mindset, I am more likely to use WFT further.	Venkatesh <i>et al.</i> (2003) and Venkatesh, Thong and Xu (2012)
Continued use behaviour (CUB)	CUB1 I intend to continue using these WFTs in the future. CUB2 I will keep using WFT in my daily life as regularly as I do now. CUB3 In the future, I will use this WFT more often. CUB4 If I could, I would like to continue using this WFT as it positively impacted my daily activities. CUB5 Overall, I will continue using WFT than use any alternative means.	Venkatesh, Thong and Xu (2012)
Openness to technology innovativeness (OTTI)	OTTI1 I like to be around unconventional people who dare to try new things. OTTI2 I am very curious about how things work. OTTI3 I like to experiment with new ways of doing things.	Yang (2005)

Construct/Variable	Measurement items	Item source
	OTTI4 I like to search for information about new products or technologies. OTTI5 I often seek out information about new products.	
Conscientiousness in health (CinH)	CinH1 I am very self-conscious about my health. CinH2 I am alert to changes in my health. CinH3 I like to experiment with new ways of doing things. CinH4 I take responsibility for the state of my health.	Michaelidou and Hassan (2008)
Neuroticism (Neu)	Neu1 I am easily worried about things. Neu2 I am easily disturbed. Neu3 I get upset easily.	John and Srivastava (1999)
Technology upgradability (TUpG)	TUpG1 WFT/SW devices have continuously been upgraded. TUpG2 WFT/SW devices will continuously be upgraded in the future. TUpG3 WFT/SW will improve its functionality (software program) while adding enhancements over an earlier version. TUpG4 WFT/SW will improve its functionality (hardware device) while providing greater performance than an earlier model.	Pae and Hyun (2006)

Control Variables

Control variables refer to factors included in a research study to reduce the error terms and increase the statistical power (Schwab, 2011). The controls included in the current study were demographic variables and socioeconomic status information of the respondents: age, gender, household income and education level.

Previous research in the innovation adoption literature has reported that demographic variables and socioeconomic status related to the three variables may influence the pattern and intensity of consumers' continuance use of technology (Chuah *et al.*, 2016; Yang *et al.*, 2016; Siepmann and Kowalczyk, 2021). As a result, these variables were included as control variables in this study. Age was captured as an open-ended question in response to which the respondents entered the numeric value of their age. Restrictions were implemented such that only numeric values equal to or above 18 could be entered for "age". Gender was recorded in two categories, male and female, while acknowledging that this binary approach does not capture the full spectrum of gender identities. However, this choice aligns with traditional gender classifications in similar studies, facilitating comparability with existing literature. Education level was measured in terms of eight levels (i.e., Some primary; Completed primary school; Some secondary; Completed secondary school; Vocational or similar; Some university but no degree; University bachelor's degree; and Graduate or Professional degree (MA, MS, MBA, PhD, JD, MD, DDS)).

Pilot Study

A pilot study was conducted prior to initiating the main study. Firstly, the researcher conducted face-to-face feedback sessions with a few pilot study participants based on convenience and availability. The pilot study sample contained a number of PhD students from the Essex Business School at the University of Essex in the UK and personal trainers at one of the local fitness centres in Essex. The online questionnaire, designed on Qualtrics, was completed using the researcher's

personal iPad, resulting in seven completed questionnaires. Secondly, an online pilot study via the Prolific platform (a survey distribution tool) recruited another seven participants using particular selection criteria by applying pre-screening filters (i.e., age, approval rate, and number of previous submissions). The researcher targeted participants, including Prolific platform users, who were experienced and had a high number of approved submissions. For the pilot survey, separate spaces for providing feedback were included after each section of the online questionnaire.

The insights gained from this feedback, in both the face-to-face and the online interactions, helped the researcher ensure that the various instructions for attempting the questions and the statements measuring the study constructs/variables were meaningful and understandable to the respondents. The online distribution of questionnaires also helped the researcher review and resolve shortcomings that might have arisen while distributing the questionnaire electronically for the main study. Minor changes were made to the questionnaire based on the feedback obtained from the pilot study, such as rewording a few of the statements measuring the constructs to make the questionnaire more understandable to the respondents.

Questionnaire Administration for the Main Study

The data for the main study were collected using online self-administered or self-completion questionnaires designed on Qualtrics. As with the pilot study, age restrictions were included in the questionnaire to collect responses only from participants aged 18 or above. The online self-administered questionnaire was distributed among an online survey panel on Prolific to increase the response rate. The Prolific platform is suitable for conducting academic and behavioural research as it provides access to a large pool of online participants. It allows researchers to post studies and recruit appropriate participants for their online research quickly and easily. It assists researchers in enabling reliable and high-quality data collection by connecting diverse people

worldwide. At the same time, the platform gives respondents a chance to attempt surveys in return for an incentive, offering them a fair reward while helping advance human knowledge.

The validity of this method and its superiority to other recruitment methods (such as via social media and the physical distribution of questionnaires) have been shown in numerous previous empirical studies that used this platform for data collection. Most importantly, as the current study applies a longitudinal investigation (data were collected at two different points in time from the same sample), the Prolific platform offers a potentially efficient and useful crowdsourcing option for repeated assessment (Stanton *et al.*, 2022), as it records Prolific participants' IDs in order to invite them again in the second wave of a longitudinal design (Kothe and Ling, 2019).

A project was created on Prolific. Additional quality assurance measures ensured that only high-quality respondents could participate in the survey. For instance, the researcher conducted a **pre-screening short survey**, recruiting a large number of participants ($n = 633$) in order to achieve the desired sample size and one eligible for the main study (the criteria were discussed in the pilot study section). The researcher targeted participants who are experienced users with a high number of approved submissions (i.e., age, "approval rate", and "the number of previous submissions"). Only participants who met these particular selection criteria were permitted to participate in the survey, without restrictions to location preferences. The participants were also paid a nominal compensation for completing the survey.

Further, this study aimed to examine consumers' continued use behaviour of WFT (i.e., they had already adopted the technology) and the role of personality traits. Therefore, all potential participants were asked to answer two screening questions (to eliminate unsuitable respondents). The first was a "multiple answers" question asking what type of technological device they have: "Do you currently have/own any of the following technological devices? (Please select all that

apply)", to choose from "Smart car", "Smartwatch", or "other device". The second question asked about the length of time they had had such a device: "For how long have you had/owned this device?" to choose from one of the two answers: "Less than 3 weeks" or "More than 3 weeks".

Finally, after sorting/filtering the data, 339 eligible participants (who had owned a smartwatch for more than three weeks) were invited to the first wave of the longitudinal study. The custom allowlist option was applied, and their Prolific IDs were recorded so that those individuals could be invited to participate again in the second wave of 267 respondents.

The questionnaire was designed on Qualtrics and programmed with a Random ID, which helped generate random Survey Completion Codes for all the survey participants. Although Prolific helps to identify participants with a unique "Prolific participants ID", which allows each participant to submit a response only once, IP address restrictions were also implemented in Qualtrics to avoid multiple responses by the same participant. Therefore, at the end of the survey, participants were not asked to submit their Prolific ID in Qualtrics as well as their Survey Completion Code before submitting the survey, as the researcher had embedded a URL parameter to record participants' unique Prolific IDs automatically, which enabled matching the participant demographic data with their answers. These steps proved beneficial as they enabled the researcher to approve or reject submitted questionnaires (in cases of poor quality), ensuring that only valid submissions received payment. In addition, these steps facilitated participants' invitation to the second wave of this longitudinal study.

The inclusion of attention-checking questions (as previously detailed in the [questionnaire design](#) section) ensured that participants paid attention while filling out the questionnaire. The survey was terminated with the appropriate message when respondents did not correctly respond to the attention-checking questions. After the final submission of the survey responses, the submissions

submitted by respondents on Prolific were verified for valid responses by matching the respondent ID with a random ID (generated autonomously by Qualtrics). Invalid submissions were rejected by the researcher and republished to allow other respondents to attempt the survey.

1st Dataset

Data were collected from 339 respondents, which generated a final sample of $n = 333$ completed and approved questionnaires. The demographic characteristics of the final sample of respondents ($n = 331$) are as follows: **Gender:** 54.1% of the respondents were women, and 44.7% were men (1.2% preferred not to say); **Age:** The respondents' ages ranged from 18 to 55 years. The average age of the respondents was 31.8 years; and **Highest education level:** The respondents' education ranged from Some primary to Graduate or Professional degrees (MA, MS, MBA, PhD, JD, MD, DDS). Among the respondents, the largest group (41.1%) had University bachelor's degrees, followed by Graduate or Professional degrees (23.7%), and Some university but no degree (10.2%), while only a few (0.3%) had Some secondary education.

2nd Dataset

Data were collected from 267 respondents who completed questionnaires. The demographic characteristics of this final sample of respondents are as follows: **Gender:** ~60% of the respondents were women; **Age:** the respondents' ages ranged from 18 to 55 years. The average age of the respondents was 33.2 years; and **Highest education level:** 65% possessed or were pursuing a university degree or higher education.

Several technical challenges arose during the data collection for both T1 and T2. However, prompt communication with the relevant support team helped resolve these issues swiftly. To mitigate participant attrition, particularly at T2, diligent follow-up efforts were made, including regular reminders to encourage survey completion. Despite these efforts, challenges related to maintaining participant engagement persisted, although the identical set of items measuring both

the adoption and use of technology and personality traits was successfully used across both datasets.

4.6 Ethical Considerations

As this PhD thesis used primary data collection, several ethical considerations needed to be considered. Firstly, the topic was researched using quantitative data involving human participation. Therefore, ethical approval from the University of Essex Ethics Committee was required to be granted before undertaking the questionnaire survey. Secondly, before conducting the surveys, each participant had to sign an informed consent form (see Appendix B) stating that they willingly participated in this research. In addition, to be allowed to answer the survey, they were asked to declare that they were 18 or older and that they consented to participate in the study. Moreover, all the participants were aware that they could withdraw from the research at any stage.

Thirdly, as this PhD thesis examines the moderating role of technology user-specific personal characteristics in consumers' continued use of WFT, it is crucial to mention that participants' mental health and well-being were not compromised. Fourthly, as part of the questionnaire research design, participants were fully informed about the study, including its purpose and nature, through a cover letter accompanying each survey. This letter explicitly highlighted that the study was the first/second part of a two-phase longitudinal research project. Consent was interpreted as participants' willingness to take part in the survey and fill out the questionnaire. This approach ensured ethical transparency and informed participation throughout the research process. Furthermore, in following the University's ethics guidelines, it is important to note that participants were not asked any uncomfortable questions in the survey. Thus, all respondents were completely anonymous (the research did not require or collect any contact details, such as email address, phone number or mailing address from the participants), and the information received was treated as confidential and used only for academic purposes. Only the researcher and supervisors can

securely access the information in password-encrypted files. Prior to the beginning of the survey, the researcher's and her supervisor's contact information was provided in case participants had any concerns regarding the questionnaire, their participation, or the way the data would be used.

4.7 Chapter Summary

This chapter outlined the research methodology employed to investigate users' continued use of WFTs, with a particular focus on the moderating effects of psychological traits on continued use intention and behaviour. Rooted in a positivist philosophical framework, the study emphasises the development of objective and measurable knowledge by testing hypotheses derived from UTAUT2. The methodology adheres to a deductive approach, aiming to validate the theoretical constructs empirically through structured data analysis.

A descriptive research design was selected as the most appropriate means of systematically measuring the relationships between constructs, such as performance expectancy, effort expectancy, and societal pressure, alongside personality traits of openness to technological innovativeness, conscientiousness in health, and neuroticism. The investigation adopted a longitudinal framework, with data collected at two distinct time points, six months apart, to capture changes in consumer intention and behaviour over time. This design enabled a dynamic analysis of the interplay between technological factors and psychological traits, offering insights into the evolution of consumer engagement. Sampling for the study employed a stratified random technique to ensure representative participation while focusing on users aged 18 to 60 with prior experience of WFT usage. Data collection leveraged online platforms, ensuring a rigorous process that included attention checks to maintain high response quality. The research employed a self-administered online questionnaire as the primary data collection tool, incorporating well-established measurement scales validated in previous studies. These scales, tailored to the

context of wearable fitness devices, utilised a five-point Likert scale format to capture nuanced responses from each participant.

The study is deeply committed to ethical research practices, ensuring participant anonymity and securing informed consent while adhering to established ethical guidelines. Through this robust methodological framework, the research aimed to provide a comprehensive understanding of the factors influencing users' continued use of WFTs. By combining insights from technological constructs and psychological dimensions, the study seeks to contribute meaningfully to the existing body of knowledge relating to technology adoption and continued use behaviour.

Chapter 5: Quantitative Analysis (1st Dataset)

A longitudinal methodology was adopted in this thesis (see section [4.4.1](#)), and the first dataset was collected using the Qualtrics and Prolific platforms, as suggested in Bryman (2012); please see the data collection method in section [4.5.1 questionnaire design](#). The questionnaire was advertised to participants who had completed the short pre-screening study to filter WFT participants (633 participants) (see the [questionnaire administration](#) section) using the following text:

This study is about the adoption and use of technology. You will be asked about your usage and your personality traits. You have been invited to participate in this study as you are eligible based on the previous short survey (owning a Fitness Smartwatch for over 3 weeks). This is the FIRST Part of a longitudinal study (two-part study), which will be approximately six months apart. It will take you about 9 minutes (each), and you will receive bonus payments when completing both parts of the longitudinal study. Please read all questions CAREFULLY to avoid rejection.

Sample Profile

This first study's (T1) recruitment commenced on 17 February 2023 and concluded on 20 March 2023 (i.e., for 32 days), resulting in a total of 331 valid users/participants ($M_{\text{age}} = 32$, standard deviation [SD] = 6.9; 54.4% women). Almost half of the users (approximately 49%) fell within the 26-to-35-year-old age bracket, and 65% possessed or were pursuing a university degree or higher education. Table 5-1 summarises the respondents' demographic profile.

Table 5–1 Respondents' demographic profile

	Frequency	Percentage
Gender		
Female	180	54.4
Male	148	44.7
Age (years)		
18–25	66	19.9
26–35	162	48.9
36–45	98	29.6
46–55	5	1.6
Education		
Completed Primary School	1	0.3
Some Secondary	1	0.3
Completed Secondary School	37	11.2
Vocational or Similar	43	13
Some university but no degree	33	10
University bachelor's degree	138	41.7
Graduate or professional degree (MA, MS, MBA, PhD, JD, MD, DDS)	77	23.3
Prefer not to say	1	0.3
Current wearable device WFT/SW brand		
Apple	133	40.2
Samsung	35	10.6
Huawei	18	5.4
Garmin	26	7.9
Fitbit	86	26
Xiaomi	16	4.8
Fossil	4	1.2
Other	13	3.9

Some initial technical challenges arose; however, prompt communication with the support team facilitated a swift resolution, allowing the survey to progress and engage participants with items measuring both technology adoption and use, as well as personality traits.

The data analysis was conducted in five steps. First, a thorough coding and preliminary examination of the collected data was conducted using IBM SPSS 28. Second, all the multi-item scale measurements were examined using exploratory factor analysis (EFA), followed by confirmatory factor analysis (CFA) to identify and remove poor-performing items. Third, the final descriptive statistics of the refined multi-item scales were presented. Fourth, two methods, Harman's single-factor test (Podsakoff *et al.*, 2003) and the marker variable method (Lindell and Whitney, 2001), were employed to rule out the impact of common method bias (CMB). Finally, path analysis was conducted using structural equation modelling (SEM) in both AMOS 28 and SmartPLS4 to test the hypotheses outlined in the conceptual framework. This included evaluating direct effects, mediating effects, and moderating effects.

The study applies the SEM technique to test the model's proposed relations among the variables. This technique was deemed appropriate for this study's investigation type since it answers queries involving multiple statistical analyses of factors between a single measured dependent variable and a set of measured independent variables (Ullman and Bentler, 2013). SEM is used to test theoretical models (Hair *et al.*, 2014) and typically comprises two types of model:

1. The measurement model, which represents the theory and specifies how the variables measured collectively define the latent factors. In this model, the observed variables are assumed to represent the underlying latent factors; and
2. The structural model, which represents a theory by specifying the relationships between the latent constructs within the model.

5.1 Data Coding

The data collected via the online questionnaire were transferred to SPSS statistical software for preliminary analysis. The necessary coding of the study variables was carried out by providing names, labels, and scale types in SPSS.

5.2 Preliminary Examination of the Data

Before initiating the main data analysis, the collected data were examined using the following steps: a) evaluation of missing data; b) identification of outliers; and c) testing the assumption for multivariate analysis (Hair *et al.*, 2014).

5.2.1 Missing Data

When one or more variables are unavailable for further data analysis, this is referred to as missing data. Researchers are responsible for identifying such missing data and taking the necessary actions to ensure that their absence does not have an impact on the generalisability of the research results (Hair *et al.*, 2014). Hair *et al.* (2014) proposed a four-step process by which to identify missing data and apply appropriate remedies to address the issue. However, no missing cases were found after examining the data collected for this study, indicating that the suggested four-step process was unnecessary.

5.2.2 Outlier Detection

The next step in the preliminary data analysis included identifying outliers in the collected data. Outliers are those observations with unusually high or low values of the study variables that stand out from the other observations (Hair *et al.*, 2014). To identify outliers in the data collected for this study, boxplots for each variable were plotted using SPSS. The boxplots revealed outliers in the total collected observations ($n = 331$). Further, multivariate outlier detection was carried out by calculating the Mahalanobis distance (D^2) of each observation (Hair *et al.*, 2014). The value of D^2 was compared against the threshold value in the chi-square (χ^2) distribution table at the 0.001

significance level with 16 degrees of freedom (df). After applying both methods (i.e., boxplots and D^2), no outliers were identified; thus, the results yielded the same final sample of $n = 331$ for further analysis.

5.2.3 Assumption Testing

According to Hair *et al.* (2014), the four assumption tests of (a) normality, (b) homoscedasticity, (c) linearity, and (d) multicollinearity have the largest effects on multivariate techniques. All these tests were carried out for the individual constructs in this study.

Normality

In research studies, normality refers to the shape of the data distribution of each variable being analysed and should, ideally, follow a normal distribution. Non-normality can be evaluated based on two factors: the shape of the distribution and the sample size. Kurtosis and skewness values can be used to measure the shape of a distribution and, for a normal distribution, these values should be zero. Any non-zero value indicates non-normality, which means a non-normal distribution pattern. Researchers can also use statistical tests such as the Kolmogorov–Smirnov (KS) test to verify if the observed distribution deviates from the normal distribution. A significant KS test result indicates that there is a variation from normality.

The present study used SPSS statistical software to plot histograms for every variable. The histograms showed deviations from the expected zero values regarding kurtosis and skewness. Studies have shown that non-normality effects are negligible for a sample size greater than 200 (Hair *et al.*, 2014). However, larger sample sizes can help reduce the negative effects of non-normality. The current study had a sample size of $n = 331$, indicating that the non-normality effects are negligible.

Nonetheless, the KS test yielded significant results, highlighting the need for further examination. Descriptive statistics displayed positive and negative combinations of skewness and kurtosis values for different variables. However, these values were below the recommended threshold levels (Hair *et al.*, 2014; Byrne, 2016). A detailed discussion of these descriptive statistics, along with the factor analyses, is presented in [section 5.3](#).

Homoscedasticity

The assumption that a dependent variable represents equal levels of variance across a range of independent variables is denoted as homoscedasticity. Suppose this dispersion (i.e., the variance of the value of the dependent variable) is unequal across the values of the independent variable. In that case, the assumption of homoscedasticity is violated, and the relationship is said to be heteroscedastic (Hair *et al.*, 2014). To test this assumption, graphical tests of equal variance dispersion (i.e., a standardised residual scatter plot of the dependent variable) were carried out, revealing the uniform dispersion of the dependent variable across the independent variables, thereby satisfying the assumption of homoscedasticity.

Linearity

When using multivariate techniques to measure the association between variables, it is important to ensure that the assumption of linearity is met. This is because correlations only show a linear relationship between the independent and dependent variables (Hair *et al.*, 2014). Scatter plots were created for the relevant variables to check for linearity in this study. The majority of the data points were found to fall along a straight line, indicating a linear relationship with only minor deviations. As a result, the assumption of linearity has been satisfied.

Multicollinearity

Multicollinearity occurs when three or more independent variables in a regression equation that predict a dependent variable are associated. The simplest method of identifying collinearity is to examine a correlation matrix of the independent variables in which high correlations (i.e., 0.90 or more) represent sufficient collinearity (Hair *et al.*, 2014). However, two common measures, tolerance and the variance inflation factor (VIF), can be calculated to assess multicollinearity statistically. Tolerance measures the variability of an independent variable not explained by the other independent variables, and high tolerance values lead to a low degree of multicollinearity. The VIF is the inverse of tolerance. The suggested cut-off value for tolerance is 0.10, and the threshold value for a VIF is 10. Upon performing linear regression, the collinearity statistics for each independent variable showed acceptable values of tolerance above 0.10 and a VIF below 10.

5.3 Factor Analysis

Factor analysis is a technique for defining sets of highly intercorrelated items, known as factors. The purpose of factor analysis is to define the underlying structure of the scale items present in an analysis. In multivariate analysis, a large number of items may overlap (i.e., correlate with other items), and it is the responsibility of the researcher to manage these items by grouping those that are highly correlated (Hair *et al.*, 2014). Factor analytic techniques can be either exploratory or confirmatory, depending on the purpose. EFA aims to search for a defined set of variables. In contrast, CFA serves a purpose in cases in which researchers have a predefined data structure based on theoretical understanding (Hair *et al.*, 2014). In this study, EFA was conducted to identify poorly performing items, followed by CFA to remove redundant or non-reflective items.

5.3.1 Exploratory Factor Analysis

The purpose of EFA is to refine measurement scales by removing low-quality items and retaining only those with strong intercorrelations. Studies such as that by Acar Guvendir and Özer Ozkan (2022) have highlighted various item removal strategies during EFA and their impact on the factor structure and the reliability of scales. The following steps were undertaken and assessment made in this study prior to performing the EFA.

Sample-to-Item Ratio

The sample-to-item ratio in CFA refers to the number of participants (sample size) relative to the number of items included in the measurement model. It is an important consideration in CFA as it can have an impact on the reliability and validity of the model estimates (Bentler and Chou, 1987). It is generally recommended to have a minimum of 5 to 10 observations (sample) per item in the measurement model (Hair *et al.*, 2014). This guideline ensures sufficient statistical power, model identification, reliable factor loadings, and measurement error estimates. A larger sample size relative to the number of items also enhances the generalisability of findings (Kline, 2012).

However, practical constraints may sometimes require the relaxation of the guideline. Researchers should aim for an adequate sample-to-item ratio to ensure robust and valid CFA results; therefore, a more acceptable ratio would be 10:1. This study's sample-to-item ratio was below the recommended threshold of 10:1, necessitating the use of group-based EFA. Group 1 included seven factors measuring constructs related to technology adoption and continued use behaviours in respect of WFT, namely PerExp, SotPrss, PEnj, DAnoy, PValu, TechH, and CUI. Group 2 comprised seven factors representing the remaining predictors: EffExp, FCons, and TUpG; CUB; and the psychological traits: OTTI, CinH, and Neu.

Data Appropriateness of Factor Analysis

Bartlett's test of sphericity is a highly effective statistical test used to analyse correlations among items in a correlation matrix. A statistically significant result ($\text{sig.} < 0.05$) obtained from the test indicates that the items are intercorrelated and the data are fit for factor analysis. In addition, the Kaiser–Meyer–Olkin (KMO) measure assesses the homogeneity of the items within a construct (Kaiser and Rice, 1974). A KMO value of ≥ 0.90 is considered excellent, but < 0.50 is deemed unacceptable (Mickey and Sharma, 1997). Therefore, Bartlett's test of sphericity and the KMO test were calculated for both groups 1 and 2 using SPSS, ensuring the validity and reliability of the data obtained.

Selecting a Factor Extraction Method

When conducting factor analysis, the choice of factor extraction method is influenced by the research objective and the existing knowledge about the relationship between the items. There are different commonly used methods but they have distinct differences (Hair *et al.*, 2014). For instance, component analysis, also called principal component analysis, is a statistical technique commonly used to reduce data and identify factors that contain small proportions of unique variance. Common factor analysis, on the other hand, is used to determine latent dimensions or

constructs by considering shared variance. It does not require much knowledge of the specific and error variance of the items (Hair *et al.*, 2014). Maximum likelihood (ML) estimation and principal axis factoring (PAF) are two widely used extraction methods (de Winter and Dodou, 2012). ML is a popular statistical estimation method, particularly in EFA, as it seeks to identify parameter values that maximise the likelihood of observing the given data under a specified statistical model. In EFA, ML is commonly employed to estimate factor loadings and other model parameters. The choice between ML and PAF depends on the data characteristics: ML is preferred when data are normally distributed; PAF is more suitable when the assumption of normality is violated, as it focuses on explaining common variance (Norris and Lecavalier, 2010). In this research study, the main objective was to maximise the differences between factors and eliminate problematic items by providing a model fit estimate. The *maximum likelihood method* was selected during the EFA as the preferred factor extraction method (as the study used AMOS for CFA and structure modelling). The outcomes of this technique will be presented in later sections, as the latent constructs were already known.

Selecting a Factor Rotation Method

When analysing and interpreting factors, it is important to simplify and assign a theoretically meaningful factor solution. To achieve this, a rotation method must be selected. There are two main methods, referred to as "orthogonal" and "oblique", as their terms refer to the relationship between the extracted factors (Hair *et al.*, 2014).

1. Orthogonal Factors: These factors are independent and uncorrelated with each other, which means that they do not share any common variance. Orthogonal rotation methods, such as Varimax, Equamax or Quartimax, aim to achieve a factor solution whereby the factors are uncorrelated. Thus, orthogonal rotation is often used when the underlying factors are expected to be conceptually distinct and unrelated (Hair *et al.*, 2014).

2. **Oblique Factors:** These are correlated with each other, indicating that they share some degree of common variance. Oblique approaches include Oblimin, Promax, Orthoblique, Dquart, and Doblmin, which allow the extracted factors to be correlated. Oblique rotation is appropriate when there is an expectation of intercorrelation or shared variance among the factors, suggesting that they are not completely independent (Hair *et al.*, 2014).

The choice between orthogonal and oblique rotation depends on the theoretical assumptions and the nature of the data. Orthogonal rotation is typically applied if the factors are expected to be independent and unrelated. However, oblique rotation is more appropriate if there are theoretical reasons to believe that the factors may be correlated or if empirical analysis suggests a substantial correlation among the factors (Hair *et al.*, 2014).

Promax rotation is a popular oblique rotation method used in factor analysis and SEM. It allows for estimating both factor loadings and inter-factor correlations, acknowledging that factors can be correlated in real-world situations. During Promax rotation, the factors are rotated to a simpler structure that retains the correlations among them while maximising the interpretability of the factors (Browne, 2001). This makes Promax particularly useful when the underlying factors are expected to be correlated or when there is evidence of substantial correlation among the factors in the data. Further, this alternative oblique rotation method is computationally faster than the Oblimin method and is sometimes used for large datasets. Therefore, in this research study, an **oblique rotation** method, specifically, Promax, was utilised to achieve the study objectives.

Factor Loadings

After applying a suitable factor extraction method and rotation technique and interpreting the factors, a decision is made to differentiate between the factors based on the factor loadings, which are an item's and the factor's correlation. Factor loadings in the range of ± 0.30 to ± 0.40 are considered sufficient for interpreting factor structure, but loadings of ± 0.50 or greater are considered practically significant. Furthermore, the value of factor loadings based on a differing sample size can be considered significant. According to Hair *et al.* (2014), loadings of 0.30 are considered significant in some cases; for example, if the sample size is above 300, corresponding to the sample size of this study ($n = 331$). Therefore, this study considered a loading value of 0.40 to be significant in the EFA analysis.

Reliability

Reliability is conceptualised as the internal consistency among the items of a scale such that the individual items of that scale should all be measuring the same construct and are thus highly intercorrelated. It is essential to guarantee that all items on a scale measure the same construct and are highly interrelated to ensure reliability. Reliability is evaluated through a diagnostic measure known as Cronbach's alpha, which has a minimum threshold value of 0.7. In exploratory research, a value with a lower limit of 0.60 may be acceptable. Statistical software packages such as SPSS are utilised to calculate Cronbach's alpha. The EFA and reliability results for the individual constructs and the two measurement groups (1 and 2) are presented based on the steps discussed earlier. The researcher performed EFA using the ML extraction method along with Promax rotation in SPSS statistical software.

EFA and Reliability Results for Individual Constructs

Performance Expectancy

The analysis contained three scale items, which produced a KMO value of 0.849 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 80.631%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.967. A Cronbach's alpha value of 0.937, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The outcomes of the EFA and reliability statistics are presented in Table 5-2.

Table 5–2 EFA and reliability results for Performance Expectancy

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)
KMO measure		0.849			
Bartlett's	Approx. χ^2	1447.165	PerExp_3 0.967	80.631	0.937
test of			PerExp_2 0.956		
sphericity	df	6	PerExp_1 0.934		
	sig.	0.000	PerExp_4 0.711		

Effort Expectancy

The analysis contained three scale items, which produced a KMO value of 0.875 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 87.394%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.990. A Cronbach's alpha value of 0.951, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The EFA and reliability statistics outcomes are presented in Table 5-3.

Table 5–3 EFA and reliability results for Effort Expectancy

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)
KMO measure		0.875			
Bartlett's test of sphericity	Approx. χ^2	2102.602	EffExp_2	0.990	87.394
			EffExp_4	0.943	
	df	10	EffExp_3	0.916	
	sig.	0.000	EffExp_7	0.904	
			EffExp_1	0.757	

Societal Pressure

The analysis contained four scale items, which produced a KMO value of 0.784 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 56.896%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.877. A Cronbach's alpha value of 0.828, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The EFA and reliability statistics outcomes are presented in Table 5-4.

Table 5–4 EFA and reliability results for Societal Pressure

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)
KMO measure		0.784			
Bartlett's test of sphericity	Approx. χ^2	534.076	SotPrss_2	0.877	56.896
			SotPrss_3	0.814	
	df	6	SotPrss_1	0.720	
	sig.	0.000	SotPrss_4	0.571	

Perceived Enjoyment

The analysis contained four scale items, which produced a KMO value of 0.796 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 87.865%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.990. A Cronbach's alpha value of 0.964, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The EFA and reliability statistics outcomes are presented in Table 5-5.

Table 5–5 EFA and reliability results for Perceived Enjoyment

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)		Total variance	Cronbach's alpha (>0.70)
KMO measure		0.796				
Bartlett's test of sphericity	Approx. χ^2	1848.087	PEnj_4	0.990	87.865	0.964
	df	6	PEnj_3	0.958		
			PEnj_1	0.937		
	sig.	0.000	PEnj_2	0.859		

Perceived Device Annoyance

The analysis contained three scale items, which produced a KMO value of 0.667 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 54.695%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.873. A Cronbach's alpha value of 0.767, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The EFA and reliability statistics outcomes are presented in Table 5-6.

Table 5–6 EFA and reliability results for Perceived Device Annoyance

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)
KMO measure		0.667			
Bartlett's test of sphericity	Approx. χ^2	278.245	DAnoy_19 0.873	54.695	0.767
	df	3	DAnoy_20 0.719		
	sig.	0.000	DAnoy_18 0.602		

Facilitating Conditions

The analysis contained four scale items, which produced a KMO value of 0.897 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 73.609%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.969. A Cronbach's alpha value of 0.943, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The EFA and reliability statistics outcomes are presented in Table 5-7.

Table 5–7 EFA and reliability results for Facilitating Conditions

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)
KMO measure		0.897			
Bartlett's test of sphericity	Approx. χ^2	1903.925	FCons_2 0.969	73.609	0.943
	df	15	FCons_3 0.894		
	sig.	0.000	FCons_4 0.885		
			FCons_5 0.839		
			FCons_6 0.795		
			FCons_1 0.747		

Technology Habit

The analysis contained four scale items, which produced a KMO value of 0.784 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 58.327%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.792. A Cronbach's alpha value of 0.842, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The outcomes of the EFA and reliability statistics are presented in Table 5-8.

Table 5–8 EFA and reliability results for Technology Habit

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)		Total variance	Cronbach's alpha (>0.70)
KMO measure			0.784			
Bartlett's test of sphericity	Approx. χ^2	561.483	TecH_1	0.792	58.327	0.842
	df	6	TecH_2	0.782		
			TecH_3	0.760		
	sig.	0.000	TecH_4	0.716		

Price Value

The analysis contained four scale items, which produced a KMO value of 0.802 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 72.225%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.978. A Cronbach's alpha value of 0.897, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The EFA and reliability statistics outcomes are presented in Table 5-9.

Table 5–9 EFA and reliability results for Price Value

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)	
KMO measure		0.802				
Bartlett's test of sphericity	Approx. χ^2	1039.555	PValu_3	0.978	72.225	0.897
	df	6	PValu_2	0.895		
			PValu_4	0.856		
	sig.	0.000	PValu_1	0.631		

Technology Upgradability

The analysis contained four scale items, which produced a KMO value of 0.768 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 60.159%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.867. A Cronbach's alpha value of 0.850, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The EFA and reliability statistics outcomes are presented in Table 5-10.

Table 5–10 EFA and reliability results for Technology Upgradability

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)
KMO measure		0.768			
Bartlett's test of sphericity	Approx. χ^2	6227.613	TUpG_3	0.867	0.850
	df	6	TUpG_6	0.840	
	sig.	0.000	TUpG_1	0.719	
			TUpG_2	0.657	

Continued Use Intention

The analysis contained three scale items, which produced a KMO value of 0.865 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 79.066%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.994. A Cronbach's alpha value of 0.947, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The outcomes of the EFA and reliability statistics are presented in Table 5-11.

Table 5–11 EFA and reliability results for Continued Use Intention

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)
KMO measure		0.865			
Bartlett's test of sphericity	Approx. χ^2	2170.094	CUI_10 0.994	79.066	0.947
	df	10	CUI_7 0.967		
			CUI_11 0.946		
	sig.	0.000	CUI_6 0.844		
			CUI_9 0.650		

Continued Use Behaviour

The analysis contained five scale items, which produced a KMO value of 0.865 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 75.232%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.995. A Cronbach's alpha value of 0.931, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The outcomes of the EFA and reliability statistics are presented in Table 5-12.

Table 5–12 EFA and reliability results for Continued Use Behaviour

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)
KMO measure		0.865			
Bartlett's test of sphericity	Approx. χ^2	1647.963	CUB_1 0.995	75.232	0.931
	df	10	CUB_3 0.905		
			CUB_4 0.881		
	sig.	0.000	CUB_5 0.858		
			CUB_2 0.662		

Openness to Technological Innovativeness

The analysis contained five scale items, which produced a KMO value of 0.866 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 62.146%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.883. A Cronbach's alpha value of 0.886, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The outcomes of the EFA and reliability statistics are presented in Table 5-13.

Table 5–13 EFA and reliability results for Openness to Technological Innovativeness

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)		Total variance	Cronbach's alpha (>0.70)
KMO measure		0.866				
Bartlett's test of sphericity	Approx. χ^2	961.644	OTTI_2	0.883	62.146	0.886
			OTTI_1	0.879		
	df	10	OTTI_5	0.867		
			OTTI_4	0.651		
	sig.	0.000	OTTI_3	0.617		

Conscientiousness in Health

The analysis contained four scale items, which produced a KMO value of 0.857 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 83.698%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.958. A Cronbach's alpha value of 0.952, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The outcomes of the EFA and reliability statistics are presented in Table 5-14.

Table 5–14 EFA and reliability results for Conscientiousness in Health

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)	
KMO measure		0.857				
Bartlett's test of sphericity	Approx. χ^2	1488.307	CinH_2	0.958	83.698	0.952
	df	6	CinH_1	0.953		
			CinH_3	0.922		
	sig.	0.000	CinH_4	0.819		

Neuroticism

The analysis contained three scale items, which produced a KMO value of 0.763 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 81.778%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.921. A Cronbach's alpha value of 0.930, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The outcomes of the EFA and reliability statistics are presented in Table 5-15.

Table 5–15 EFA and reliability results for Neuroticism

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)	
KMO measure		0.763				
Bartlett's test of sphericity	Approx. χ^2	805.542	Neu_4	0.921	81.778	0.930
	df	3	Neu_2	0.918		
			Neu_1	0.873		
	sig.	0.000				

EFA – Group 1

For Group 1, EFA was conducted for 27 items using the **ML** factor extraction method and **Promax** rotation. The initial analysis showed a KMO measure of 0.897, which is more than 0.50, indicating an adequate sample, suggesting data appropriateness for conducting the analysis. Bartlett's test of sphericity, which tests the hypothesis that the correlation matrix is an identity matrix (meaning that the variables are unrelated), was significant, with a value of below 0.50. The selection of factor extraction based on eigenvalues > 1 resulted in a seven-factor structure with all the loadings above the cap of 0.4.

Nonetheless, conceptually, the items should load on seven different factors since the items measured seven different constructs. Hence, the analysis revealed cross-loadings of items in the resulting factor structure. A solution for this, according to Hair *et al.* (2014), would be to identify a fixed number of factors to be extracted based on theoretical grounds, which allows problematic items to be detected or the removal of those problematic items. Thus, CUI_9 was removed. Afterwards, CFA was used to test the unidimensionality of the factors. Table 5-16 (a pattern matrix) demonstrates the final seven-factor and total variance explained (seven factors were extracted, as expected).

Table 5–16 EFA – final results – Group 1

Pattern Matrix ^a							
	Factor						
	1	2	3	4	5	6	7
CUI_10	1.036						
CUI_7	0.981						
CUI_11	0.919						
CUI_6	0.753						
PEnj_4		1.034					
PEnj_3		0.985					
PEnj_1		0.897					
PEnj_2		0.743					
PValu_3			0.989				
PValu_2			0.916				
PValu_4			0.844				
PValu_1			0.586				
PerExp_3				0.973			
PerExp_2				0.958			
PerExp_1				0.910			
PerExp_4				0.473			
SotPrss_2					0.905		
SotPrss_3					0.819		
SotPrss_1					0.691		
SotPrss_4					0.533		
TecH_1						0.807	
TecH_2						0.792	
TecH_3						0.752	
TecH_4						0.697	
DAnoy_19							0.880
DAnoy_20							0.723
DAnoy_18							0.549

Extraction method: maximum likelihood.

Rotation method: Promax with Kaiser normalisation.

a. Rotation converged in 6 iterations.

Note: Extraction method: maximum likelihood; Rotation method: Promax with Kaiser normalisation. Kaiser–Meyer–Olkin measure of sampling adequacy = 0.897; Bartlett's test of sphericity approx. $\chi^2 = 9022.308$; df = 378; sig. = 0.000

EFA – Group 2

For Group 2, EFA was conducted for 32 items using the **ML** factor extraction method and **Promax** rotation. The initial analysis showed a KMO measure of 0.887, which is more than 0.50, indicating an adequate sample, suggesting the appropriateness of the data for conducting the analysis. Bartlett's test of sphericity, which tests the hypothesis that the correlation matrix is an identity matrix (meaning that the variables are unrelated), was significant, with a value of below 0.50. The selection of a factor extraction method based on eigenvalues > 1 resulted in a seven-factor structure with all the loadings above the cap of 0.40. Afterwards, CFA was used to test the unidimensionality of the factors. Table 5-17 (a pattern matrix) demonstrates the final seven factors and total variance explained (seven factors were extracted, as expected).

Table 5–17 EFA – final results – Group 2

Pattern Matrix ^a							
	Factor						
	1	2	3	4	5	6	7
FCons_2	0.993						
FCons_3	0.902						
FCons_4	0.898						
FCons_5	0.830						
FCons_6	0.771						
FCons_1	0.706						
CUB_1		0.995					
CUB_3		0.930					
CUB_4		0.873					
CUB_5		0.842					
CUB_2		0.653					
EffExp_2			0.989				
EffExp_7			0.935				
EffExp_4			0.918				
EffExp_3			0.898				
EffExp_1			0.693				
CinH_1				0.972			
CinH_2				0.954			
CinH_3				0.925			
CinH_4				0.788			
OTTI_2					0.893		
OTTI_5					0.882		
OTTI_1					0.877		
OTTI_4					0.653		
OTTI_3					0.559		
TUpG_3						0.891	
TUpG_6						0.843	
TUpG_1						0.689	
TUpG_2						0.621	
Neu_4							0.924
Neu_2							0.918
Neu_1							0.872

Extraction method: maximum likelihood.

Rotation method: Promax with Kaiser normalisation.^a

a. Rotation converged in 6 iterations.

Note: Extraction method: maximum likelihood; Rotation method: Promax with Kaiser normalisation. Kaiser–Meyer–Olkin measure of sampling adequacy = 0.887; Bartlett's test of sphericity approx. $\chi^2 = 10221.612$; $df = 496$; $sig. = 0.000$

5.3.2 Confirmatory Factor Analysis

In the previous section, EFA was explained as a statistical technique used to identify underlying factors that describe patterns of correlations among the variables observed. EFA is a data-driven approach primarily used for exploring and understanding data structure when there is limited theoretical knowledge about how the variables should be grouped (Norris and Lecavalier, 2010). Thus, EFA is exploratory in nature by identifying factors that maximise the common variance among observed variables and allowing factors to emerge from the data without imposing specific constraints. This approach gives the researcher information about how many factors are suitable to represent the data that have been collected, depending on the results of the factor loading (Hair *et al.*, 2014).

Confirmatory factor analysis differs from EFA in that the researcher specifies both the number of factors and the items that will load onto each factor. This assists the researcher in deciding whether to accept or discard a theory by showing how the theoretically predicted factors correspond to the actual data (Hair *et al.*, 2014). CFA is a specific form/technique of factor analysis frequently employed in fields such as the social sciences, business, and psychology to validate and assess theoretical constructs. CFA examines how well-observed variables correspond to the expected underlying factors based on a theorised relationship, making it particularly valuable when researchers have specific theoretical expectations about the structure of variables. This technique enables researchers to evaluate whether their data support a hypothesised model or theoretical framework, often informed by measurement theory. The process involves two key steps. First, researchers develop hypotheses about the factors underlying the measures and impose constraints on the model based on these prior assumptions. Second, the researchers use CFA to

confirm or reject the hypotheses, providing insights into how well the proposed model fits the observed data (Costa and Sarmento, 2019).

In summary, EFA is used for exploring and uncovering underlying patterns in data when little is known about the underlying structure, whereas CFA is employed to test specific hypotheses with regard to the relationships between variables and latent factors based on prior knowledge or theoretical expectations (and thus test the fit of a predefined measurement model to the data). According to Hair *et al.* (2014), CFA is a multi-step process that entails the following steps: I) development of a measurement model; II) measurement model specification and identification; III) assessment of measurement model fit; and IV) assessment of measurement model validity.

Development of a Measurement Model

The development of a measurement model in CFA is a complex process that requires both theoretical insight and empirical testing. Such a crucial step assesses and validates latent constructs or variables. As mentioned earlier, CFA is a statistical technique to assess and confirm the factor structure of a set of observed variables and to determine whether these indicators are measuring a single underlying construct or dimension (latent variable) (Costa and Sarmento, 2019). Researchers start by specifying a theoretical model that describes how the observed variables are related to latent constructs. They often use specialised software, such as AMOS, to conduct CFA and evaluate model fit. Additionally, error terms are specified for each observed variable to account for measurement error. This model is represented as a set of factor loadings, indicating the strength of the relationship between each observed variable and its corresponding latent construct (Shi *et al.*, 2016), which is then tested using statistical techniques to assess its goodness of fit with the observed data. If the model fits the data well, it provides evidence for the validity of the measurement model, indicating that the observed variables are indeed measuring the intended latent constructs. If the model does not fit the data, however, researchers may need

to revise the model by adding or removing variables, modifying factor loadings, or considering correlated errors (Fornell and Larcker, 2016).

Unidimensionality is crucial when obtaining an overall measurement model for CFA when more than two constructs are being analysed (Gerbing and Anderson, 1988). Unidimensionality in CFA is a fundamental assumption and property of a measurement model that refers to the idea that a collection of measured items should only be related to one construct (Hair *et al.*, 2014). In other words, if a set of variables is considered unidimensional, they all tap into the same underlying trait or dimension. Thus, it is important that researchers test unidimensionality empirically using CFA to assess whether this assumption holds and to validate measurement models. Constructs should also be classified as reflective or formative. The foundation of reflective measurement theory is that latent constructs are responsible for the variables measured. In contrast, formative measurement theory assumes that formative constructs are not latent. The inability of the measured items to define the constructs is thus a flaw in a formative measurement model (Hair *et al.*, 2014). In this study, the constructs used in the CFA are reflective and latent. Consequently, in the CFA diagrams, the direction of the arrows is drawn from the latent constructs to the measured items, reflecting the causality inherent in reflective measurement models.

Measurement Model Specification and Identification

While CFA investigates measurement theory, researchers identify the indicators (items) that measure the specific constructs based on a theoretical foundation. Moreover, for model identification, degrees of freedom (the degree of identification) are used to determine whether a measurement model is under-identified, just identified, or over-identified. Degrees of freedom (df) signify the number of values in the final estimation of a model that are free to vary, given the data and the model's constraints (Bollen and Stine, 1992).

The following formula represents the df equation in CFA: $df = \frac{1}{2} (p(p+1)) - k$, where p refers to the total number of measured items, and k is the total number of paths to estimate, which can be used to determine the degrees of freedom. Further, the formula depends on several factors: the number of observations (N), the total sample size, or the number of cases or participants in the study; the number of parameters (P), which includes the fixed and free parameters in the model, such as factor loadings, intercepts, and variances. P is influenced by the number of factors, indicators, and factor correlations; and model constraints, such as equality constraints on factor loadings or intercepts, which reduce the number of free parameters and influence the df.

Hence, a model's df is critical in hypothesis testing and assessing model fit through fit indices such as the comparative fit index (CFI), chi-square statistic, and root mean square error of approximation (RMSEA). Understanding df is essential, as it helps determine whether a model adequately fits the data and draws valid conclusions from the analysis. A good-fitting model should have a chi-square value that is not statistically significant, indicating that the model is a plausible representation of the data (Kline, 2012). Moreover, an overidentified model with positive df is advised when conducting CFA (Hair *et al.*, 2014).

Assessment of Measurement Model Fit

After specifying a measurement model, the researcher infers its goodness of fit (GOF). This indicator compares the estimated covariance matrix with the observed covariance matrix (i.e., comparing theory to reality). This comparison evaluates how well the model represents the real-world data, whereby a higher similarity between the values of the two matrices indicates a better model fit. The quality of the GOF is measured in terms of fit indices, which can be absolute or incremental (Hair *et al.*, 2014).

Absolute Fit Indices

Absolute fit is the first category of fit indices, and includes the χ^2 statistic, a mathematical function of N (the sample size) and the difference between observed and estimated covariances. In addition, χ^2 and N are associated as the value of χ^2 increases with an increase in the value of N (larger sample sizes). Subsequently, to have a good model fit, low values of χ^2 are recommended. Normed χ^2 is another measure of the ratio of chi-square to the degrees of freedom ($\chi^2:df$), for which Hair *et al.* (2014) suggested a value of less than 3:1 as indicating a better fit.

RMSEA is a widely used fit index in SEM, including CFA, and measures the discrepancy between the observed data and the model-implied covariance structure, providing a measure of how well the model fits the data, and can be calculated by the equation $RMSEA = \sqrt{\hat{F}_0 / df_t}$, where $\hat{F}_0 = \max[(T_T - df_T)/(N - 1), 0]$.

Where T_T = T statistic for the target model; and df_T = df for the target model (Hu and Bentler, 1999).

Thus, RMSEA considers the error of approximation in the population and asks, "How well would the model, with unknown but optimally chosen parameter values, fit the population covariance matrix if it were available" (Browne and Cudeck, 1992, pp. 137-138). It quantifies the discrepancy between the observed data and the model-implied data, adjusted for model complexity, to assess the model's fit to the population. RMSEA is less influenced by sample size than some other fit indices, such as the χ^2 statistic, which makes it particularly useful for larger datasets but still reliable for smaller samples (helping to ensure that the fit assessment is robust and not overly influenced by sample-specific characteristics). Therefore, RMSEA is valuable as a control for sample size (Cheung, Eggers and de Vries, 2021). It helps assess how well the model generalises to the population beyond just fitting the observed sample data. It also evaluates how well the model is likely to perform with a new random sample from the same population. Again, Hair *et al.* (2014)

recommended that a lower RMSEA indicates a better fit, with values below 0.07 often considered acceptable.

Incremental Fit Indices

The second category of fit indices contains the incremental fit indices, which compare the model fit to some alternative baseline model (null model). The CFI is the first index insensitive to model complexity under this category, whereby better-fitting models should have a CFI value greater than 0.90. The second index is the Tucker–Lewis index (TLI), which assesses the normed χ^2 of null and specified models. TLI values can also be less than 0 or above 1. TLI values approaching 1 are considered good for a good model fit (Hair *et al.*, 2014).

Assessment of the Measurement Model Validity Construct

Construct validity has been, and still is, a crucial concept in psychometrics for almost 70 years since the original version in Cronbach and Meehl (1955). In their classic article "Construct Validity in Psychological Tests", the researchers argued that to solve the challenge of scientific psychology concerns regarding measuring hypothetical constructs in a convincing, valid way, one must demonstrate that one's measure of a given construct relates to measures of other constructs in theoretically predictable ways (Smith, 2005, p. 396). Construct validity pertains to the accuracy of measurement, ensuring that the measured items accurately capture the intended latent constructs (Hair *et al.*, 2014). In CFA, establishing construct validity is assessed through two key components: convergent validity and discriminant validity.

Convergent Validity

Convergent validity is one facet of construct validity and examines the degree of correlation among multiple indicators of the same construct. It is evaluated by considering factor loadings, average variance extracted (AVE), and construct reliability (CR) (Hair *et al.*, 2014). High factor loadings between observed variables and the latent construct suggest strong convergent validity. A general guideline is that factor loadings should exceed 0.50, with values of 0.70 or higher being ideal (Hair

et al., 2014). When analysing SEM in a software package such as AMOS, the standardised regression coefficients provide valuable information about how well each observed variable measures its corresponding latent construct by indicating the **factor loadings** essential for assessing convergent validity and understanding the quality of the measurement model in SEM. Table 5-18 presents the factor loadings evaluated for practical significance, as recommended in Hair *et al.* (2014).

Table 5–18 Table of loadings for practical significance (Hair *et al.*, p. 112)

Significant factor loadings based on sample size	
Sample size	Sufficient factor loading
50	0.75
60	0.70
70	0.65
85	0.60
100	0.55
120	0.50
150	0.45
200	0.40
250	0.35
350	0.30

Average variance extracted is a statistic used in SEM and CFA to assess the convergent validity of a latent construct, representing the average variance extracted from item loadings on the construct (Hair *et al.*, 2014). A commonly accepted guideline is that the AVE value should exceed 0.50, indicating that the variance explained by the latent construct is greater than the variance attributed to measurement error. This demonstrates adequate convergent validity, suggesting that the indicators reliably reflect the latent construct they are intended to measure (Fornell and Larcker, 2016). To calculate the AVE for a particular latent construct, the sum of the squared standardised factor loadings for all the indicators related to that construct is then divided by the sum of the error variances for those indicators. In CFA, this is calculated as follows: the total of the squared multiple

correlations + the total sum of each variable, divided by the number of factors in that variable, using Equation (1) as follows:

$$\text{Equation (1)} \quad \frac{\sum_{i=1}^n L_i^2}{n}$$

Where, L_i = standardised factor loadings and n = number of items. A common guideline is that the AVE value should be greater than 0.50 to demonstrate that the latent construct explains more variance than measurement error, suggesting sufficient convergent validity.

Construct reliability is the last crucial concept in CFA for assessing convergent validity (internal consistency and reliability of latent constructs measured by their indicators) and is computed using the following formula (Hair *et al.*, 2014):

$$\text{Equation (2)} \quad CR = \frac{(\sum_{i=1}^n L_i)^2}{(\sum_{i=1}^n L_i)^2 + (\sum_{i=1}^n e_i)}$$

Where, L_i = standardised factor loadings, n = number of items, and e = error variance terms for a construct = $1 - L_i^2$.

To establish satisfactory convergent validity, it is generally advisable to aim for a CR value exceeding 0.70, indicating a high level of reliability. Nonetheless, CR values ranging from 0.60 to 0.70 might be deemed acceptable if other convergent validity indicators demonstrate strong performance (Hair *et al.*, 2014). To conclude, in CFA, ensuring satisfactory construct reliability is fundamental as it confirms that the variables observed consistently measure the underlying construct. Thus, CR is used as a quality control metric to enhance measurement model validity (Fornell and Larcker, 2016).

Discriminant Validity

Discriminant validity is the other form of construct validity in CFA and is a vital component in assessing whether a construct is distinct from other constructs, ensuring that latent factors are correlated less with each other than their respective indicators (Kline, 2012). To test this form of validity, the AVE value of each latent construct should be greater than the squared correlation estimates with all the other constructs (Hair *et al.*, 2014). Failing to establish discriminant validity can lead to construct overlap and undermine the validity of the measurement model (Fornell and Larcker, 2016). The following section presents the CFA results for the two measurement models conducted in AMOS 28.

a) CFA – Measurement Model 1

Specification and Identification Measurement

Measurement model 1 is specified with seven reflective latent constructs. The seven latent constructs are as follows: continued use intention, reflected by four items (CUI_6, CUI_7, CUI_10, and CUI_11); perceived enjoyment, reflected by four items (PEnj_1 to PEnj_4); price value, reflected by four items (PValu_1 to PValu_4); performance expectancy, reflected by four items (PerExp_1 to PerExp_4); societal pressure, reflected by four items (SotPrss_1 to SotPrss_4); technology habit, reflected by four items (TechH_1 to TechH_4); and perceived device annoyance, reflected by three items (DAnoy_18, DAnoy_19, and DAnoy_20). Further error terms were linked to each observed item within the measurement model. The degrees of freedom were computed for measurement model 1 identification. Specifically, there were a total of 27 items (denoted as "p"), and the count of **distinct parameters to be estimated** was 75 (represented as "k"). Hence, inserting these values into the equation: $df = \frac{1}{2} (p(p+1)) - k$, the degrees of freedom were computed as $df = \frac{1}{2} (27(27+1)) - 75 = 303$; this represents positive degrees of freedom, suggesting that measurement model 1 was overidentified, making it a suitable choice for conducting CFA. Figure

5-1 below illustrates the final measurement model 1, which exhibits robust model fit and construct validity (and encompasses all 27 measured items).

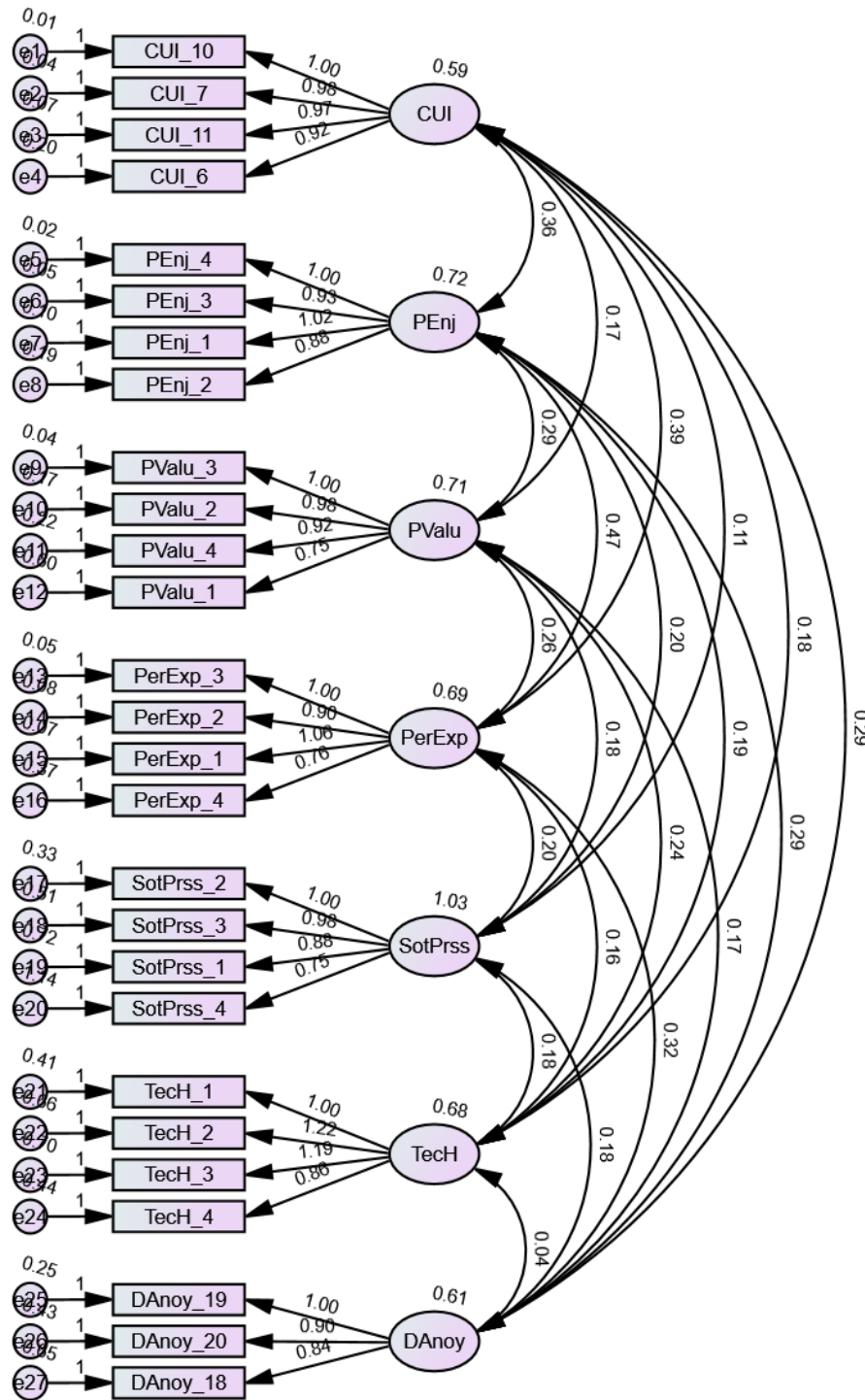


Figure 5-1 Final measurement model 1

$\chi^2 = 657.267$, $df = 303$, $RMSEA = 0.060$, $CFI = 0.959$, $TLI = 0.952$

Assessment of Model Fit and Construct Validity

In the CFA, a model fit and construct validity assessment involving seven latent constructs and 27 observed items was performed. The initial measurement model was examined for construct validity and model fit. Subsequently, guided by the EFA outcomes, the initial construct validity, model fit, and assessments, a problematic item (CUI_9) was systematically removed to accomplish an optimal model fit and construct validity. The model fit evaluation relied on absolute fit indices (such as χ^2/df and RMSEA) and incremental fit indices (including CFI and TLI). Fit statistics from the initial CFA analysis are shown in Table 5-19. These results indicated good model fit indices.

Table 5–19 Final fit statistics – measurement model 1

Model fit indices	χ^2	(df)	$\chi^2/df < 3$	RMSEA <0.07 with CFI >0.92	CFI >0.90	TLI >0.90
All items (27)	658.267	(303)	2.172	0.60	0.959	0.952

The values of the construct validity measures were also examined. In AMOS output, factor loadings are presented as standardised weights. The preliminary findings indicated that a majority of the items had factor loadings surpassing the desirable threshold of 0.70. Further, the AVE of all seven latent constructs was calculated using Equation (1). For instance, the AVE of perceived device annoyance was calculated as $0.880 + 0.723 + 0.549 / 3 = 0.717$. A similar procedure was applied to calculate the AVEs for the remaining latent constructs. In the initial analysis, the AVEs for all latent constructs exceeded the threshold of 0.50.

CR was then computed using Equation (2). As an illustration, the CR for the latent construct perceived device annoyance was determined in the following manner:

$$(0.840 + 0.734 + 0.628)^2 / (0.840 + 0.734 + 0.628)^2 + (0.294 + 0.461 + 0.606) = 0.764$$

The same calculation procedure was applied to determine the CR values for the remaining latent constructs. The initial assessment indicated that all construct CR values exceeded the minimum threshold of 0.70. Table 5-20 displays the CR and AVE values for all the latent constructs within the measurement model.

Table 5–20 Convergent validity results for measurement model 1

	CR	AVE	TechH	CUI	PEnj	PValu	PerExp	SotPrss	DAnoy
TechH	0.848	0.583	0.764						
CUI	0.968	0.884	0.280	0.940					
PEnj	0.967	0.881	0.277	0.545	0.938				
PValu	0.911	0.724	0.347	0.255	0.408	0.851			
PerExp	0.943	0.808	0.233	0.617	0.662	0.369	0.899		
SotPrss	0.838	0.570	0.220	0.142	0.233	0.211	0.239	0.755	
DAnoy	0.781	0.546	0.061	0.478	0.444	0.253	0.491	0.233	0.739

Note: CR = construct reliability; AVE = average variance extracted; TechH = technology habit; CUI = continued use intention; PE_{enj} = perceived enjoyment; PValu = price value; PerExp = performance expectancy; SotPrss = societal pressure; DAnoy = perceived device annoyance.

Lastly, the discriminant validity of all the latent constructs was examined. This involved comparing each construct's AVE with the square of its correlation with other latent constructs. All latent constructs met the criteria for discriminant validity. Table 5-21 shows the final factor loadings, CR, and AVEs for measurement model 1.

Table 5–21 Final factor loadings, CR, and AVEs for measurement model 1

Items		Latent construct	Factor loading	CR	AVE
CUI_10	<---	Continued use intention	0.994	0.968	0.884
CUI_7	<---		0.968		
CUI_11	<---		0.946		
CUI_6	<---		0.845		
DAnoy_19	<---	Perceived device annoyance	0.840	0.781	0.546
DAnoy_20	<---		0.734		
DAnoy_18	<---		0.628		
PEnj_4	<---	Perceived enjoyment	0.988	0.967	0.881
PEnj_3	<---		0.960		
PEnj_1	<---		0.940		
PEnj_2	<---		0.861		
SotPrss_2	<---	Societal pressure	0.870	0.838	0.570
SotPrss_3	<---		0.813		
SotPrss_1	<---		0.726		
SoPrss_4	<---		0.579		
PValu_3	<---	Price value	0.975	0.911	0.724
PValu_2	<---		0.897		
PValu_4	<---		0.859		
PValu_1	<---		0.634		
TecH_1	<---	Technology habit	0.789	0.848	0.583
TecH_2	<---		0.777		
TecH_3	<---		0.761		
TecH_4	<---		0.727		
PerExp_3	<---	Performance expectancy	0.963	0.943	0.808
PerExp_2	<---		0.932		
PerExp_1	<---		0.959		
PerExp_4	<---		0.718		

b) CFA – Measurement Model 2

Specification and Identification Measurement

Measurement model 2 is specified with seven reflective latent constructs. The seven latent constructs are as follows: effort expectancy, reflected by five items (EffExp_1 to EffExp_4 and EffExp_7); technology upgradability, reflected by four items (TUpG_1 to TUpG_3 and TUpG_6); facilitating conditions, reflected by six items (FCons_1 to FCons_6); continued use behaviour, reflected by five items (CUB_1 to CUB_5); openness to technological innovativeness, reflected by five items (OTTI_1 to OTTI_5); conscientiousness in health, reflected by four items (CinH_1 to CinH_4); and neuroticism, reflected by three items (Neu_1, Neu_2, and Neu_4). Further error terms were linked to each observed item within the measurement model. The degrees of freedom were computed for measurement model 2 identification. Specifically, there were a total of 32 items (denoted as "p"), and the count of **distinct parameters to be estimated** was 85 (represented as "k"). Hence, inserting these values into the equation: $df = \frac{1}{2} (p(p+1)) - k$, the degrees of freedom were computed as $df = \frac{1}{2} (32(32+1)) - 85 = 443$, which presents positive degrees of freedom. This suggests that measurement model 2 was overidentified, making it a suitable choice for conducting CFA. Figure 5-2 below illustrates the final measurement model 2, which exhibits robust model fit and construct validity (encompassing all 32 items measured).

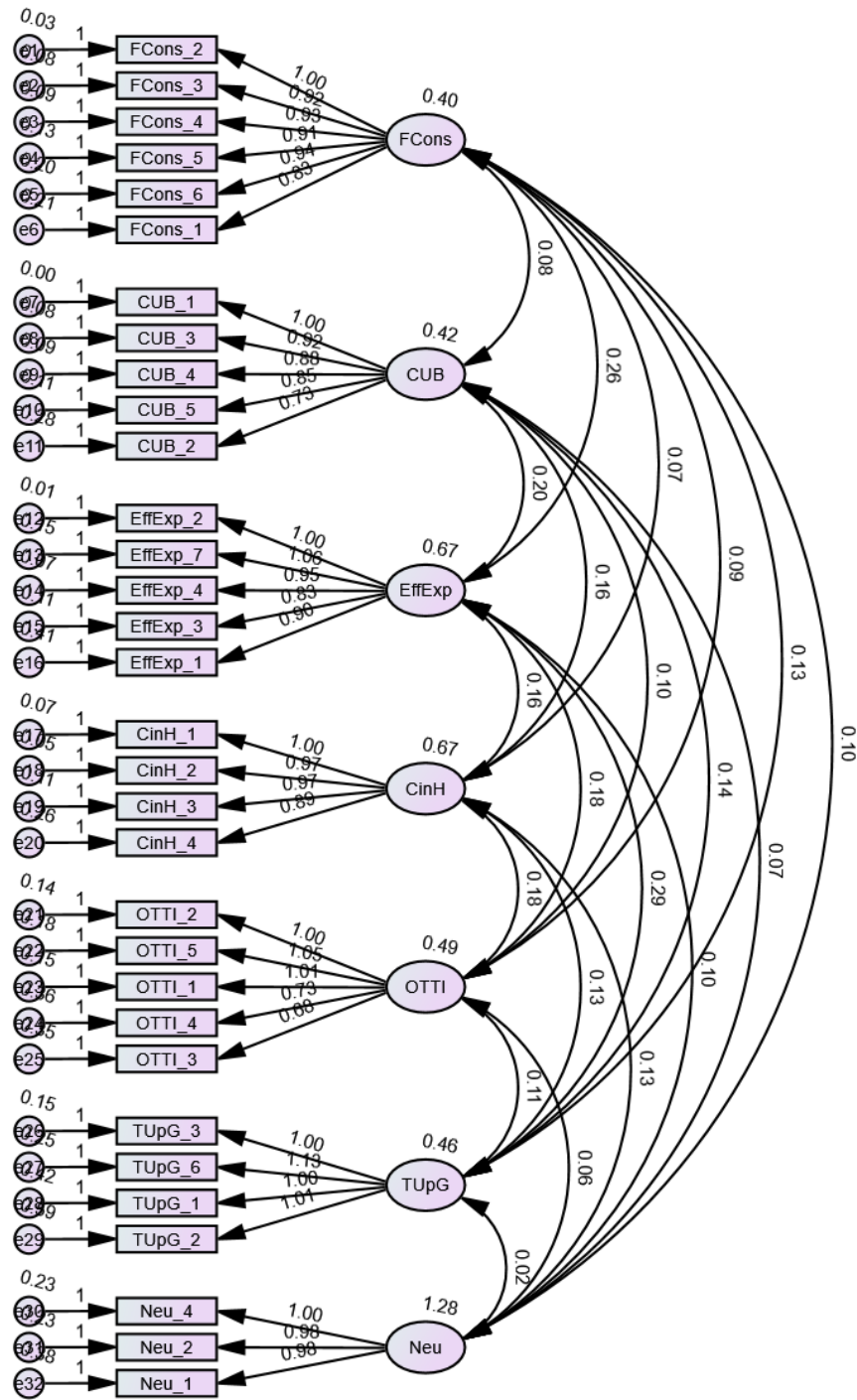


Figure 5-2 Final measurement model 2

$\chi^2 = 829.856$, $df = 443$, $RMSEA = 0.051$, $CFI = 0.962$, $TLI = 0.957$

Assessment of Model Fit and Construct Validity

In CFA, a model fit and construct validity assessment was performed involving seven latent constructs and 32 observed items. The initial measurement model was examined for construct validity and model fit. Subsequently, guided by the EFA outcomes, the initial construct validity, model fit, and assessments, problematic items were systematically removed to accomplish an optimal model fit and construct validity. The initial model fit evaluation relied on absolute fit indices (such as χ^2/df and RMSEA) and incremental fit indices (including CFI and TLI). Fit statistics from the initial CFA analysis are shown in Table 5-22. These results indicated good model fit indices.

Table 5–22 Final fit statistics – measurement model 2

Model fit indices	χ^2	(df)	$\chi^2/\text{df} < 3$	RMSEA <0.07 with CFI >0.92	CFI >0.90	TLI >0.90
32 items	829.856	(443)	2.738	0.051	0.962	0.957

The values of the construct validity measures were also examined. In the AMOS output, factor loadings are presented as standardised weights. The preliminary findings indicated that a majority of the items had factor loadings surpassing the desirable threshold of 0.70. Further, the AVE of all seven latent constructs was calculated using Equation (1). For instance, the AVE of neuroticism was calculated as $0.920 + 0.919 + 0.873 / 3 = 0.904$. A similar procedure was applied to calculate the AVEs for the remaining latent constructs. In the initial analysis, the AVEs for all latent constructs exceeded the threshold of 0.50, except for behaviour intentions and effort expectancy.

Subsequently, CR was computed using Equation (2). As an illustration, the CR for the latent construct perceived device annoyance was determined in the following manner:

$$(0.920 + 0.919 + 0.873)2 / (0.920 + 0.919 + 0.873)2 + (0.154 + 0.155 + 0.238) = 0.931$$

The same calculation procedure was applied to determine the CR values for the remaining latent constructs. The initial assessment indicated that all construct CR values exceeded the minimum threshold of 0.70. Table 5-23 displays the CR and AVE values for all the latent constructs within the measurement model.

Table 5–23 Convergent validity results for measurement model 2

	CR	AVE	TUpG	FCons	CUB	EffExp	CinH	OTTI	Neu
TUpG	0.855	0.599	0.774						
FCons	0.923	0.670	0.281	0.818					
CUB	0.938	0.753	0.319	0.182	0.868				
EffExp	0.945	0.777	0.525	0.469	0.386	0.882			
CinH	0.953	0.836	0.239	0.131	0.306	0.255	0.914		
OTTI	0.890	0.623	0.222	0.209	0.228	0.309	0.314	0.789	
Neu	0.922	0.798	0.014	0.108	0.090	0.066	0.148	0.076	0.893

Note: CR = construct reliability; AVE = average variance extracted; TUpG = technology upgradability; FCons = facilitating conditions; CUB = continued use behaviour; EffExp = effort expectancy; CinH = conscientiousness in health; OTTI = openness to technological innovativeness; Neu = neuroticism.

Lastly, the discriminant validity of all the latent constructs was examined. This involved comparing each construct's AVE with the square of its correlation with other latent constructs. All latent constructs met the criteria for discriminant validity. Table 5-24 demonstrates the final factor loadings, CR, and AVEs for measurement model 2.

Table 5–24 Final factor loadings, CR, and AVEs for measurement model 2

Items		Latent construct	Factor loading	CR	AVE
FCons_2	<---	Facilitating conditions	0.967	0.944	0.738
FCons_3	<---		0.894		
FCons_4	<---		0.885		
FCons_5	<---		0.841		
FCons_6	<---		0.798		
FCons_1	<---	Continued use behaviour	0.751	0.937	0.752
CUB_1	<---		0.995		
CUB_3	<---		0.905		
CUB_4	<---		0.881		
CUB_5	<---		0.858		
CUB_2	<---	Effort expectancy	0.663	0.958	0.821
EffExp_2	<---		0.990		
EffExp_7	<---		0.916		
EffExp_4	<---		0.944		
EffExp_3	<---		0.904		
EffExp_1	<---	Conscientiousness in health	0.759	0.953	0.837
CinH_1	<---		0.952		
CinH_2	<---		0.959		
CinH_3	<---		0.922		
CinH_4	<---	Openness to technological innovativeness	0.820	0.890	0.622
OTTI_2	<---		0.882		
OTTI_5	<---		0.865		
OTTI_1	<---		0.880		
OTTI_4	<---		0.651		
OTTI_3	<---	Technology upgradability	0.623	0.857	0.603
TUpG_3	<---		0.865		
TUpG_6	<---		0.836		
TUpG_1	<---		0.723		
TUpG_2	<---	Neuroticism	0.664		
Neu_4	<---		0.920		
Neu_2	<---		0.919		
Neu_1	<---		0.873		

5.4 Common Method Bias

Common method bias is a potential issue in research, including CFA, whereby data collected from a single source may lead to inflated relationships between variables due to shared measurement characteristics rather than true relationships between the constructs (Podsakoff *et al.*, 2003). CMB is a systematic error resulting from the method or instrument used for data collection, rather than the constructs being studied. Researchers can employ several strategies to assess and control CMB and address it in CFA. These include procedural remedies, such as ensuring confidentiality, anonymity, and minimising response bias, and other statistical techniques; for example, Harman's single-factor test in SPSS is used to assess and control for CMB. This test involves conducting EFA on all items in a dataset. If a single dominant factor emerges, it may indicate the presence of CMB (Podsakoff *et al.*, 2003).

In conclusion, CMB can threaten the validity of CFA results, potentially leading to erroneous conclusions. Therefore, researchers must be vigilant in identifying and mitigating its presence to ensure the robustness of their findings. To address this, researchers can introduce a method factor in their CFA model to capture the variance attributed to the measurement technique, thus isolating the true constructs of interest (Podsakoff *et al.*, 2003).

In the current study, Harman's single-factor test was conducted in SPSS for both groups (1 and 2) with all items loading on a single factor, exhibiting no CMB, and achieving the threshold value of less than 50% (see Appendix E) (Podsakoff *et al.*, 2003). The CMB analysis was not limited to a single tool. In addition to Harman's single-factor test, CMB in AMOS was employed for groups 1 and 2. Excel formulas were used to calculate the difference between standardised regression weights with and without a common latent factor (CLF) (see Appendix F). CFA yielded the result that neither Group 1 nor Group 2 had any items affected by the CLF (indicating that CMB is not a problem). Lastly, using SmartPLS, CMB was assessed using VIF values in the inner model. Kock

(2015) states that an inner model lacks CMB if all VIFs exceed 3.3 (resulting from a full collinearity test). As shown in Appendix G, all VIFs in the internal model are below 3.3, confirming that CMB is not a cause for concern.

5.5 Path Analysis

SEM is a robust statistical method used in CFA to examine complex relationships among observed variables and latent (unobserved) constructs. SEM integrates measurement and structural models to assess the validity of theoretical models and hypotheses, allowing researchers to analyse the measurement quality of the indicators and the structural relationships between latent constructs. It provides a comprehensive understanding of how the variables interact, making it valuable in various fields, including the social sciences and psychology (Hair *et al.*, 2014). Researchers use SEM to validate theoretical models and gain insights into causal relationships among variables, ultimately enhancing the rigour of their research findings.

As such, SEM follows a series of well-defined steps. The initial stages encompass defining individual constructs, crafting a measurement model, and evaluating its validity, as discussed in the preceding section (Hair *et al.*, 2014). Subsequent phases involve specifying the structural model and assessing its validity.

5.5.1 Structural Model – Specification

In this phase, a structural model incorporates two distinct types of constructs: exogenous constructs, representing multi-item equivalents of independent variables; and endogenous constructs, symbolising multi-item equivalents of dependent variables. When illustrating their dependence in a visual path diagram, exogenous constructs are linked to endogenous constructs through single-headed arrows (Hair *et al.*, 2014).

In the current study, a structural model was developed, based on theory, which included exogenous constructs denoting perceived factors linked to users' CUI towards wearable fitness technology (an endogenous construct) with a single-headed arrow. Furthermore, the endogenous constructs are not entirely explained, hence warranting the inclusion of error terms (Hair *et al.*, 2014). Figures 5-3 and 5-4 below demonstrate the structural models without and with the control variables, respectively, developed in AMOS 28.

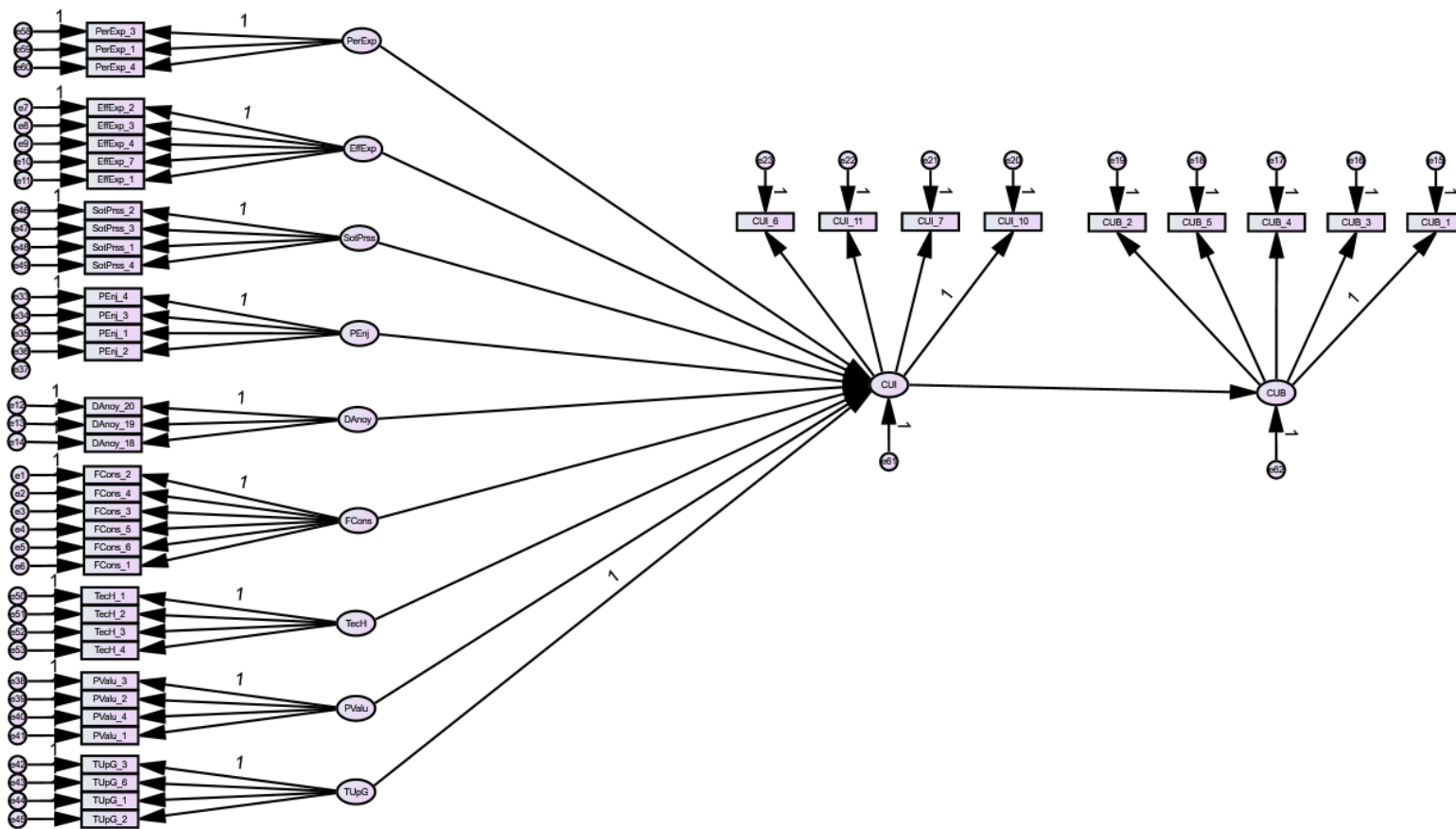


Figure 5-3 Structural model without control variables

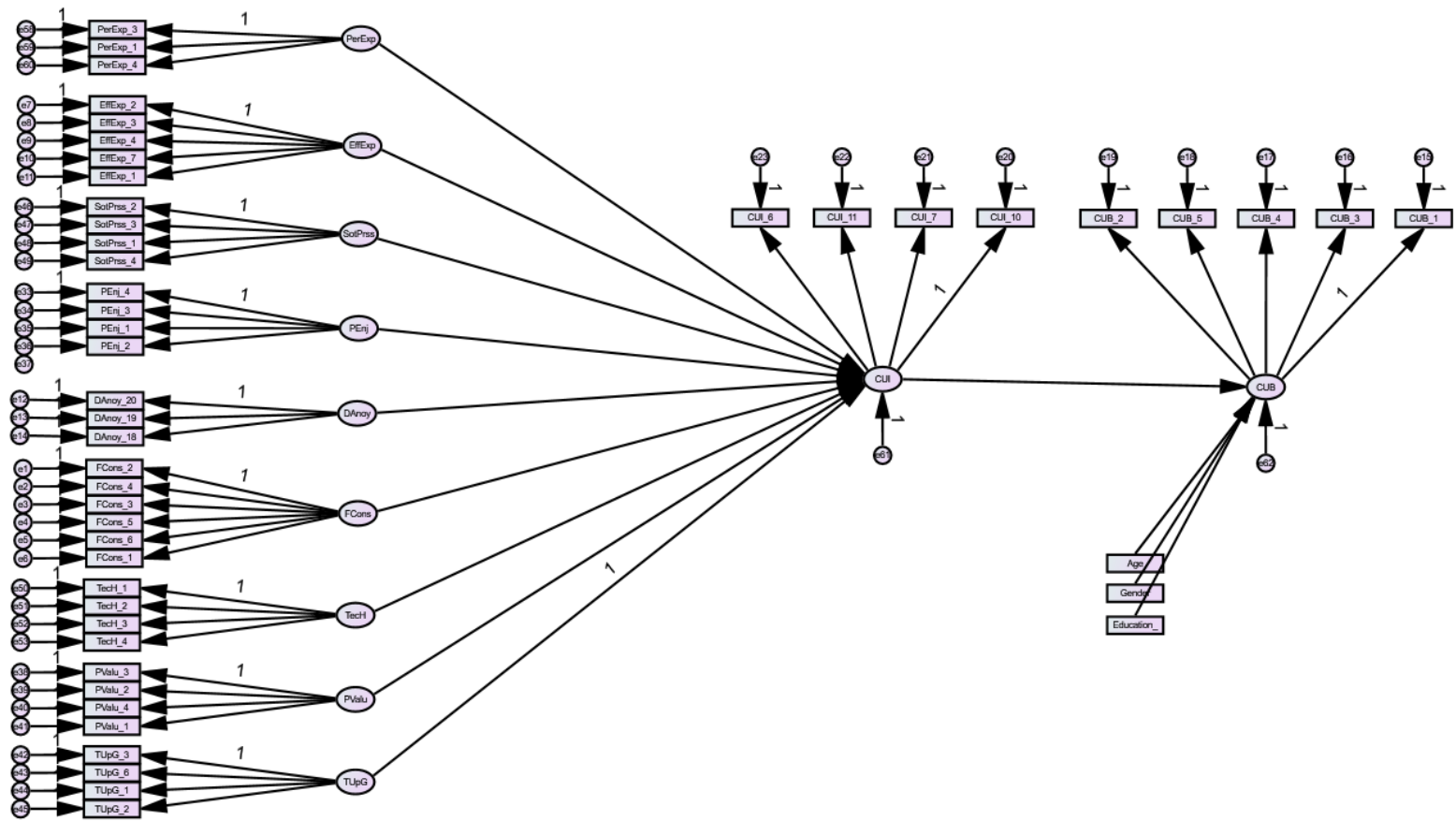


Figure 5-4 Structural model with control variables

5.5.2 Assessing Structural Model Validity

In this stage, the GOF statistics were evaluated. The results in Table 5-25 demonstrate that the model fit statistics meet the required threshold values for both structural models (with and without control variables), indicating their adequacy.

Table 5–25 Model fit statistics for the structural models

Model fit indices		χ^2	(df)	$\chi^2/\text{df} < 3$	RMSEA <0.07 with CFI >0.92	CFI >0.90	TLI >0.90
Without control variables		2277.990	(1160)	1.963	0.054	0.901	0.913
With control variables		2096.5	(1521)	1.378	0.034	0.968	0.966

The statistics suggest that the structural model with control variables exhibits a better fit than the model without the controls. Therefore, the decision was made to keep the control variables for further examination during the hypotheses testing.

5.5.3 Hypotheses Testing

This section presents the findings for all the proposed hypotheses, covering direct effects, mediating effects, and moderating effects. Given that the hypotheses are directional, one-tailed tests are used to report the results. According to Cho and Abe (2013, p. 1265), relying on two-tailed tests for directional hypotheses can result in "inaccurate or mistaken empirical conclusions at a given level of significance α ".

a) Direct Effect

Hypotheses H1(a) to (i) proposed that all the perceived factors are positively related to continued use intention towards wearable fitness devices; except for H1(e), where it is negatively related.

H2 proposed that continued use intention is positively related to continued use behaviour. These hypotheses were tested at a significance level of 5%. The summarised results are presented in Table 5-26.

Table 5–26 Direct effects test results (with controls)

Hypotheses	Paths	Standardised estimates
H1(a)	Performance expectancy → Continued use intention	0.359**
H1(b)	Effort expectancy → Continued use intention	0.206**
H1(c)	Societal pressure → Continued use intention	-0.074*
H1(d)	Perceived enjoyment → Continued use intention	0.165**
H1(e)	Perceived device annoyance → Continued use intention	0.099*
H1(f)	Facilitating conditions → Continued use intention	0.19
H1(g)	Technology habit → Continued use intention	0.108*
H1(h)	Price value → Continued use intention	-0.069
H1(i)	Technology upgradability → Continued use intention	0.138*
H2	Continued use intention → Continued use behaviour	0.227**
Controls		
	Age → Continued use behaviour	0.042
	Gender → Continued use behaviour	0.047
	Education → Continued use behaviour	0.032

Note: n = 331

Significant at ** $p < 0.01$; * $p < 0.05$

The results indicate that perceived device annoyance ($\beta = 0.099$, $t = 2.560$, $p = 0.010$); perceived enjoyment ($\beta = 0.165$, $t = 3.308$, $p = 0.001$); effort expectancy ($\beta = 0.206$, $t = 3.607$, $p < 0.001$); performance expectancy ($\beta = 0.359$, $t = 6.758$, $p < 0.001$); technology habit ($\beta = 0.108$, $t = 2.516$, $p = 0.012$); and technology upgradability ($\beta = 0.138$, $t = 3.153$, $p = 0.002$) have statistically significant positive relationships with users' CUI towards wearable fitness devices. However, societal pressure ($\beta = -0.074$, $t = 1.965$, $p = 0.049$) revealed a significant negative relationship.

Therefore, these results render support for hypotheses H1(a), H1(b), H1(c), H1(d), H1(e), H1(g) and H1(i). However, the effects of the remaining two perceived factors were found to be statistically non-significant: facilitating conditions ($\beta = 0.019$, $t = 0.436$, $p = 0.663$) and price value ($\beta = -0.069$, $t = 1.832$, $p = 0.067$). Hence, hypotheses H1(f) and H1(h) are not supported. Regarding hypothesis H2, it was proposed that users' continued use intention towards wearable fitness devices is positively related to continued use behaviour. The result indicates that users' CUI towards WFTs has a significant positive influence on CUB ($\beta = 0.227$, $t = 4.013$, $p < 0.001$), thereby supporting hypothesis H2 (see Table 5-27 from SmartPLS).

Table 5–27 Path coefficient, mean, SD, t-values, and p-values (bootstrapping)

	Original sample (O)	Sample mean (M)	Standard deviation (SD)	t-statistics (O/SD)	p-values
DAnoy -> Continued Use Intention	0.099	0.095	0.038	2.560	0.010 (S)
EffExp -> Continued Use Intention	0.206	0.206	0.057	3.607	0.000 (S)
FCons -> Continued Use Intention	0.019	0.018	0.043	0.436	0.663 (NS)
PEnj -> Continued Use Intention	0.165	0.163	0.050	3.308	0.001 (S)
PValu -> Continued Use Intention	-0.069	-0.070	0.037	1.832	0.067 (NS)
PerExp -> Continued Use Intention	0.359	0.356	0.053	6.758	0.000 (S)
SotPrss -> Continued Use Intention	-0.074	-0.066	0.038	1.965	0.049 (S)
TUpG -> Continued Use Intention	0.138	0.136	0.044	3.153	0.002 (S)
TechH -> Continued Use Intention	0.108	0.110	0.043	2.516	0.012 (S)
Continued Use Intention -> Continued Use Behaviour	0.227	0.231	0.056	4.013	0.000 (S)

Note: $p < 0.05$ is considered significant (S), and $p \geq 0.05$ is considered not significant (NS).

The analysis reveals that effort expectancy, performance expectancy, perceived enjoyment, technology upgradability, and technological habit have a positive influence on continued use intention, which, in turn, has a significant influence on continued use behaviour. On the other hand, device annoyance and societal pressure have notable effects, although in different directions. Facilitating conditions and price value do not, however, have a significant influence on continued use intention.

b) Mediation Analysis

When there is an independent variable that affects a dependent variable through an intervening variable, it is called mediation. This intervening variable is also known as a mediating variable or mediator. If the mediation process involves only one mediating variable, it is called simple mediation. However, if there is more than one mediating variable, it is referred to as multiple mediation (Preacher and Hayes, 2008). Figure 5-5 provides an example of a simple mediation process.

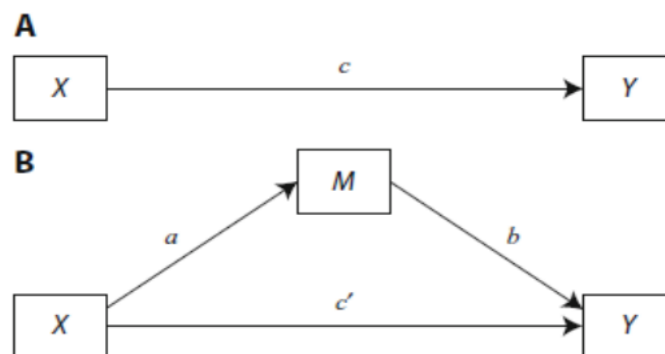


Figure 5-5 Simple mediation process (Preacher and Hayes, 2008)

Where X = independent variable

Y = dependent variable

M = mediating variable

a = effect of X on M

b = effect of M on Y partialling out the effect of X

as the causal effect of X can be divided into indirect and direct effects (in a basic mediation model).

c = total effect of X on Y = sum of direct and indirect effects = $c' + ab$

In this study, the results of the mediating effect of users' continued use intention towards WFT between perceived factors and continued use behaviour are presented using the approach outlined in Preacher and Hayes (2008) for H3(a) to (i).

This approach to mediation analysis was adopted because prior research in the field of IS adoption has provided evidence of its application (i.e., Venkatesh, Thong and Xu, 2012; Alalwan, Dwivedi and Williams, 2016; Mehra, Rajput and Paul, 2022). Specifically, those perceived factors that revealed a significant direct influence on users' CUI towards WFT (see [section 5.5.3\(a\)](#)) were included in the mediation analysis.

The Mediating Role of Continued Use Intention

The third aim of this study was to examine the mediating role of CUI towards WFT in the relationship between perceived factors and CUB. In this regard, this study uncovered the role of the CUI towards WFT as an underlying mechanism through which variables are related, and explains how and why perceptions of different factors influence CUB. Partial mediation was observed for performance expectancy (H1a), perceived enjoyment (H1d), technological habit (H1g), price value (H1h), and technology upgradability (H1i). These findings suggest that although these factors have a direct influence on continued use behaviour, their association is significantly enhanced through the mediating role of CUI. For instance, the inclusion of CUI as a mediator reveals that users' intention to continue using wearable fitness technology bridges the gap between their perceptions of the technology's performance, price value, and adaptability and their CUB.

In contrast, effort expectancy (H1b), societal pressure (H1c), perceived device annoyance (H1e), and facilitating conditions (H1f) exhibited no mediation effects, as their influence on CUB was either insignificant or not routed through CUI. This indicates that these factors might play a more peripheral role in driving long-term use compared to other key predictors (see Figures 5-6 and 5-7 below). Hence, an important finding is:

Key finding – The analysis underlines the critical mediating role of CUI in amplifying the effects of performance expectancy, perceived enjoyment, technological habit, perceived value, and technology upgradability on CUB, whereas factors such as effort expectancy, social pressure, and perceived device annoyance lack significant mediation effects.

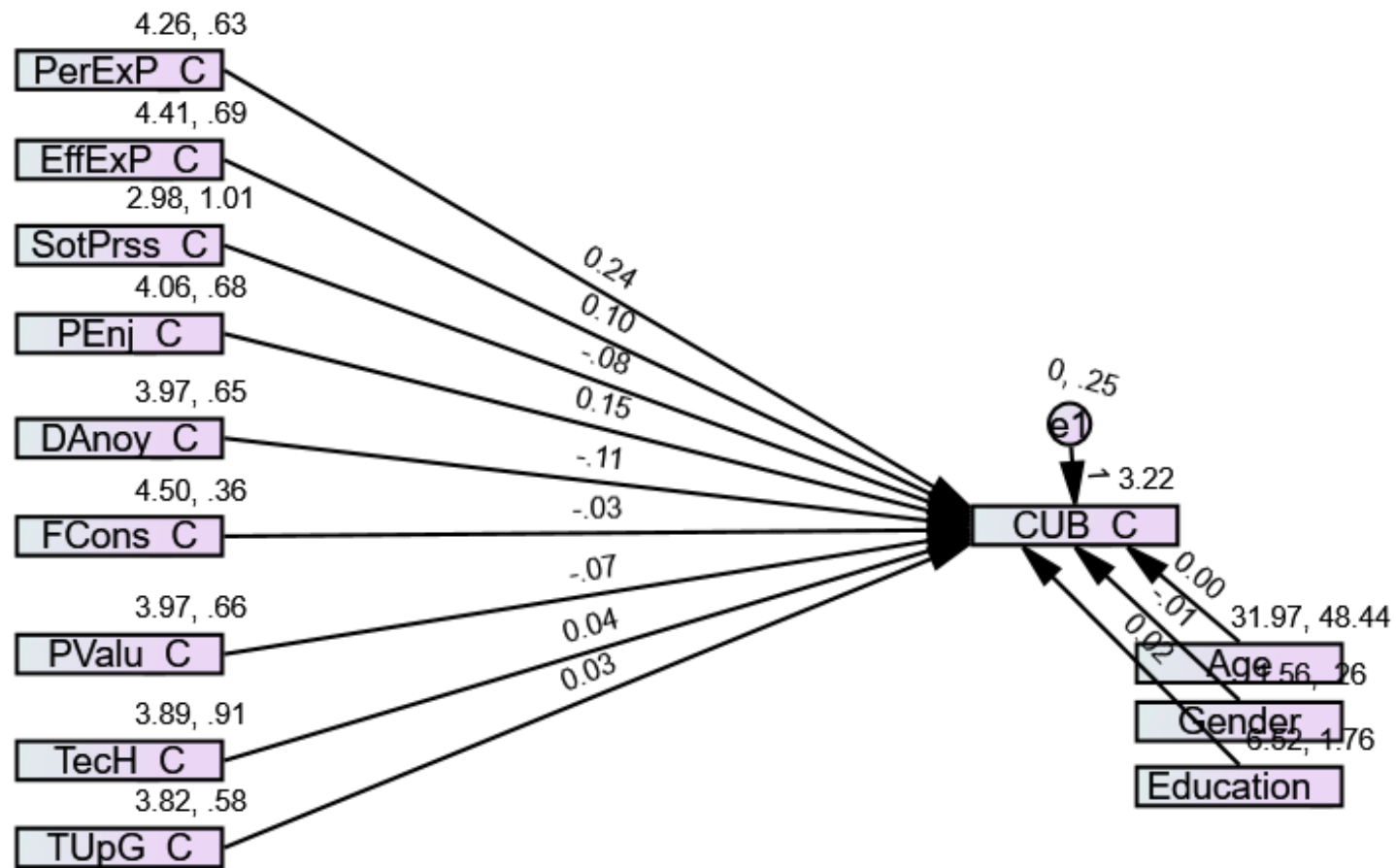


Figure 5-6 Structural model path diagram (without the mediator, Continued Use Intention – CUI)

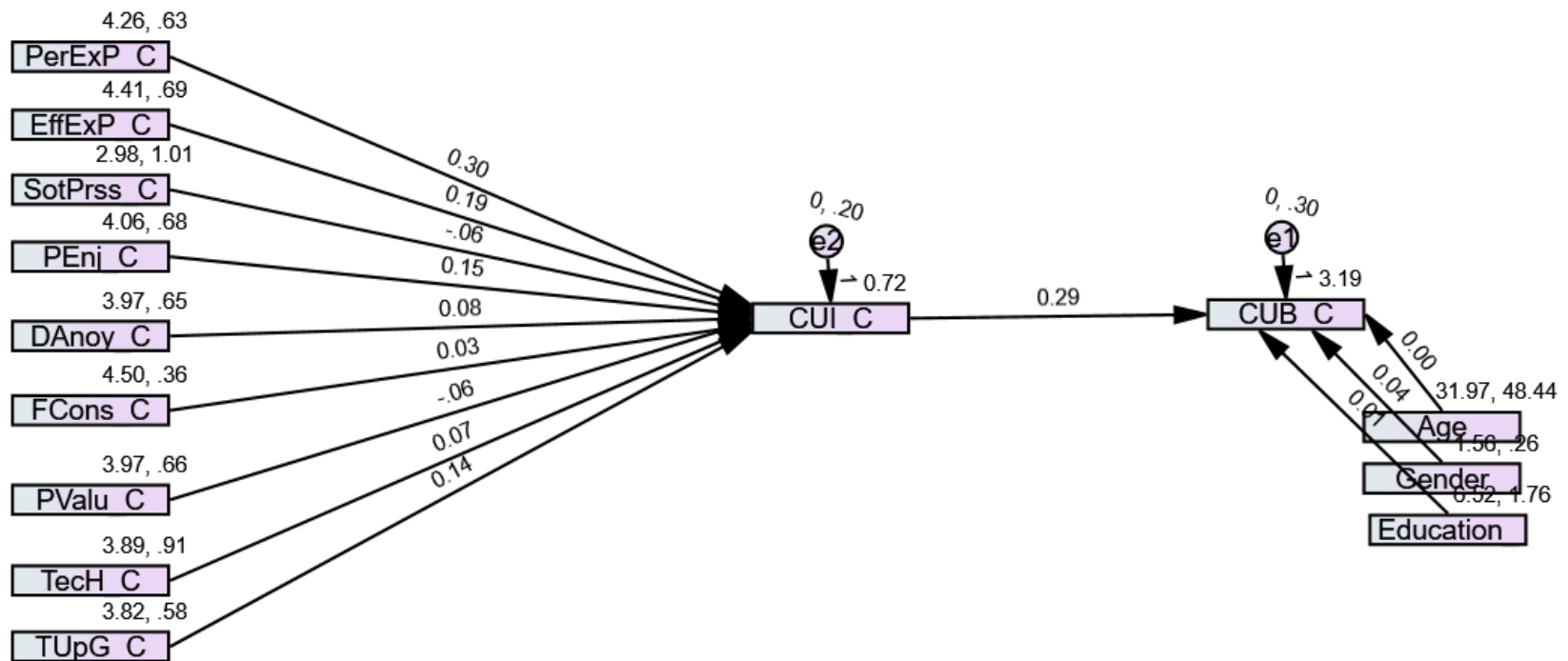


Figure 5-7 Structural model path diagram (with the mediator, Continued Use Intention – CUI)

c) Moderation Analysis

Conceptually, interaction effects are a system of three variables, wherein one variable is the independent variable, the second is the outcome variable, and the third is the moderator variable. Interaction effects occur when the influence of the independent variable on the outcome variable varies depending on the value of the moderator variable (Jaccard and Turrissi, 2003). In the analysis of two-way interactions, the researcher assesses the effect of two independent variables on the outcome variable. One independent variable is the focal variable, and the impact of this variable on the outcome variable varies as a function of the second independent variable, which is considered the moderator variable (Jaccard and Turrissi, 2003). Figure 5-8 illustrates a moderated causal relationship presenting a two-way interaction, where X is the focal independent variable, Y is the outcome variable, and Z is the moderator variable.

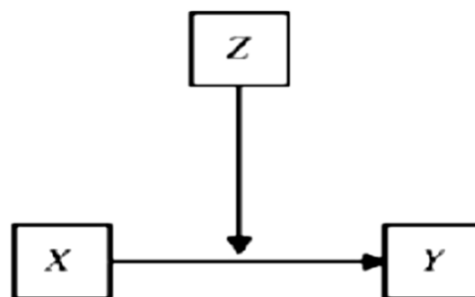


Figure 5-8 Two-way interaction (Jaccard and Turrissi, 2003)

Personality Traits as Moderators

In this study, two-way interactions were carried out in which users' psychological traits (both general personality and technology user-specific characteristics) were considered as the moderator variables (Z), continued use intention was the focal independent variable (X), and continued use behaviour was the outcome variable (Y). To test the moderating effects of users' psychological traits, SEM was employed in IBM SPSS and SmartPLS, which comprised the effects of the focal constructs (continued use intention and users' psychological traits), control

variables (age, gender, income and education level), and interaction terms (CUI x users' psychological traits).

Before the analysis was performed, all moderator and predictive variables were standardised to reduce the chances of multicollinearity. To investigate the moderating effects of users' psychological traits on the relationship between CUI and CUB towards WFT, a non-parametric bootstrapping method with 5,000 resamples at 95% confidence intervals, as proposed in Preacher and Hayes (2008), was employed in IBM SPSS. This method included either openness to technological innovativeness (H4), conscientiousness in health (H5), or neuroticism (H6), following the approach outlined in Stock, Totzauer and Zacharias (2014). The results of the interaction effects between CUI and CUB are presented in the following sections.

Moderating Role of Openness to Technological Innovativeness

The analysis revealed a significant negative moderating effect of OTTI on the relationship between CUI and CUB ($\beta = -0.097$, $t = 1.998$, $p = 0.046$). This suggests that higher levels of openness to using innovative technology weaken the positive relationship between CUI and CUB (see Figure 5-9).

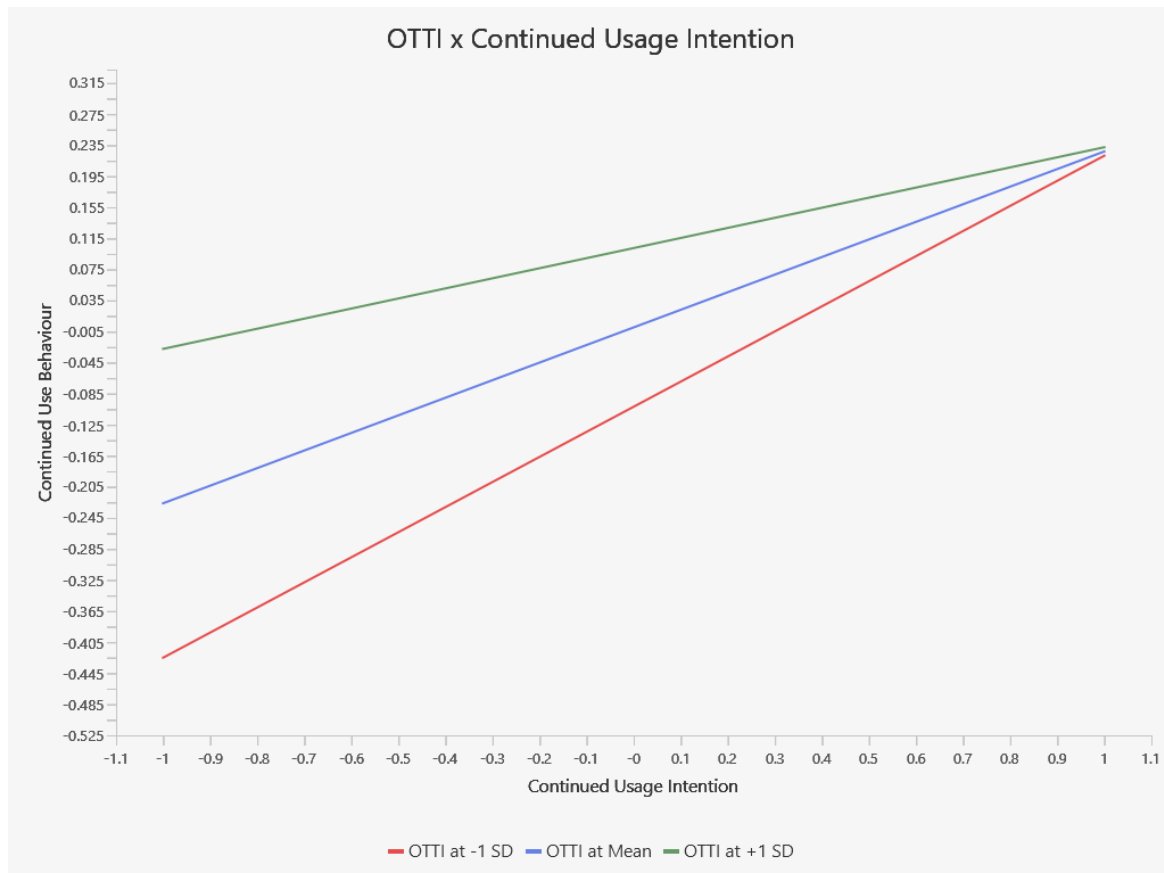


Figure 5-9 Moderating role of OTTI in the relationship between consumers' continued use intention and continued use behaviour towards WFT

Moderating Role of Conscientiousness in Health

The analysis revealed a significant negative moderating effect of CinH on the relationship between CUI and CUB ($\beta = -0.139$, $t = 2.216$, $p = 0.027$). This indicates that greater concerns about health reduce the strength of the positive relationship between CUI and CUB (Figure 5-10).

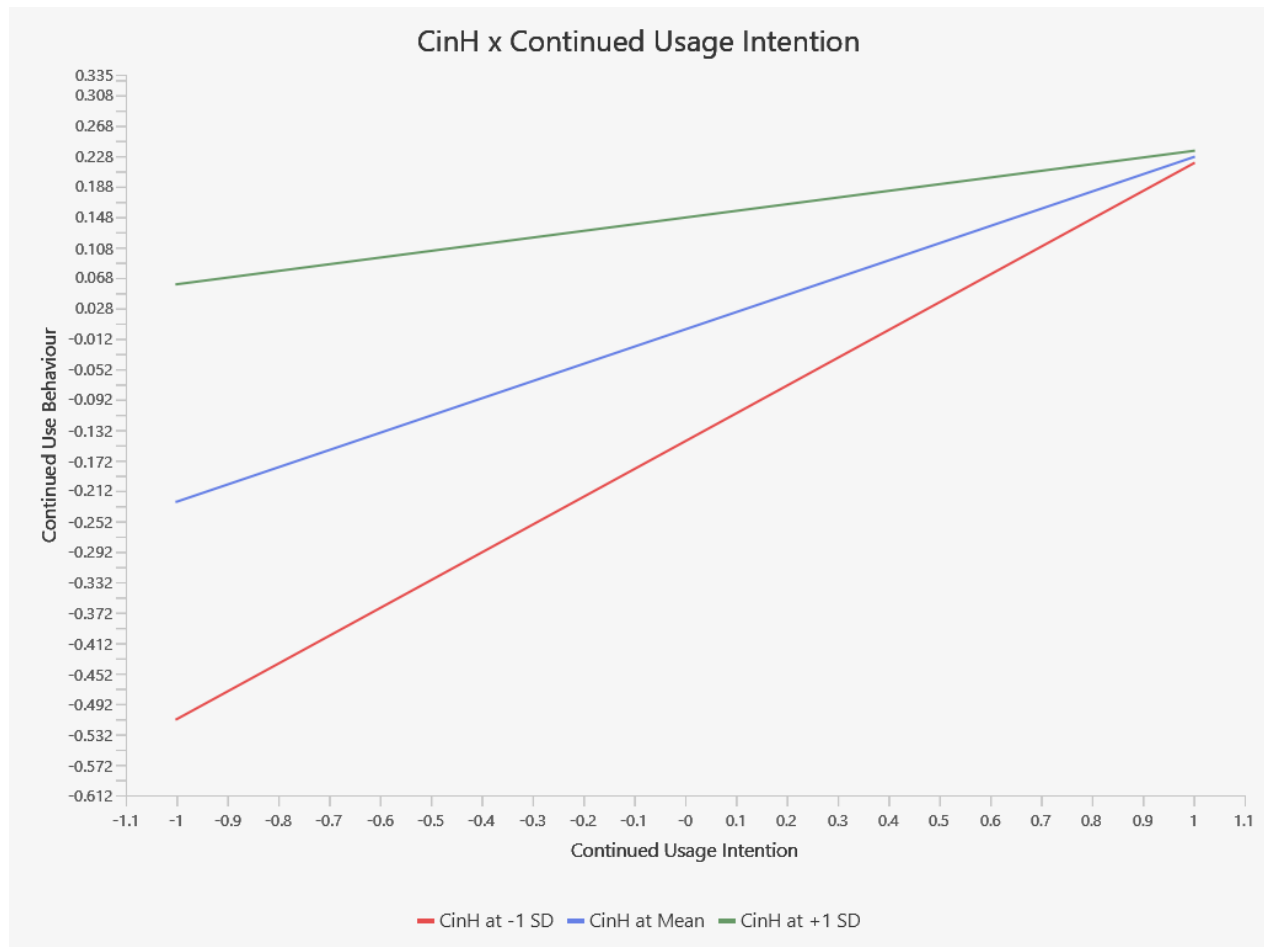


Figure 5-10 Moderating role of CinH in the relationship between consumers' continued use intention and continued use behaviour towards WFT

Moderating Role of Neuroticism

The analysis revealed a significant positive moderating effect of Neu on the relationship between CUI and CUB ($\beta = 0.149$, $t = 2.775$, $p = 0.006$). This suggests that higher levels of neuroticism enhance a positive relationship between CUI and CUB (Figure 5-11).

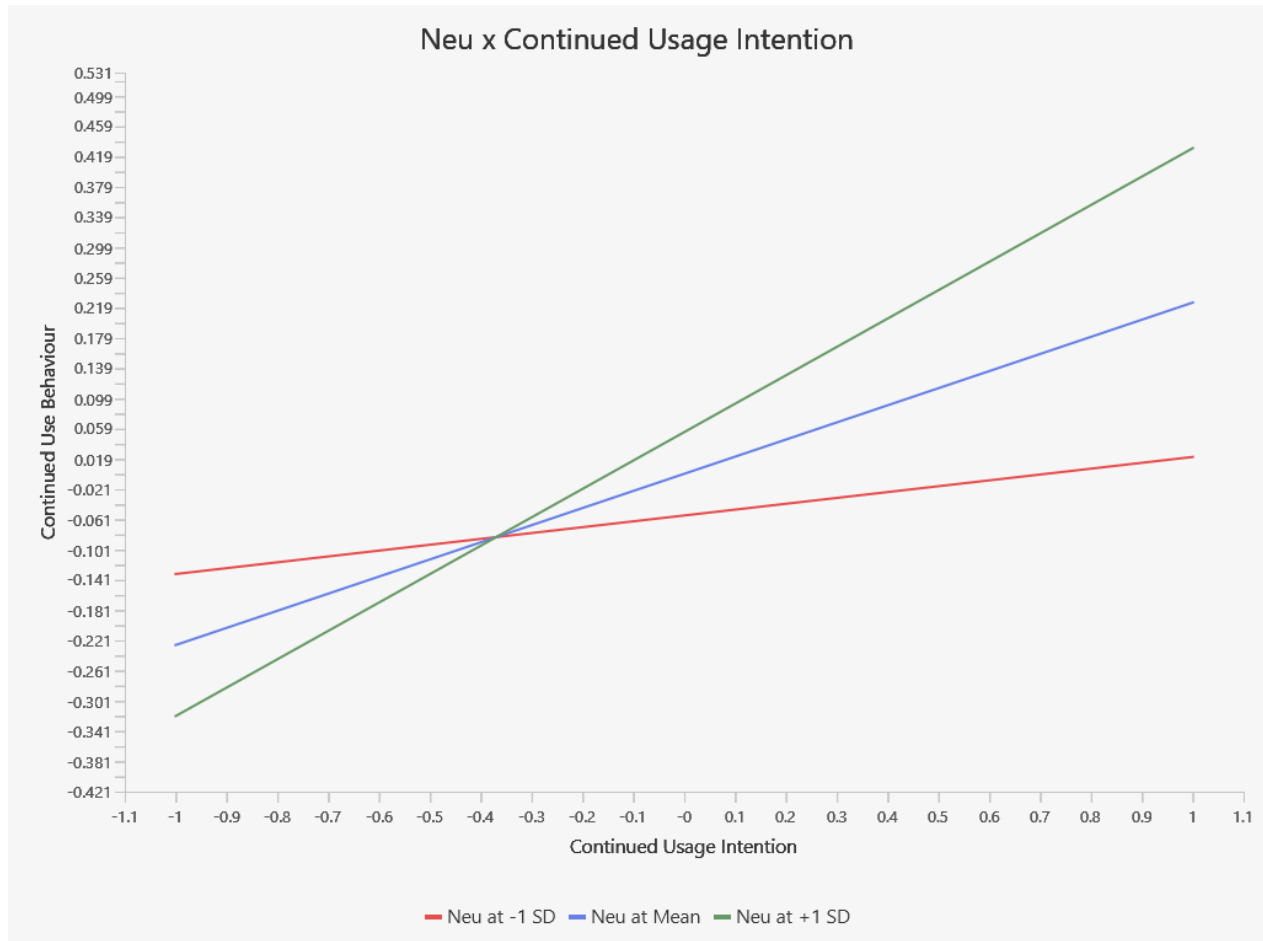


Figure 5-11 Moderating role of Neu on the relationship between consumers' continued use intention and continued use behaviour towards WFT

The moderating effects analysis indicates that OTTI and CinH negatively moderate the relationship between CUI and CUB, weakening this positive relationship. Conversely, Neu positively moderates the relationship, strengthening the link between CUI and CUB. These findings provide deeper insights into how individual differences and psychological factors

influence CUB in relation to wearable fitness devices, thereby enriching the understanding of technology continuance use behaviour within the framework of UTAUT2. The results indicating moderating effects are presented in Table 5-28, detailing the path coefficients, t-values, and significance levels.

Table 5–28 Moderators' path coefficients, mean, SD, t-values, and p-values (bootstrapping)

	Original sample (O)	Sample mean (M)	Standard deviation (SD)	t-statistics (O/SD)	p-values
OTTI x Continued Use Intention -> Continued Use Behaviour	-0.097	-0.089	0.048	1.998	0.046 (S)
CinH x Continued Use Intention -> Continued Use Behaviour	-0.139	-0.139	0.063	2.216	0.027 (S)
Neu x Continued Use Intention -> Continued Use Behaviour	0.149	0.140	0.054	2.775	0.006 (S)

Note: p-values < 0.05 are considered significant **(s)**

5.6 Conclusion of the 1st Dataset Analysis

Quantitative data analysis was conducted on 331 user responses using IBM SPSS 28.0 statistics, AMOS 28.0 and SmartPLS software. The data collected were analysed through preliminary and factor analyses, along with descriptive analyses of the study constructs. This was followed by the testing of the hypotheses proposed in Chapter 3, which state the direct effect of perceived factors on continued use intention, the direct effect of continued use intention on continued use behaviour, the mediating effect of continued use intention between perceived factors and continued use behaviour, and, finally, the moderating effects of users' psychological traits on the relationship between continued use intention and their continued use behaviour. Table 5-29 provides a summary of the results of testing the hypotheses and further elaboration is presented in the section below.

Table 5–29 Summary of results of testing the hypotheses

Hypothesis (hypothesised sign)	Result
Direct effects	
<i>H1(a) PerExp -> CUI (+)</i>	S
<i>H1(b) EffExp -> CUI (+)</i>	S
<i>H1(c) SotPrss -> CUI (+)</i>	S
<i>H1(d) PEnj -> CUI (+)</i>	S
<i>H1(e) DAnoy -> CUI (-)</i>	S
<i>H1(f) FCons -> CUI (+)</i>	NS
<i>H1(g) TechH -> CUI (+)</i>	S
<i>H1(h) PValu -> CUI (+)</i>	NS
<i>H1(i) TUpG -> CUI (+)</i>	S
<i>H2 Continued Use Intention -> Continued Use Behaviour (+)</i>	S
Mediating effect of behavioural intention	
<i>H3(a) PerExp -> R -> CUB (+)</i>	S
<i>H3(b) EffExp -> R -> CUB (+)</i>	NS
<i>H3(c) SotPrss -> R -> CUB (+)</i>	NS
<i>H3(d) PEnj -> R -> CUB (+)</i>	S
<i>H3(e) DAnoy -> R -> CUB (+)</i>	NS
<i>H3(f) FCons -> R -> CUB (+)</i>	NS
<i>H3(g) TechH -> R -> CUB (+)</i>	S
<i>H3(h) PValu -> R -> CUB (+)</i>	S
<i>H3(i) TUpG -> R -> CUB (+)</i>	S
Moderating effects of openness to technological innovativeness	
<i>H4 OTTI x CUI -> CUB (+)</i>	S
Moderating effects of conscientiousness in health	
<i>H5 CinH x CUI -> CUB (+)</i>	S
Moderating effect of neuroticism	
<i>H6 Neu x CUI -> CUB (-)</i>	S

Notes: S = supported; NS = not supported

5.6.1 Direct Effect Findings

In the first dataset, the analysis reveals several key findings regarding the factors influencing CUI and CUB towards wearable fitness technologies, consistent with the SmartPLS findings presented in Table 5-27. Effort expectancy (EffExp), performance expectancy (PerExp), perceived enjoyment (PEnj), technology upgradability (TUpG), and technological habit (TechH) were all found to have a positive and significant influence on CUI, as indicated by their significant p-values ($p < 0.05$). Among these, performance expectancy demonstrated the strongest effect ($\beta = 0.359$, $p = 0.000$), emphasising the importance of users' expectations regarding the usefulness of the technology in driving their intention to continue using it. Perceived enjoyment ($\beta = 0.165$, $p = 0.001$) and effort expectancy ($\beta = 0.206$, $p = 0.000$) also emerged as significant predictors, highlighting the role of intrinsic motivation and ease of use in shaping CUI. Similarly, technology upgradability ($\beta = 0.138$, $p = 0.002$) and technological habit ($\beta = 0.108$, $p = 0.012$) were found to play critical roles, reflecting the importance of routine use and the adaptability of technology in fostering continued use.

Conversely, device annoyance (DAnoy) ($\beta = 0.099$, $p = 0.010$) and societal pressure (SotPrss) ($\beta = -0.074$, $p = 0.049$) showed significant but varied effects. Device annoyance had a positive influence, suggesting that users who perceive less annoyance are more likely to continue using the technology. Societal pressure, although significant, had a negative effect, indicating that external social expectations may not be a strong driver of CUI in this context. Facilitating conditions (FCons) ($\beta = 0.019$, $p = 0.663$) and price value (PValu) ($\beta = -0.069$, $p = 0.067$) were not, however, found to have a significant influence on CUI. This suggests that external support structures and cost considerations are less critical in determining users' decisions to sustain the use of WFTs. Finally, CUI ($\beta = 0.227$, $p = 0.000$) was found to have a significant and positive influence on CUB, highlighting the pivotal role of intention as a mediator between antecedent

factors and continued use. **These findings** provide valuable insights into the drivers of sustained engagement with WFTs, emphasising the interplay between intrinsic motivators, technology adaptability, and habitual use while highlighting the limited role of external pressures and cost considerations. Figure 5-12 presents the path coefficient results in SmartPLS.

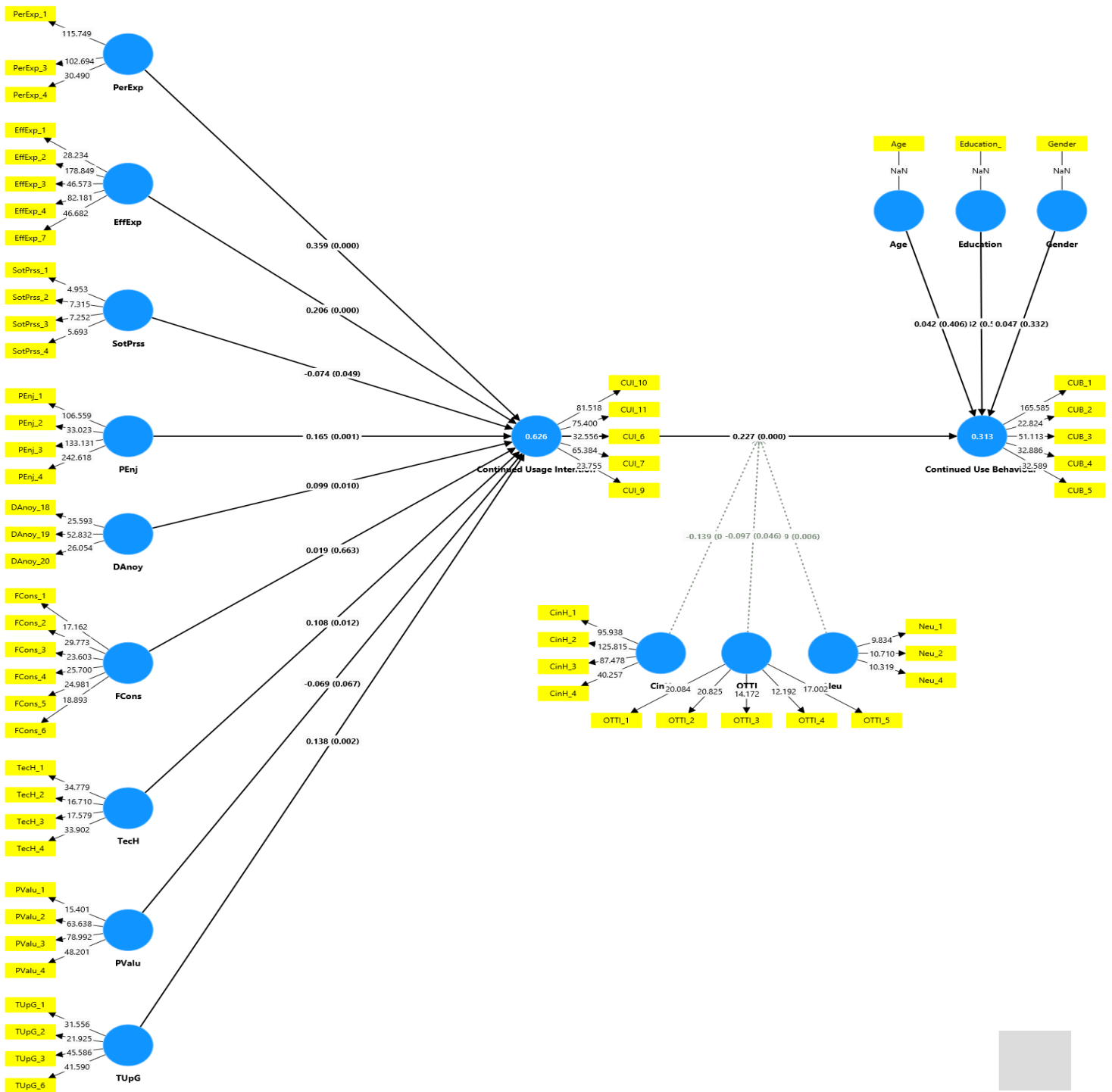


Figure 5-12 Path coefficient results

Legend: → Direct effect - - - - - → Moderating effect

5.6.2 Mediating Effect Findings

The analysis highlights the critical mediating role of CUI in amplifying the effects of performance expectancy, perceived enjoyment, technological habit, price value, and technology upgradability on CUB. These findings demonstrate that users' beliefs about the technology's utility, intrinsic motivation, established habits, price value, and adaptability are translated into continued use through strong usage intentions. In contrast, effort expectancy, societal pressure, and device annoyance show no significant mediating effects, suggesting that these factors play a limited role in driving long-term engagement. Effort expectancy and societal pressure may be more influential during initial adoption, whereas device annoyance appears to be less relevant over time. **Overall Key Insights:** CUI is pivotal in mediating the impact of core factors such as performance expectancy, perceived enjoyment, and technological habit on CUB. Conversely, effort expectancy, societal pressure, and device annoyance lack significant mediation effects, underscoring the importance of focusing on intrinsic motivators, habits, and adaptable features to promote continued use.

5.6.3 Moderating Effect Findings

The findings regarding the moderating role of personality traits provide intriguing and somewhat surprising insights into the dynamics of CUI and CUB towards WFTs. The analysis highlights the nuanced and complex nature of personality traits in influencing user behaviour, with both inhibitory and amplifying effects observed. First, **OTTI** demonstrated a significant negative moderating effect on the relationship between CUI and CUB ($\beta = -0.097$, $t = 1.998$, $p = 0.046$). This indicates that users who are more open to adopting innovative technologies may paradoxically exhibit weaker links between their intentions to continue using WFT and their CUB. A possible explanation is that such individuals are likely to explore new technologies frequently, which could dilute their long-term engagement with a specific device. This finding is surprising,

as OTTI is often associated with positive technology adoption behaviours, yet it appears to undermine continued use in this context. Second, **CinH** also exerted a significant negative moderating effect on the relationship between CUI and CUB ($\beta = -0.139$, $t = 2.216$, $p = 0.027$). This suggests that users with heightened concerns about their health may feel less inclined to translate their intentions into consistent use of WFT. One possible explanation is that such individuals might perceive wearable devices as less reliable or sufficient for addressing their health needs, leading to disengagement despite their initial intentions. This finding is noteworthy and counterintuitive, as health-related motivations are generally expected to reinforce, rather than weaken, CUB.

Conversely, **Neu** exhibited a significant positive moderating effect on the relationship between CUI and CUB ($\beta = 0.149$, $t = 2.775$, $p = 0.006$). This indicates that individuals with higher levels of neuroticism are more likely to translate their intentions into continued use behaviours. This result is particularly surprising, as neuroticism is often associated with negative emotions and behaviours, yet appears to enhance the alignment between intention and behaviour in this context. A plausible explanation is that neurotic individuals may have a heightened sensitivity to health-related risks or goals, making them more committed to using WFT as a coping mechanism. **Overall Key Insights:** These findings underscore the significant, yet unexpected, moderating role of personality traits in shaping the relationship between CUI and CUB. Whereas OTTI and CinH weaken the relationship, Neu strengthens it, revealing a complex interplay between personality characteristics and continued technology use. These insights challenge conventional assumptions and emphasise the need to consider personality-driven variability when designing and marketing WFTs to foster long-term adoption.

Chapter 6: Quantitative Analysis (2nd Dataset)

A longitudinal methodology was adopted in this thesis (see section [4.3.2](#)), and data was collected prospectively. Prospective studies are generally considered more reliable for establishing cause-and-effect relationships because data is collected as events unfold (Caruana *et al.*, 2015). After six months, the Time 2 (T₂) study, similar to the first study, was conducted using Qualtrics and Prolific, as suggested by Bryman (2012); see data collection in section [4.5.1](#) advertised to participants who had completed the Time 1 (T₁) study using a custom allowlist, as per the instructions provided by (Kothe and Ling, 2019). The study was advertised, like study T₁, on the Prolific platform using the following text:

This study is about the adoption and use of technology. You will be asked about your usage and your personality traits. You have been invited to participate in this study as you are eligible after completing the first one. This is a SECOND Part of a longitudinal study (two-part study). It will take you no more than 9 minutes, and you will be reimbursed upon completion. Please read all questions CAREFULLY to avoid rejection, as your submission will be rejected in case of contradictory answers.

Sample profile

Similar to the T₁ study, certain technical challenges arose; however, prompt communication with the support team facilitated a swift resolution. Diligent efforts were made to mitigate attrition, including thorough follow-ups, particularly regarding returned submissions. Regular reminders were sent to eligible participants to encourage the completion of their second dataset. As the survey progressed, participants engaged with the identical set of items used in the previous assessment, measuring both the adoption and use of technology and the assessment of personality traits, as completed in T₁. At T₂, 328 participants, from the 331 valid respondents in T₁, had been invited (99%), where recruitment commenced on 31.10.2023 and concluded on 12.12.2023 (for 42 days with a time lag of 6 months), resulting in a total of **267** users/respondents (80.7% response rate; M_{age}=33, standard deviation [SD] =6.7; ~60% women).

Almost half of the users (approximately 50.6%) fell within the 26- to 35-year-old age bracket, and 65% possessed or were pursuing a university degree or higher education. Table 6-1 summarises the respondents' demographic profile.

Table 6–1 Respondents demographic profile

	Frequency	Percentage
Gender		
Female	160	59.9
Male	107	40.1
Age (years)		
18–25	40	15.1
26–35	135	50.6
36–45	83	30.8
46–55	9	3.5
Education		
Completed Primary School	1	0.4
Some Secondary	1	0.4
Completed Secondary School	27	10.1
Vocational or Similar	30	11.2
Some university but no degree	26	9.7
University bachelor's degree	125	46.8
Graduate or professional degree (MA, MS, MBA, PhD, JD, MD, DDS)	56	21
Prefer not to say	1	0.4
Current wearable device WFT/SW brand		
Apple	108	40.4
Samsung	28	10.5
Huawei	18	6.7
Garmin	19	7.1
Fitbit	70	26.2
Xiaomi	14	5.2
Fossil	1	0.4
Other	9	3.4

Studies stressed the importance of strategic resource allocation in maximum study retention and participant engagement in longitudinal cohort studies (Teague *et al.*, 2018). Attrition rate, referring to the loss of panellists over time (Mondino *et al.*, 2021, p. 2814), can significantly compromise the validity of findings. Consequently, implementing effective retention strategies is essential to ensure sample representativeness (Booker, Harding and Benzeval, 2011). The response rate assesses participant engagement and cooperation/retention when completing study assessments. Therefore, both metrics are crucial indicators of the quality and rigour of longitudinal research and were closely monitored to ensure the validity and reliability of study findings (Gustavson *et al.*, 2012).

Meta-analyses and systematic reviews are invaluable for providing aggregated data and analyses on attrition rates across multiple longitudinal studies. Table 6-2 focuses specifically on attrition rates, summarising longitudinal studies that employed survey designs conducted over two waves (T1 and T2). These studies focus exclusively on disciplines similar to the context of the current research, such as mental health and well-being (Lemyre, Palmer-Cooper and Messina, 2023) and mental health and ageing (Dahlberg *et al.*, 2022). Table 6-2 shows that the attrition rate varies from 14% to 73% (with an average of 39.2%, which aligns with the typical attrition rate of around 40% observed in similar studies employing custom-designed surveys). Needless to say, low attrition rates reduce bias and do not affect the validity and generalisability of study findings (Mondino *et al.*, 2021). Thus, the current study attrition rate at T2 (19.3%) is adequate for longitudinal studies of this nature.

Table 6–2 The attrition rate in various longitudinal studies and their characteristics

Study	Study title	Sample characteristics	Attrition rate (%)	Key findings
Evans <i>et al.</i> (2021)	Effects of the COVID-19 lockdown on mental health, well-being, sleep, and alcohol use in a UK student sample	n= 254 19.76 M age 86% Female 65% White	16	Significant decrease in mental well-being. Significant reduction in alcohol use. No significant changes in sleep quality.
Owens <i>et al.</i> (2022)	Mental Health and Well-being in Young People in the UK During Lockdown (COVID-19)	n =254 21.12 M age 73% Female	35	No significant change in Mental well-being. Significant decrease in sleep disturbance.
Savage <i>et al.</i> (2021)	Nine Months into the COVID-19 Pandemic: A Longitudinal Study Showing Mental Health and Movement Behaviours Are Impaired in UK Students	n =255 70% aged under 22 years 76% Female 82% White	73	Significant decrease in mental well-being. Significant reduction in physical activity and a significant increase in sedentary behaviours. Changes in sedentary behaviour negatively affected changes in mental well-being in regression analyses.
Ang, Monte and Tsai (2022)	First-Year College Students' Adjustment During the COVID-19 Pandemic: The Protective Roles of Hope and Gratitude	n=408 17.97 M age 71% Female 41% Asian American	14	Controlling for age, gender, ethnicity, and T1 life satisfaction, T1 hope and gratitude were associated with T2 life satisfaction increases in regression analyses. COVID-19 experience correlated with lower life satisfaction.

Audet <i>et al.</i> (2021)	Zooming their way through university: Which Big 5 traits facilitated students' adjustment to online courses during the COVID-19 pandemic	n =167 19.75 M age 88% Female 56% European descent	52	Significant decrease in well-being. Openness to experience is significantly associated with increases in subjective well-being in regression analyses.
Hasratian <i>et al.</i> (2021)	Fear and Coping in Students during the Early Stages of the COVID-19 Pandemic: A Combined Cross-Sectional and Longitudinal Study	n = 58 19.67 M age 74% Female 72% Caucasian	67	Significant decrease in PANAS Positive. Significant reduction in alcohol use.
Dubar, Watkins and Hill (2021)	Examining the Direction of Effects Between COVID-19 Experiences, General Well-being, Social Media Engagement and Insomnia Symptoms Among University Students	n =344 21.8 Mage 66% White 64% Female	44	Problematic use of social media and COVID-19 experience were significantly correlated with lower general well-being.
Slykerman, Li and Mitchell (2022)	Students' Experience of Online University Education During the COVID-19 Pandemic: Relationships to Psychological Health	n= 391	19	Significant increase in well-being.
Margelisch <i>et al.</i> (2017)	Marital stability, satisfaction and well-being in old age: variability and continuity in long-term continuously married older persons	n= 252 74.3 M age	33	Identifying groups of long-term married persons with respect to marital satisfaction and comparing them longitudinally concerning their well-being outcomes, marital stressors, personality and socio-demographic variables.

6.1 Data Coding

Following the completion of the second data collection, the analysis was conducted using IBM SPSS 28.0, following the same steps outlined for the first dataset in the previous chapter. Additionally, a set of t-tests was utilised for discerning significant mean differences between the two groups, contributing to the comprehensive examination of the hypotheses as this approach diverged from the one-way analysis of variance (ANOVA), which is used for comparing means among three or more groups, which is not the case in the current thesis. Starting with data coding (detailed in section 5.1).

6.2 Preliminary Examination of the Data

Similar to the first dataset, details on the preliminary data examination can be found in section 5.2 of the previous chapter, with missing data discussed in section 5.2.1. After reviewing the data collected for the second study, no missing cases were identified (one case was an unengaged response). Outlier detection, detailed in section 5.2.2, was carried out using both boxplots and Mahalanobis D^2 tests, with no outliers detected. This resulted in a final sample size of $n=267$ for further analysis. Furthermore, all four assumption tests were conducted for the individual constructs in this study: (a) normality, (b) homoscedasticity, (c) linearity, and (d) multicollinearity. As discussed in section 5.2.3, these assumptions are critical due to their significant impact on the application of multivariate techniques (Hair *et al.*, 2014).

6.3 Factor Analysis

6.3.1 Exploratory Factor Analysis

In the second dataset, EFA, which aims to search for a defined set of variables, was conducted to identify poorly performing items, followed by CFA to remove redundant or non-reflective items (see details in sections [5.3.1](#) and [5.3.2](#)). Regarding the **sample-to-item ratio**, similar to the first dataset, two groups were analysed, suggesting a necessity for group-based EFA.

Data Appropriateness of Factor Analysis

Both Bartlett's sphericity test and the KMO test were performed for Groups 1 and 2 in SPSS to ensure the validity and reliability of the data.

Selecting factor Extraction and Rotation methods

The **ML** method was selected during the EFA as the preferred factor extraction method (as the study used AMOS for CFA and structure modelling) in order to maximise differences between factors and eliminate problematic items by providing a Model Fit estimate as the latent constructs were already known (see later sections that present the outcomes of this technique) and utilising the **oblique rotation** method, specifically **Promax**, to achieve its objectives.

Factor Loading

Corresponding to Hair *et al.* (2014), this second study's sample size ($n = 267$) considered a loading value of 0.40 significant in the EFA analysis (see Table 5-18 of Loadings for Practical Significance).

Reliability

The EFA and reliability results for individual constructs and two measurement groups (1 and 2) are presented based on the steps discussed earlier. The researcher performed EFA using the ML extraction method along with Promax rotation in SPSS statistical software.

EFA and Reliability Results for Individual Constructs

Performance Expectancy

The analysis contained three scale items, which produced a KMO value of 0.842 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 84.709 %. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.968. A Cronbach's alpha value of 0.957, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The outcomes of the EFA and reliability statistics are presented in Table 6-3.

Table 6–3 EFA and reliability results for Performance Expectancy

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)
KMO measure		0.842			
Bartlett's	Approx. χ^2	1221.644	PerExp_1	0.968	
test of			PerExp_3	0.941	
sphericity	df	6	PerExp_4	0.896	84.709
	sig.	0.000	PerExp_2	0.874	0.957

Effort Expectancy

The analysis contained three scale items, which produced a KMO value of 0.915 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 82.035%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.932. A Cronbach's alpha value of 0.957, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The EFA and reliability statistics outcomes are presented in the table below (6-4).

Table 6–4 EFA and reliability results for Effort Expectancy

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)
KMO measure		0.915			
Bartlett's test of sphericity	Approx. χ^2	1449.444	EffExp_7 0.932		
	df	10	EffExp_1 0.920		
	sig.	0.000	EffExp_4 0.905	82.035	0.957
			EffExp_3 0.893		
			EffExp_2 0.878		

Societal Pressure

The analysis contained four scale items, which produced a KMO value of 0.841 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 73.535%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.917. A Cronbach's alpha value of 0.912, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The EFA and reliability statistics outcomes are presented in Table 6-5.

Table 6–5 EFA and reliability results for Societal Pressure

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)
KMO measure		0.841			
Bartlett's test of sphericity	Approx. χ^2	788.912	SotPrss_2 0.917		
	df	6	SotPrss_3 0.916	73.535	0.912
	sig.	0.000	SotPrss_1 0.838		
			SotPrss_4 0.748		

Perceived Enjoyment

The analysis contained four scale items, which produced a KMO value of 0.876 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 84.396%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.940. A Cronbach's alpha value of 0.955, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The EFA and reliability statistics outcomes are presented in Table 6-6.

Table 6–6 EFA and reliability results for Perceived Enjoyment

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)		Total variance	Cronbach's alpha (>0.70)
KMO measure		0.876				
Bartlett's test of sphericity	Approx. χ^2	1146.858	PEnj_2	0.940	84.396	0.955
	df	6	PEnj_3	0.930		
			PEnj_4	0.903		
	sig.	0.000	PEnj_2	0.902		

Perceived Device Annoyance

The analysis contained three scale items, which produced a KMO value of 0.772 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 85.069%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.917. A Cronbach's alpha value of 0.939, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The EFA and reliability statistics outcomes are presented in Table 6-7.

Table 6–7 EFA and reliability results for Perceived Device Annoyance

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)
KMO measure			0.772		
Bartlett's test of sphericity	Approx. χ^2	709.964	DAnoy_20 0.917	85.069	0.939
	df	3	DAnoy_19 0.917		
	sig.	0.000	DAnoy_18 0.916		

Facilitating Conditions

The analysis contained four scale items, which produced a KMO value of 0.942 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 84.039%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.968. A Cronbach's alpha value of 0.969, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The EFA and reliability statistics outcomes are presented in Table 6-8.

Table 6–8 EFA and reliability results for Facilitating Conditions

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)
KMO measure			0.942		
Bartlett's test of sphericity	Approx. χ^2	2113.492	FCons_2 0.968	84.039	0.969
	df	15	FCons_1 0.934		
	sig.	0.000	FCons_6 0.934		
			FCons_5 0.931		
			FCons_3 0.910		
			FCons_4 0.817		

Technology Habit

The analysis contained four scale items, which produced a KMO value of 0.862 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 86.676%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.952. A Cronbach's alpha value of 0.962, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The outcomes of the EFA and reliability statistics are presented in Table (6-9).

Table 6–9 EFA and reliability results for Technology Habit

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)		Total variance	Cronbach's alpha (>0.70)
KMO measure			0.862			
Bartlett's test of sphericity	Approx. χ^2	1279.643	TechH_1	0.952	86.676	0.962
	df	6	TechH_2	0.927		
			TechH_3	0.927		
	sig.	0.000	TechH_4	0.917		

Price Value

The analysis contained four scale items, which produced a KMO value of 0.841 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 76.365%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.914. A Cronbach's alpha value of 0.928, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The EFA and reliability statistics outcomes are presented in Table 6-10.

Table 6–10 EFA and reliability results for Price Value

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)
KMO measure		0.841			
Bartlett's	Approx. χ^2	851.386	PValu_3	0.914	76.365 0.928
test of	df	6	PValu_2	0.872	
sphericity			PValu_4	0.871	
	sig.	0.000	PValu_1	0.836	

Technology Upgradability

The analysis contained four scale items, which produced a KMO value of 0.859 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 81.766%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.936. A Cronbach's alpha value of 0.946, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The EFA and reliability statistics outcomes are presented in Table 6-11.

Table 6–11 EFA and reliability results for Technology Upgradability

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)	Total variance	Cronbach's alpha (>0.70)
KMO measure		0.859			
Bartlett's	Approx. χ^2	1042.788	TUpG_6	0.936	81.766 0.946
test of	df	6	TUpG_3	0.916	
sphericity			TUpG_1	0.882	
	sig.	0.000	TUpG_2	0.882	

Continued Use Intention

The analysis contained three scale items, which produced a KMO value of 0.861 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 58.047%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.838. A Cronbach's alpha value of 0.869, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The outcomes of the EFA and reliability statistics are presented in Table 6-12.

Table 6–12 EFA and reliability results for continued use intention

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)		Total variance	Cronbach's alpha (>0.70)
KMO measure		0.861				
Bartlett's	Approx. χ^2	623.805	CUI_9	0.838	58.047	0.869
test of			CUI_6	0.798		
sphericity	df	10	CUI_7	0.772		
	sig.	0.001	CUI_10	0.728		
			CUI_11	0.661		

Continued Use Behaviour

The analysis contained five scale items, which produced a KMO value of 0.909 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 78.400%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.940. A Cronbach's alpha value of 0.946, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The outcomes of the EFA and reliability statistics are presented in Table 6-13.

Table 6–13 EFA and reliability results for Continuance Use

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)		Total variance	Cronbach's alpha (>0.70)
KMO measure		0.909	CUB_4	0.940	78.400	0.946
Bartlett's	Approx. χ^2	1356.533	CUB_2	0.933		
test of	df	10	CUB_3	0.907		
sphericity			CUB_1	0.905		
	sig.	0.000	CUB_5	0.724		

Openness to Technological Innovativeness

The analysis contained five scale items, which produced a KMO value of 0.908 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 82.155%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.943. A Cronbach's alpha value of 0.957, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The outcomes of the EFA and reliability statistics are presented in Table 6-14.

Table 6–14 EFA and reliability results for Openness to Technological Innovativeness

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)		Total variance	Cronbach's alpha (>0.70)
KMO measure		0.908			82.155	0.957
Bartlett's	Approx. χ^2	1473.162	OTTI_4	0.943		
test of	df	10	OTTI_1	0.919		
sphericity			OTTI_5	0.901		
	sig.	0.000	OTTI_2	0.901		
			OTTI_3	0.866		

Conscientiousness in Health

The analysis contained four scale items, which produced a KMO value of 0.854 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 88.483%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.962. A Cronbach's alpha value of 0.968, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. The outcomes of the EFA and reliability statistics are presented in Table 6-15.

Table 6–15 EFA and reliability results for Conscientiousness in Health

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)		Total variance	Cronbach's alpha (>0.70)
KMO measure		0.854				
Bartlett's test of sphericity	Approx. χ^2	1414.917	CinH_2	0.962	88.483	0.968
	df	6	CinH_4	0.955		
			CinH_1	0.933		
	sig.	0.000	CinH_3	0.912		

Neuroticism

The analysis contained three scale items, which produced a KMO value of 0.760 (i.e., greater than 0.50) and a significant Bartlett's test of sphericity, demonstrating the appropriateness of the data. The total variance explained by the item combination is 80.635%. The factor loadings of all the items were higher than the required threshold of 0.40, demonstrating the intercorrelation of the items, with the highest value being 0.926. A Cronbach's alpha value of 0.925, which is higher than the required value of 0.70 and which indicates internal consistency, was found in the reliability statistics. Additionally, according to the item-total statistics, Cronbach's alpha value showed no improvement. The outcomes of the EFA and reliability statistics are presented in Table 6-16.

Table 6–16 EFA and reliability results for Neuroticism

KMO and Bartlett's test (KMO >0.50, BTS sig. <0.05)			Factor loadings (>0.40)		Total variance	Cronbach's alpha (>0.70)
KMO measure		0.760				
Bartlett's test of sphericity	Approx. χ^2	617.488	Neu_4	0.926	80.635	0.925
	df	3	Neu_2	0.894		
	sig.	0.000	Neu_1	0.873		

EFA – Group 1

For Group 1, EFA was conducted for 28 items using the **ML** factor extraction method and **Promax** rotation. The initial analysis showed a KMO measure of 0.884, which is more than 0.50, indicating an adequate sample, suggesting data appropriateness for conducting the analysis. Bartlett's test of sphericity, which tests the hypothesis that the correlation matrix is an identity matrix (meaning that the variables are unrelated), was significant, with a value of below 0.50. The selection of factor extraction based on eigenvalues > 1 resulted in a seven-factor structure with all the loadings above the cap of 0.40. Afterwards, the CFA was used to test the unidimensionality of the factors. Table 6-17 (a pattern matrix) demonstrates the final seven-factor and total variance explained (seven factors have been extracted, as expected)

Table 6–17 EFA – final results – Group 1

Pattern Matrix ^a							
	Factor						
	1	2	3	4	5	6	7
TecH_1	0.952						
TecH_3	0.931						
TecH_2	0.924						
TecH_4	0.902						
PerExp_1		0.961					
PerExp_4		0.952					
PerExp_3		0.906					
PerExp_2		0.846					
PEnj_2			0.943				
PEnj_3			0.933				
PEnj_4			0.913				
PEnj_1			0.879				
PValu_4				0.899			
PValu_3				0.897			
PValu_1				0.838			
PValu_2				0.837			
SotPrss_2					0.916		
SotPrss_3					0.914		
SotPrss_1					0.845		
SotPrss_4					0.747		
CUI_9						0.834	
CUI_6						0.809	
CUI_11						0.718	
CUI_10						0.698	
CUI_7						0.682	
DAnoy_20							0.920
DAnoy_19							0.915
DAnoy_18							0.903

Extraction Method: Maximum Likelihood.

Rotation Method: Promax with Kaiser Normalisation.^a

a. Rotation converged in 6 iterations.

Note: Extraction method: maximum likelihood; Rotation method: Promax with Kaiser normalisation. Kaiser-Meyer-Olkin measure of sampling adequacy = 0.884; Bartlett's test of sphericity approx. $\chi^2 = 7233.588$; df = 378; sig. = 0.000

EFA – Group 2

For Group 2, EFA was conducted for 32 items using the **ML** factor extraction method and **Promax** rotation. The initial analysis showed a KMO measure of 0.896, which is more than 0.50, indicating an adequate sample, suggesting the appropriateness of the data for conducting the analysis. Bartlett's test of sphericity, which tests the hypothesis that the correlation matrix is an identity matrix (meaning that the variables are unrelated), was significant, with a value of below 0.50. The selection of a factor extraction method based on eigenvalues > 1 resulted in a seven-factor structure with all the loadings above the cap of 0.40. Afterwards, the CFA was used to test the unidimensionality of the factors. Table 6-18 (a pattern matrix) demonstrates the final seven factors and total variance explained (seven factors were extracted, as expected).

Table 6–18 EFA – final results – Group 2

Pattern Matrix ^a							
	Factor						
	1	2	3	4	5	6	7
FCons_5	0.975						
FCons_2	0.966						
FCons_6	0.957						
FCons_1	0.912						
FCons_3	0.894						
FCons_4	0.765						
EffExp_7		0.950					
EffExp_4		0.928					
EffExp_1		0.899					
EffExp_3		0.887					
EffExp_2		0.863					
OTTI_4			0.948				
OTTI_1			0.916				
OTTI_5			0.905				
OTTI_2			0.900				
OTTI_3			0.861				
CinH_2				0.955			
CinH_4				0.952			
CinH_1				0.939			
CinH_3				0.914			
CUB_4					0.993		
CUB_2					0.941		
CUB_1					0.892		
CUB_3					0.874		
CUB_5					0.571		
TUpG_6						0.940	
TUpG_3						0.902	
TUpG_1						0.891	
TUpG_2						0.884	
Neu_4							0.924
Neu_2							0.908
Neu_1							0.860

Extraction method: maximum likelihood.

Rotation method: Promax with Kaiser Normalisation.^a

a. Rotation converged in 6 iterations.

Note: Extraction method: maximum likelihood; Rotation method: Promax with Kaiser normalisation. Kaiser-Meyer-Olkin measure of sampling adequacy = 0.896; Bartlett's test of sphericity approx. $\chi^2 = 9936.103$; df = 496; sig. = 0.000

6.3.2 Confirmatory Factor Analysis

Similar to the first dataset, CFA is performed, as detailed in section [5.3.2](#), employing a multi-step process: I) development of a measurement model; II) measurement model specification and identification; III) assessment of measurement model fit; and IV) assessment of measurement model validity (Hair *et al.*, 2014).

a) CFA – Measurement Model 1

Specification and Identification Measurement

Measurement model 1 is specified with seven reflective latent constructs. The seven latent constructs are as follows: continued use intention, reflected by five items (CUI_6, CUI_7, CUI_9, CUI_10 and CUI_11); perceived enjoyment, reflected by four items (PEnj_1 to PEnj_4); price value, reflected by four items (PValu_1 to PValu_4); performance expectancy, reflected by four items (PerExp_1 to PerExp_4); societal pressure, reflected by four items (SotPrss_1 to SotPrss_4); technology habit, reflected by four items (TechH_1 to TechH_4); and perceived device annoyance, reflected by three items (DAnoy_18, DAnoy_19, and DAnoy_20). Further error terms were linked to each observed item within the measurement model.

The degrees of freedom were computed for the measurement model 1 identification. Specifically, there were a total of 28 items (denoted as "p"), and the count of **distinct parameters to be estimated** was 75 (represented as "k"). Hence, inserting these values into the equation: $df = \frac{1}{2}(p(p+1)) - k$, the degrees of freedom were computed as $df = \frac{1}{2}(28(28+1)) - 77 = 329$, this represents positive degrees of freedom, suggesting that measurement model 1 was overidentified, making it a suitable choice for conducting Confirmatory Factor Analysis (CFA).

Figure 6-1 below illustrates the final measurement model 1, which exhibits robust model fit and construct validity (and encompasses all 28 measured items).

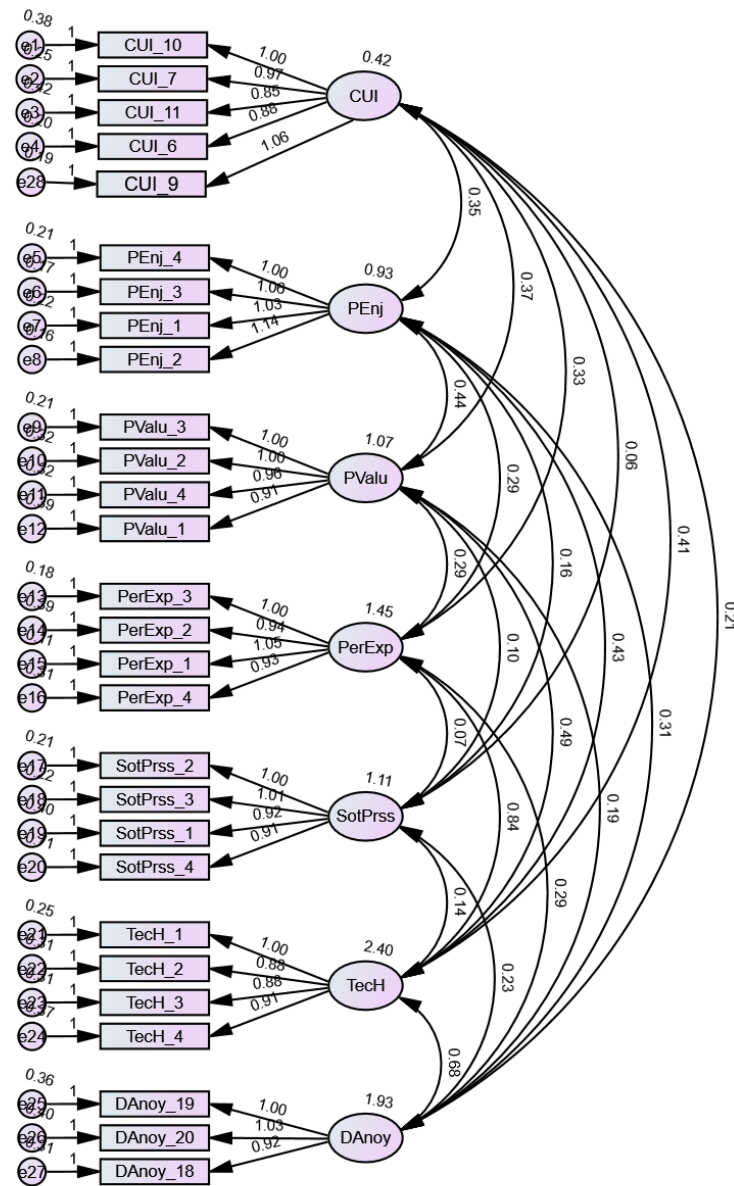


Figure 6-1 Final measurement model 1

$\chi^2 = 573.197$, $df = 329$, $RMSEA = 0.53$, $CFI = 0.966$, $TLI = 0.961$

Assessment of Model Fit and Construct Validity

In the CFA, a model fit and construct validity assessment involving seven latent constructs and 28 observed items was performed. The initial measurement model was examined for construct validity and model fit. Subsequently, guided by the EFA outcomes, the initial construct validity, model fit, and assessments accomplished an optimal model fit and construct validity. The model fit evaluation relied on absolute fit indices (such as χ^2/df and RMSEA) and incremental fit indices (including CFI and TLI). Fit statistics from the initial CFA analysis are shown in Table 6-19. These results indicated a good model fit indices.

Table 6–19 Final fit statistics – measurement model 1

Model fit indices	χ^2	(df)	$\chi^2/\text{df} < 3$	RMSEA <0.07 with CFI >0.92	CFI >0.90	TLI >0.90
All items (28)	573.197	(329)	1.742	0.53	0.966	0.961

The values of the construct validity measures were also examined. In AMOS output, factor loadings are presented as standardised weights. The preliminary findings indicated that all of the items had factor loadings surpassing the desirable threshold of 0.70. Further, the AVE of all seven latent constructs was calculated using Equation (1). For instance, the AVE of the perceived device annoyance was calculated as $0.918 + 0.916 + 0.917 / 3 = 0.917$. A similar procedure was applied to calculate the AVEs for the remaining latent constructs. In the initial analysis, the AVEs for all latent constructs exceeded the threshold of 0.50.

CR was then computed using Equation (2). As an illustration, the CR for the latent construct perceived device annoyance was determined in the following manner:

$$(0.918 + 0.916 + 0.917)^2 / (0.918 + 0.916 + 0.917)^2 + (0.157 + 0.161 + 0.159) = 0.941$$

The same calculation procedure was applied to determine the CR values for the remaining latent constructs. The initial assessment indicated that all construct CR values exceeded the minimum threshold of 0.70. Table 6-20 displays the CR and AVE values for all the latent constructs within the measurement model.

Table 6–20 Final convergent validity results for measurement model 1

	CR	AVE	TechH	CUI	PEnj	PValu	PerExp	SotPrss	DAnoy
TechH	0.964	0.870	0.933						
CUI	0.868	0.569	0.407	0.754					
PEnj	0.956	0.846	0.288	0.570	0.920				
PValu	0.922	0.746	0.306	0.534	0.451	0.864			
PerExp	0.955	0.841	0.447	0.407	0.250	0.217	0.917		
SotPrss	0.916	0.734	0.085	0.099	0.150	0.108	0.061	0.857	
DAnoy	0.938	0.834	0.324	0.253	0.228	0.153	0.187	0.147	0.914

Note: CR = construct reliability; AVE = average variance extracted; TechH = technology habit; CUI = continued use intention; PEnj = perceived enjoyment; PValu = price value; PerExp = performance expectancy; SotPrss = societal pressure; DAnoy = perceived device annoyance.

Lastly, the discriminant validity of all the latent constructs was examined. This involved comparing each construct's AVE with the square of its correlation with other latent constructs. All latent constructs met the criteria for discriminant validity. Table 6-21 shows the final factor loadings, CR, and AVEs for measurement model 1.

Table 6–21 Final factor loadings, CR and AVE for measurement model 1

Items		Latent construct	Factor loading	CR	AVE
CUI_10	<---	Continued use intention	0.727	0.872	0.579
CUI_7	<---		0.783		
CUI_11	<---		0.651		
CUI_6	<---		0.788		
CUI_9	<---		0.843		
PEnj_4	<---	Perceived enjoyment	0.902	0.956	0.844
PEnj_3	<---		0.929		
PEnj_1	<---		0.903		
PEnj_2	<---		0.940		
PValu_3	<---	Price value	0.915	0.928	0.763
PValu_2	<---		0.875		
PValu_4	<---		0.868		
PValu_1	<---		0.835		
PerExp_3	<---	Performance expectancy	0.943	0.957	0.847
PerExp_2	<---		0.875		
PerExp_1	<---		0.966		
PerExp_4	<---		0.894		
SotPrss_2	<---	Societal pressure	0.917	0.917	0.735
SotPrss_3	<---		0.916		
SotPrss_1	<---		0.837		
SotPrss_4	<---		0.748		
Tech_1	<---	Technology habit	0.952	0.963	0.867
Tech_2	<---		0.927		
Tech_3	<---		0.927		
Tech_4	<---		0.918		
DAnoy_19	<---	Perceived device annoyance	0.918	0.941	0.841
DAnoy_20	<---		0.916		
DAnoy_18	<---		0.917		

b) CFA – Measurement model 2

Specification and Identification Measurement

Measurement model 2 is specified with seven reflective latent constructs. The seven latent constructs are as follows: effort expectancy, reflected by five items (EffExp_1 to EffExp_4 and EffExp_7); technology upgradability, reflected by four items (TUpG_1 to TUpG_3 and TUpG_6); facilitating conditions, reflected by six items (FCons_1 to FCons_6); continued use behaviour, reflected by five items (CUB_1 to CUB_5); openness to technological innovativeness, reflected by five items (OTTI_1 to OTTI_5); conscientiousness in health, reflected by four items (CinH_1 to CinH_4); and neuroticism, reflected by three items (Neu_1, Neu_2 and Neu_4). Further error terms were linked to each observed item within the measurement model. The degrees of freedom were computed for measurement model 2 identification. Specifically, there were a total of 32 items (denoted as "p"), and the count of distinct parameters to be estimated was 77 (represented as "k"). Hence, inserting these values into the equation: $df = \frac{1}{2} (p(p+1)) - k$, the degrees of freedom were computed as $df = \frac{1}{2} (32(32+1)) - 77 = 451$, which presents positive degrees of freedom. This suggests that measurement model 2 was overidentified, making it a suitable choice for conducting CFA. Figure 6-2 below illustrates the final measurement model 2, which exhibit robust model fit and construct validity (encompassing all 32 items measured).

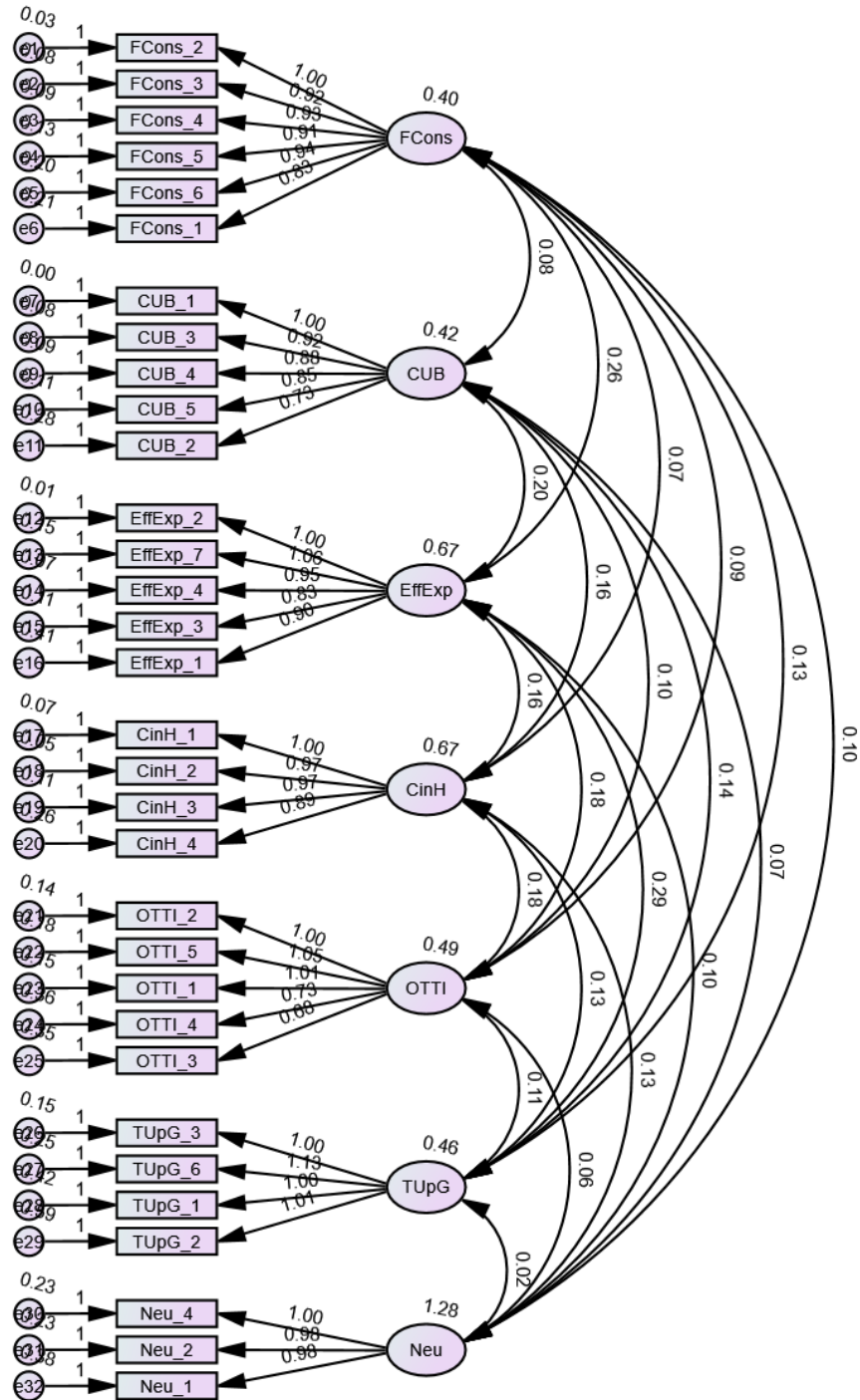


Figure 6-2 Final measurement model 2

 $\chi^2 = 829.856$, $df = 443$, $RMSEA = 0.051$, $CFI = 0.962$, $TLI = 0.957$

Assessment of Model Fit and Construct Validity

In CFA, a model fit and construct validity assessment was performed involving seven latent constructs and 32 observed items. The initial measurement model was examined for construct validity and model fit. Subsequently, guided by the EFA outcomes, the initial construct validity, model fit, and assessments, problematic items were systematically removed to accomplish an optimal model fit and construct validity. The initial model fit evaluation relied on absolute fit indices (such as χ^2/df and RMSEA) and incremental fit indices (including CFI and TLI). Fit statistics from the initial CFA analysis are shown in Table 6-22. These results indicated a good model fit indices.

Table 6–22 Final fit statistics – measurement model 2

Model fit indices	χ^2	(df)	$\chi^2/df < 3$	RMSEA <0.07 with CFI >0.92	CFI >0.90	TLI >0.90
32 items	829.856	(443)	1.670	0.051	0.962	0.957

The values of the construct validity measures were also examined. In the AMOS output, factor loadings are presented as standardised weights. The preliminary findings indicated that a majority of the items had factor loadings surpassing the desirable threshold of 0.70. Further, the AVE of all seven latent constructs was calculated using Equation (1). For instance, the AVE of neuroticism was calculated as $0.928 + 0.892 + 0.873 / 3 = 0.898$. A similar procedure was applied to calculate the AVEs for the remaining latent constructs. In the initial analysis, the AVEs for all latent constructs exceeded the threshold of 0.50, except for behaviour intentions and effort expectancy.

Subsequently, CR was computed using Equation (2). As an illustration, the CR for the latent construct perceived device annoyance was determined in the following manner:

$$(0.928 + 0.892 + 0.873)2 / (0.928 + 0.892 + 0.873)2 + (0.139 + 0.204 + 0.238) = 0.925$$

The same calculation procedure was applied to determine the CR values for the remaining latent constructs. The initial assessment indicated that all construct CR values exceeded the minimum threshold of 0.70. Table 6-23 displays the CR and AVE values for all the latent constructs within the measurement model.

Table 6–23 Convergent validity results for measurement model 2

	CR	AVE	TUpG	FCons	CUB	EffExp	CinH	OTTI	Neu
TUpG	0.945	0.810	0.900						
FCons	0.967	0.830	0.131	0.911					
CUB	0.943	0.770	0.295	0.580	0.877				
EffExp	0.953	0.804	0.165	0.339	0.454	0.897			
CinH	0.967	0.881	-0.055	-0.029	-0.121	0.109	0.939		
OTTI	0.958	0.819	0.080	0.136	0.125	0.074	0.098	0.905	
Neu	0.886	0.721	0.229	0.173	0.255	0.074	0.152	0.072	0.849

Note: CR = construct reliability; AVE = average variance extracted; TUpG = technology upgradability; FCons = facilitating conditions; CUB = continued use behaviour; EffExp = effort expectancy; CinH = conscientiousness in health; OTTI = openness to technological innovativeness; Neu = neuroticism.

Lastly, the discriminant validity of all the latent constructs was examined. This involved comparing each construct's AVE with the square of its correlation with other latent constructs.

All latent constructs met the criteria for discriminant validity. Table 6-24 demonstrates the final factor loadings, CR and AVEs for measurement model 2.

Table 6–24 Final factor loadings, CR and AVEs for measurement model 2

Items		Latent construct	Factor loading	CR	AVE
FCons_2	<---	Facilitating conditions	0.968	0.969	0.841
FCons_3	<---		0.910		
FCons_4	<---		0.818		
FCons_5	<---		0.930		
FCons_6	<---		0.933		
FCons_1	<---	Continued use behaviour	0.935	0.948	0.786
CUB_1	<---		0.906		
CUB_3	<---		0.909		
CUB_4	<---		0.936		
CUB_5	<---		0.731		
CUB_2	<---	Effort expectancy	0.933	0.958	0.820
EffExp_2	<---		0.879		
EffExp_7	<---		0.930		
EffExp_4	<---		0.903		
EffExp_3	<---		0.893		
EffExp_1	<---	Conscientiousness in health	0.922	0.969	0.885
CinH_1	<---		0.933		
CinH_2	<---		0.962		
CinH_3	<---		0.912		
CinH_4	<---		0.955		
OTTI_2	<---	Openness to technological innovativeness	0.901	0.958	0.822
OTTI_5	<---		0.901		
OTTI_1	<---		0.920		
OTTI_4	<---		0.943		
OTTI_3	<---		0.866		
TUpG_3	<---	Technology upgradability	0.917	0.947	0.818
TUpG_6	<---		0.936		
TUpG_1	<---		0.882		
TUpG_2	<---		0.881		
Neu_4	<---	Neuroticism	0.928	0.926	0.806
Neu_2	<---		0.892		
Neu_1	<---		0.873		

6.4 Common Method Bias (CMB)

In the second dataset, like the first study, CMB was employed in AMOS and SmartPLS; see appendices H, I and J confirming that CMB is not a cause for concern (for more elaboration, see section [5.4](#)).

6.5 Path Analysis

Utilising SEM (see section [5.5](#)) in the second dataset to validate the study's theoretical model and gain insights into causal relationships among variables, ultimately enhancing the rigour of research findings, which follows a series of well-defined steps. The initial stages encompass defining individual constructs, crafting a measurement model, and evaluating its validity, as discussed in the preceding section (Hair *et al.*, 2014). Subsequent phases involve specifying the structural model and scrutinising its validity.

6.5.1 Structural Model - Specification

In this second study, based on the underpinning theory, a structural model (see section 5.5.1) was developed, which included exogenous constructs denoting perceived factors linked to users' behaviour intention towards using their wearable fitness technology (an endogenous construct) with a single-headed arrow. Furthermore, the endogenous constructs are not entirely explained, hence warranting the inclusion of error terms (Hair *et al.*, 2014). The structural models, with and without control variables, were developed using IBM AMOS 28.0 and are similar to those presented in the previous chapter (Figures 5-4 and 5-5).

6.5.2 Assessing Structural Model Validity

In this stage, the GOF statistics were evaluated. The results in Table 6-25 demonstrate that the model fit statistics meet the required threshold values for both structural models (with and without control variables), indicating their adequacy.

Table 6–25 Model fit statistics for the structural models

Model fit indices		χ^2	(df)	$\chi^2/\text{df} < 3$	RMSEA <0.07 with CFI >0.92	CFI >0.90	TLI >0.90
Without control variables		2181.685	(1304)	1.673	0.050	0.921	0.917
With control variables		2829.971	(1620)	1.782	0.048	0.905	0.900

The statistics suggest that the structural model with control variables exhibits a better fit than the model without the controls. Therefore, the decision was made to keep the control variables for further examination during the hypotheses testing.

6.5.3 Hypotheses Testing

This section presents the findings for all the proposed hypotheses, including direct effects, mediating effects, and moderating effects. As these hypotheses are directional, one-tailed test results will be reported. This approach is taken because the use of two-tailed tests for directional hypotheses can result in inaccurate or mistaken empirical conclusions at a given level of significance α (Cho and Abe, 2013, p. 1265).

a) Direct Effect

Hypotheses H1(a) to (i) proposed that all the perceived factors are positively related to CUI towards wearable fitness devices, except for H1(e) where it is negatively related. H2 proposed that continued use intention is positively related to continued use behaviour. These hypotheses were tested at a significance level of 5%. The summarised results are presented in Table 6-26.

Table 6–26 Direct effects test results (with controls)

Hypo-theses	Paths	Standardised estimates
H1(a)	Performance expectancy → Continued use intention	0.097*
H1(b)	Effort expectancy → Continued use intention	0.265**
H1(c)	Societal pressure → Continued use intention	0.009
H1(d)	Perceived enjoyment → Continued use intention	0.205**
H1(e)	Perceived device annoyance → Continued use intention	0.005
H1(f)	Facilitating conditions → Continued use intention	0.258**
H1(g)	Technology habit → Continued use intention	0.119*
H1(h)	Price value → Continued use intention	0.145**
H1(i)	Technology upgradability → Continued use intention	0.148**
H2	Continued use intention → Continued use behaviour	0.666**
Controls		
	Age → Continued use behaviour	-0.033
	Gender → Continued use behaviour	0.080
	Education → Continued use behaviour	-0.004

Note: n = 267

Significant at ** $p < 0.01$; * $p < 0.05$

The results indicate that perceived enjoyment ($\beta = 0.205$, $t = 4.657$, $p < 0.001$); effort expectancy ($\beta = 0.265$, $t = 5.523$, $p < 0.001$); performance expectancy ($\beta = 0.097$, $t = 2.134$, $p = 0.033$); facilitating condition ($\beta = 0.258$, $t = 5.276$, $p < 0.001$); price value ($\beta = 0.145$, $t = 3.129$, $p = 0.002$); technology habit ($\beta = 0.119$, $t = 2.558$, $p = 0.011$); and technology upgradability ($\beta = 0.148$, $t = 3.593$, $p < 0.001$) have statistically significant positive relationships with users' CUI towards wearable fitness devices. Therefore, these results render support for hypotheses H1(a), H1(b), H1(d), H1(f), H1(g), H1(h) and H1(i). However, the effects of the remaining two perceived factors were found to be statistically non-significant: perceived device annoyance ($\beta = 0.005$, $t = 0.104$, $p = 0.917$) and societal pressure ($\beta = 0.009$, $t = 0.205$, $p = 0.838$). Hence, hypotheses H1(c) and H1(e) are not supported. Regarding hypothesis H2, it was proposed that users' continued use

intention towards wearable fitness devices is positively related to continued use behaviour. The result indicates that users' CUI towards wearable fitness devices has a significant positive influence on CUB ($\beta = 0.227$, $t = 4.013$, $p < 0.001$), thereby supporting hypothesis H2 (see Table 6-27 from SmartPLS).

Table 6–27 Path Coefficients, Mean, SD, t-values and p-values (bootstrapping)

	Original sample (O)	Sample mean (M)	Standard deviation (SD)	t-statistics (O/SD)	p-values
DAnoy -> Continued Use Intention	0.005	0.004	0.043	0.104	0.917 (NS)
EffExp -> Continued Use Intention	0.265	0.264	0.048	5.523	0.000 (S)
FCons -> Continued Use Intention	0.258	0.258	0.049	5.276	0.000 (S)
PEnj -> Continued Use Intention	0.205	0.205	0.044	4.657	0.000 (S)
PValu -> Continued Use Intention	0.145	0.144	0.046	3.129	0.002 (S)
PerExp -> Continued Use Intention	0.097	0.097	0.046	2.134	0.033 (S)
SotPrss -> Continued Use Intention	0.009	0.014	0.043	0.205	0.838 (NS)
TUpG -> Continued Use Intention	0.148	0.148	0.041	3.593	0.000 (S)
TechH -> Continued Use Intention	0.119	0.120	0.047	2.558	0.011 (S)
Continued Use Intention -> Continued Use Behaviour	0.666	0.663	0.055	12.001	0.000 (S)

Note: $p < 0.05$ is considered significant (**S**), and $p \geq 0.05$ is considered not significant (NS).

The analysis reveals that effort expectancy, performance expectancy, facilitating conditions, perceived enjoyment, perceived value, technology upgradability, and technological habit positively influence continued use intention, which in turn significantly influences continued use behaviour. On the other hand, device annoyance and societal pressure do not significantly influence the CUI. These findings offer valuable insights into the determinants of continued use behaviour for wearable fitness devices, guided by the UTAUT2.

d) Mediation Analysis

The mediation process was previously explained (see section 5.5.3(b)), where this approach to mediation analysis was adopted due to evidence of its application in prior research within the IS field (e.g, Venkatesh, Thong and Xu, 2012; Alalwan, Dwivedi and Williams, 2016; Mehra, Rajput and Paul, 2022). Specifically, perceived factors that revealed a significant direct influence on users' continued use intention towards WFT (see section [5.5.3\(a\)](#)) were included in the mediation analysis.

The Mediating Role of Continued Use Intention

As presented previously in the first dataset, the fifth aim of this study was to investigate the mediating role of CUI towards WFT in the relationship between perceived factors and CUB. This study revealed that CUI serves as a key essential mechanism that explains how and why perceptions of various factors impact CUB. Full mediation was observed for performance expectancy (H1a), effort expectancy (H1b), and technology upgradability (H1i), indicating that the effects of these factors on CUB are entirely channelled through CUI. This finding highlights the crucial role of intention in bridging the relationship between users' expectations, adaptability of technology, and continued use behaviour. Partial mediation effects were identified for perceived enjoyment (H1d), facilitating conditions (H1f), technological habit (H1g), and price value (H1h). These factors not only directly influence CUB but also exhibit an amplified effect when mediated by CUI. This indicates that these predictors maintain both independent and mediated pathways to impact long-term behaviour.

Conversely, no mediation effects were found for societal pressure (H1c) and device annoyance (H1e), as their influence on CUB remained insignificant. These results suggest that external pressures and perceived frustrations with the technology do not significantly contribute to users' continued use intentions or behaviour (see Figures 6-3 and 6-4). Hence, an important finding is:

Key finding – Consumers' CUI fully mediates the effects of performance expectancy, effort expectancy, and technology upgradability on CUB. Meanwhile, partial mediation is observed for perceived enjoyment, facilitating conditions, technological habit, and price value, further emphasising the critical role of CUI in sustaining long-term engagement with WFTs. Factors such as societal pressure and device annoyance remain non-significant in their mediating role.

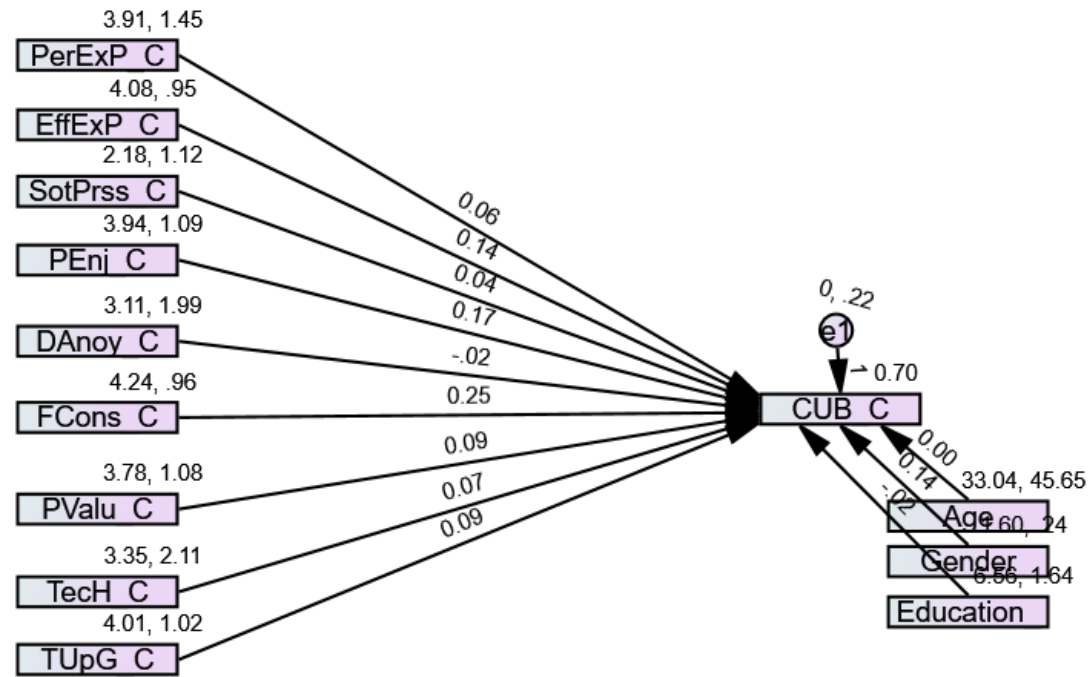


Figure 6-3 Structural model path diagram (without the mediator, Continued Use Intention – CUI)

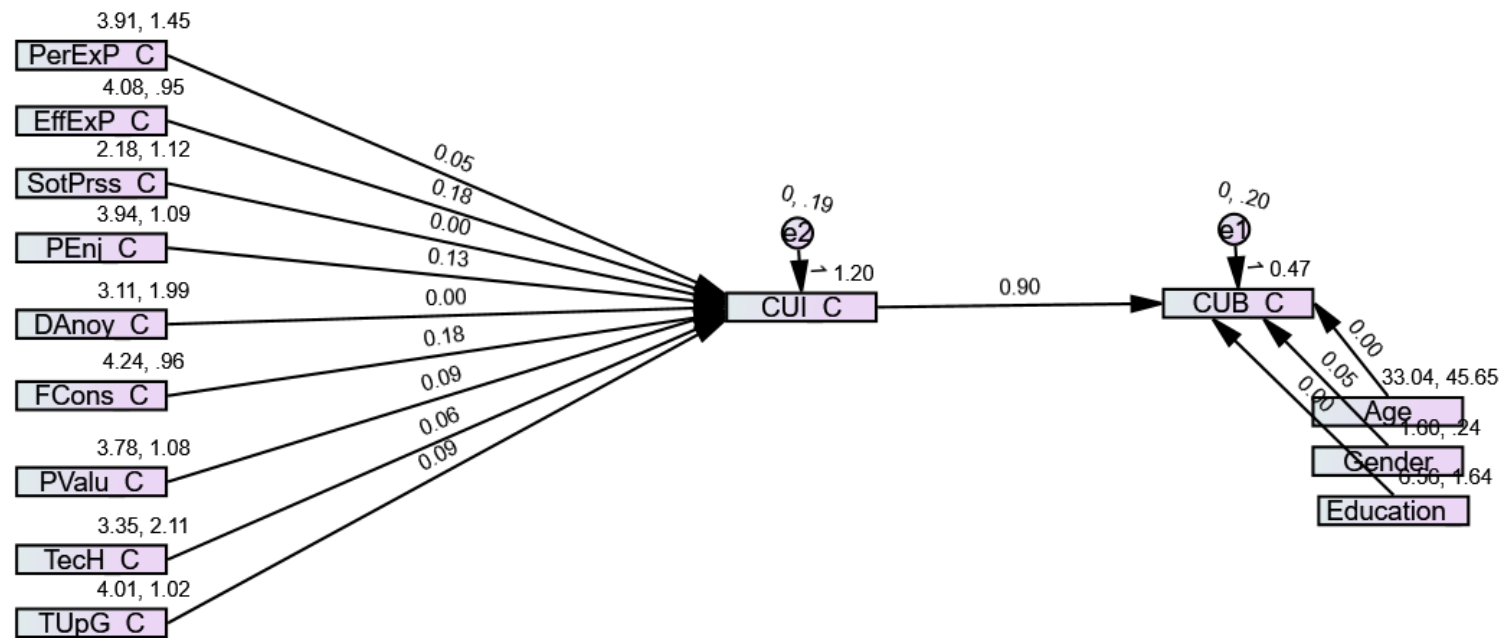


Figure 6-4 Structural model path diagram (with the mediator, Continued Use Intention – CUI)

e) Moderation Analysis

The three-variable system was previously elaborated upon in the last chapter (see section [5.5.3.c](#)).

The same approach was applied to the first dataset in the previous chapter to conduct the moderation analysis.

The Moderating Role of Openness to Technological Innovativeness

The analysis revealed a non-significant moderating effect of OTTI on the relationship between CUI and CUB ($\beta = 0.009$, $t = 0.371$, $p = 0.711$). This indicates that OTTI does not have a notable impact on the relationship between CUI and CUB (see Figure 6-5).

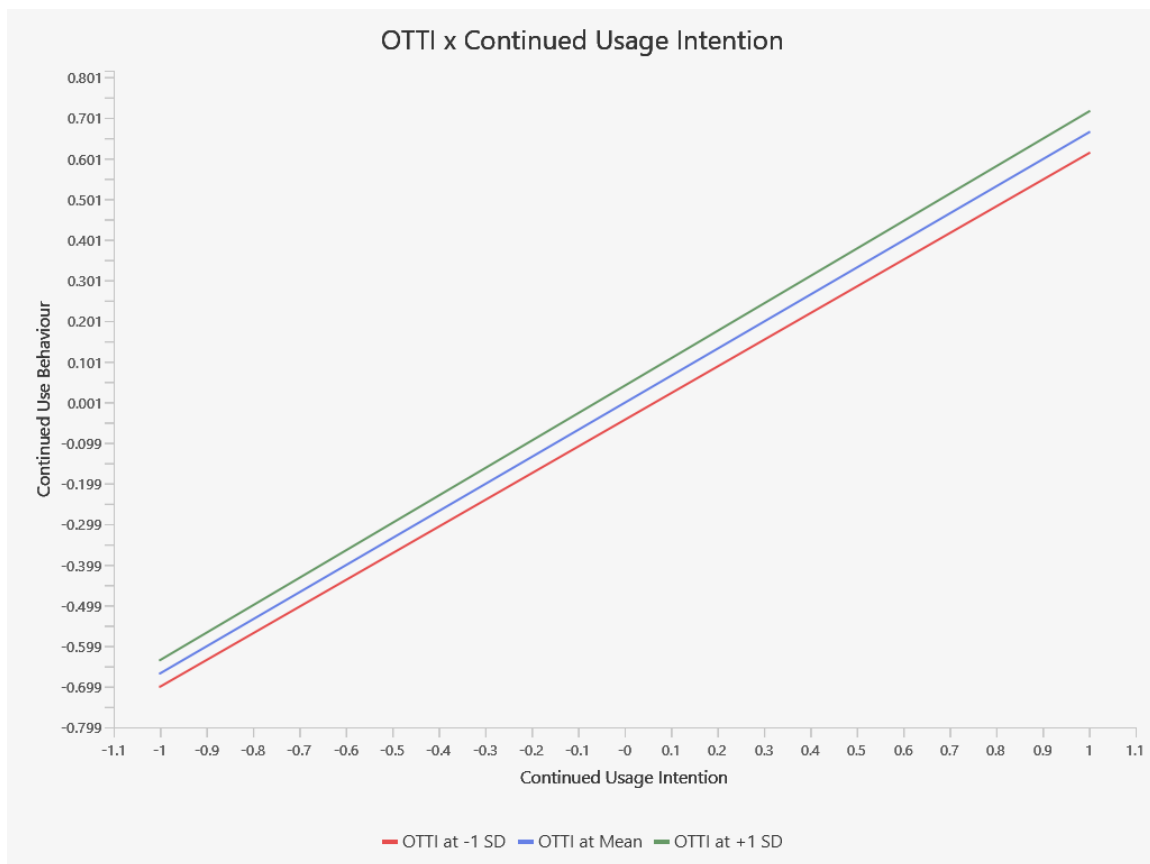


Figure 6-5 Moderating role of OTTI in the relationship between consumers' continued use intention and continued behaviour toward WFT

The Moderating Role of Conscientiousness in Health

The analysis revealed a non-significant moderating effect of CinH on the relationship between CUI and CUB ($\beta = -0.021$, $t = 0.563$, $p = 0.574$). This suggests that CinH does not significantly influence the relationship between CUI and CUB (Figure 6-6).

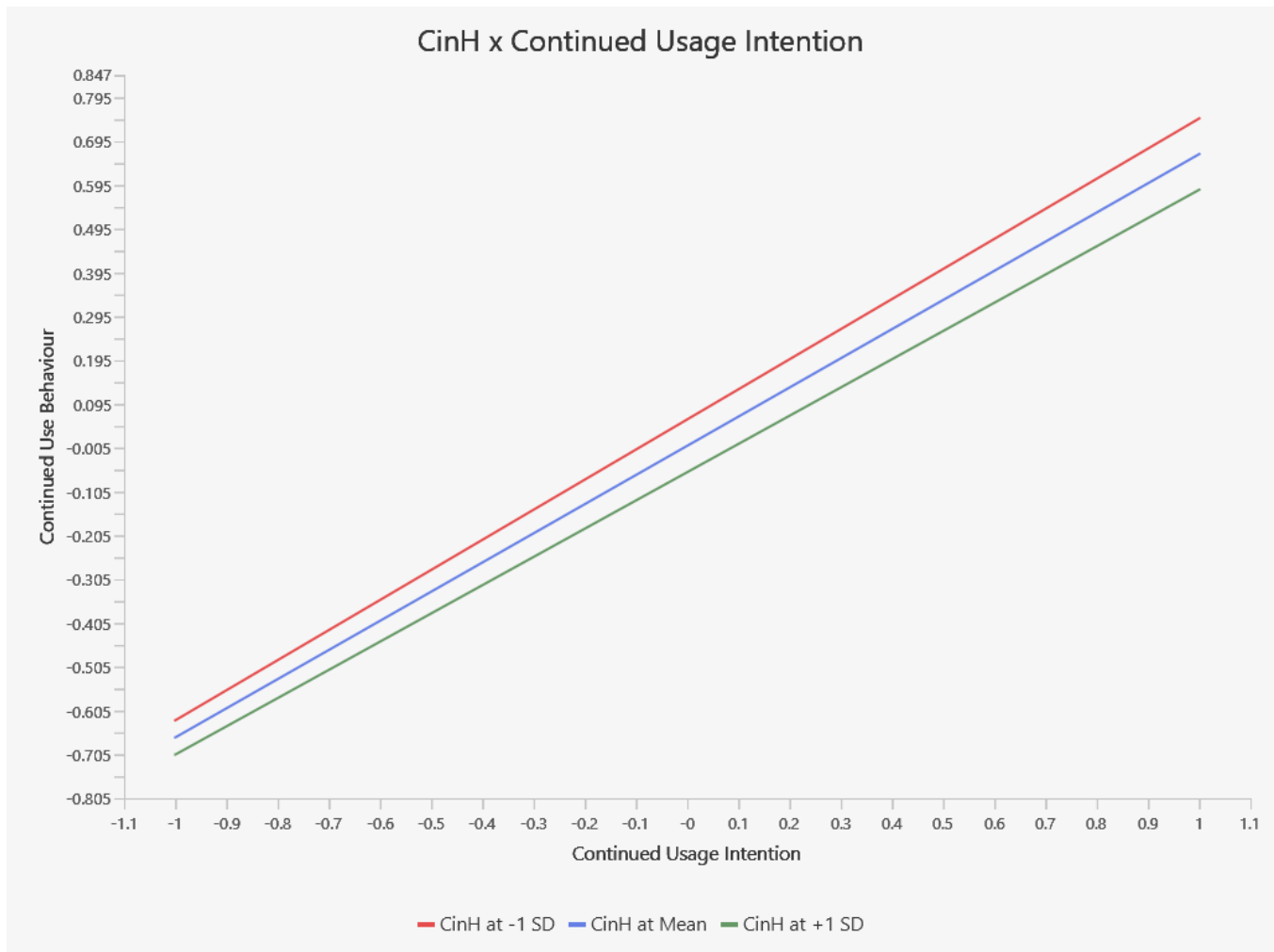


Figure 6-6 Moderating role of CinH in the relationship between consumers' continued use intention and continued behaviour toward WFT

The Moderating Role of Neuroticism

The analysis revealed a significant negative moderating effect of Neu on the relationship between CUI and CUB ($\beta = -0.099$, $t = 3.233$, $p = 0.001$). This suggests that higher levels of neuroticism weaken the positive relationship between CUI and CUB (Figure 6-7).

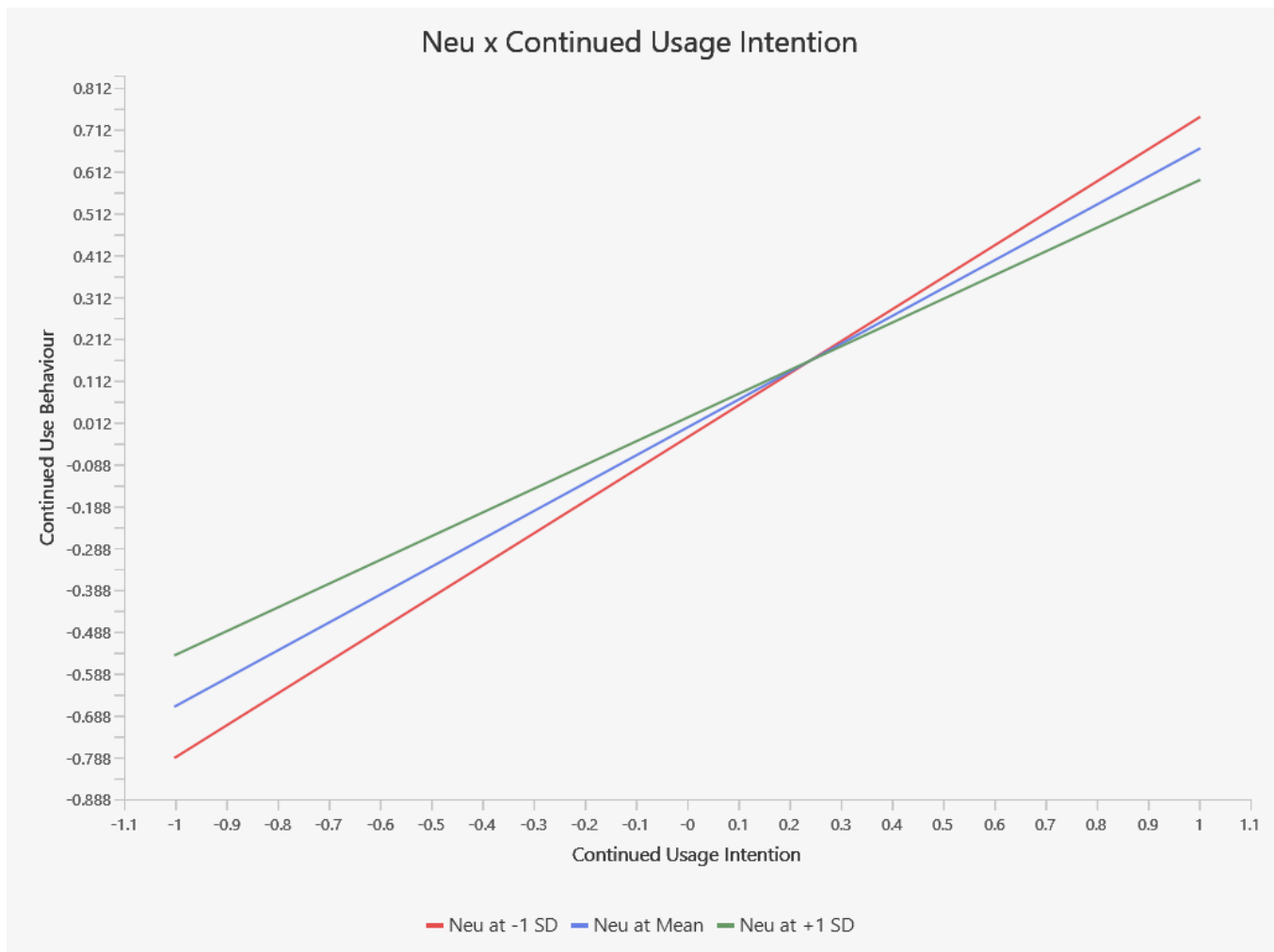


Figure 6-7 Moderating role of Neu in the relationship between consumers' continued use intention and continued behaviour to use WFT

The moderating effects analysis indicates that OTTI and CinH do not significantly moderate the relationship between CUI and CUB, suggesting these factors have a negligible impact on this relationship. Conversely, neuroticism significantly negatively moderates this relationship, weakening the link between CUI and CUB. These findings provide deeper insights into how individual psychological traits influence the continued use behaviour of WFT, thereby enriching the understanding of technology continuance use behaviour within the framework of UTAUT2. The results of the moderating effects are presented in Table 6-28, detailing the path coefficients, t-values, and significance levels.

Table 6–28 Moderators' path coefficients, mean, SD, t-values and p-values (bootstrapping)

	Original sample (O)	Sample mean (M)	Standard deviation (SD)	t-statistics (O/SD)	p- values
OTTI x Continued Use Intention -> Continued Use Behaviour	0.009	0.010	0.025	0.371	0.711 (NS)
CinH x Continued Use Intention -> Continued Use Behaviour	-0.021	-0.021	0.038	0.563	0.574 (NS)
Neu x Continued Use Intention -> Continued Use Behaviour	-0.099	-0.098	0.031	3.233	0.001 (S)

Note: p-values < 0.05 are considered significant (**s**), NS = not significant

6.6 Conclusion of the 2nd Dataset Analysis

Like the first dataset (see section 5.6), the quantitative data analysis was conducted on 267 user responses using IBM SPSS 28.0 statistics, AMOS 28.0 and SmartPLS software. The data collected were analysed through preliminary and factor analyses, along with descriptive analyses of the study constructs. This was followed by the testing of the hypotheses proposed in Chapter 3, which state the direct effect of perceived factors on CUI, the direct effect of CUI on CUB, the mediating effect of CUI between perceived factors and CUB, and finally, the moderating effects of users' psychological characteristics on the relationship between users' CUI and their CUB. Table 6-29 provides a summary of the hypotheses' results and further elaboration in the section below.

Table 6–29 Summary of results of testing the hypotheses

Hypothesis (hypothesised sign)	Result
Direct effects	
<i>H1(a) PerExp -> CUI (+)</i>	S
<i>H1(b) EffExp -> CUI (+)</i>	S
<i>H1(c) SotPrss -> CUI (+)</i>	NS
<i>H1(d) PEnj -> CUI (+)</i>	S
<i>H1(e) DAnoy -> CUI (-)</i>	NS
<i>H1(f) FCons -> CUI (+)</i>	S
<i>H1(g) Tech -> CUI (+)</i>	S
<i>H1(h) PValu -> CUI (+)</i>	S
<i>H1(i) TUpG -> CUI (+)</i>	S
<i>H2 Continued Use Intention -> Continued Use Behaviour (+)</i>	S
Mediating effect of behavioural intention	
<i>H3(a) PerExp -> R -> CUB (+)</i>	S
<i>H3(b) EffExp -> R -> CUB (+)</i>	S
<i>H3(c) SotPrss -> R -> CUB (+)</i>	NS
<i>H3(d) PEnj -> R -> CUB (+)</i>	S
<i>H3(e) DAnoy -> R -> CUB (+)</i>	NS
<i>H3(f) FCons -> R -> CUB (+)</i>	S
<i>H3(g) Tech -> R -> CUB (+)</i>	S
<i>H3(h) PValu -> R -> CUB (+)</i>	S
<i>H3(i) TUpG -> R -> CUB (+)</i>	S
Moderating effects of openness to technological innovativeness	
<i>H4 OTTI x CUI -> CUB (+)</i>	NS
Moderating effects of conscientiousness in health	
<i>H5 CinH x CUI -> CUB (+)</i>	NS
Moderating effect of neuroticism	
<i>H6 Neu x CUI -> CUB (-)</i>	S

Notes: S = supported; NS = not supported

6.6.1 Direct Effect Findings

In the second dataset, the analysis reveals several key findings regarding the factors influencing CUI and CUB towards WFTs, consistent with the SmartPLS findings presented in Table 6-27. Effort expectancy ($\beta = 0.265$, $p = 0.000$), performance expectancy ($\beta = 0.097$, $p = 0.033$), facilitating conditions ($\beta = 0.258$, $p = 0.000$), perceived enjoyment ($\beta = 0.205$, $p = 0.000$), price value ($\beta = 0.145$, $p = 0.002$), technology upgradability ($\beta = 0.148$, $p = 0.000$), and technological habit ($\beta = 0.119$, $p = 0.011$) were all found to have a positive and significant influence on CUI. These findings highlight the multifaceted nature of factors driving sustained engagement with wearable fitness devices. Among these, effort expectancy exhibited the strongest influence on CUI, indicating the importance of perceived ease of use in motivating users to continue engaging with the technology.

In contrast, device annoyance ($\beta = 0.005$, $p = 0.917$) and societal pressure ($\beta = 0.009$, $p = 0.838$) were not found to significantly impact CUI. This suggests that external pressures and potential frustrations associated with device use are less critical to users' sustained engagement compared to intrinsic motivators and facilitating conditions. Furthermore, CUI ($\beta = 0.666$, $p = 0.000$) was identified as a strong predictor of continued use behaviour, highlighting its mediating role in translating these key antecedents into continued behavioural outcomes. This significant pathway emphasises the pivotal function of intention in driving users' continued interaction with WFTs. **These findings** provide valuable insights into the determinants of continued use behaviour, offering both theoretical contributions and practical implications. For instance, the results suggest that enhancing perceived enjoyment, facilitating conditions, and technology upgradability could be effective strategies for manufacturers and marketers aiming to improve user retention. Additionally, the limited role of societal pressure and device annoyance underscores the importance of focusing on user-centric design and functionality to ensure long-term engagement. Figure 6-8 presents the path coefficient results in SmartPLS.

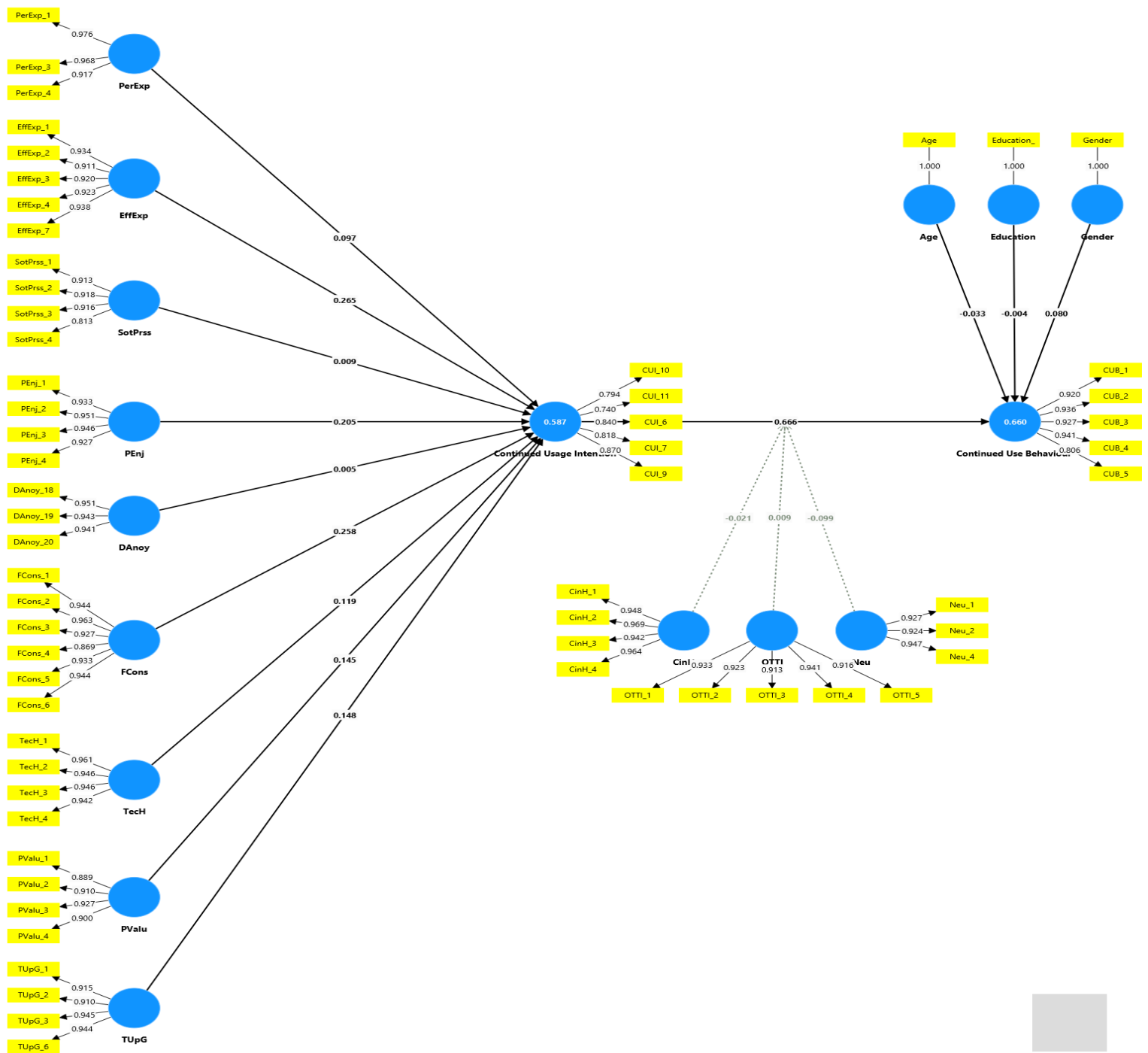


Figure 6-8 Path coefficients results

Legend: $\rightarrow$ Direct effect $\cdots\rightarrow$ Moderation effect

6.6.2 Mediating Effect Findings

The analysis reveals that CUI fully mediates the effects of performance expectancy, effort expectancy, and technology upgradability on CUB. This underscores the importance of CUI as a central mechanism that translates users' expectations, ease of use, and adaptability of the technology into continued use behaviour. Partial mediation is observed for perceived enjoyment, facilitating conditions, technological habit, and price value, indicating that these factors, directly and indirectly, influence CUB through CUI. This highlights the dual pathways through which these predictors drive long-term engagement with WFTs. In contrast, societal pressure and device annoyance remain non-significant in their mediating roles, suggesting that these factors do not play a substantial part in sustaining long-term use behaviour. Their limited impact further emphasises the importance of intrinsic motivators and technology-centred attributes over external pressures or initial frustrations.

Overall Key Insights: CUI fully mediates performance expectancy, effort expectancy, and technology upgradability while partially mediating perceived enjoyment, facilitating conditions, technological habit, and price value. Societal pressure and device annoyance remain insignificant, reinforcing the critical role of CUI in driving sustained engagement with WFTs through both direct and indirect pathways.

6.6.3 Moderating Effect Findings

The findings from the second dataset provide further insights into the moderating effects of personality traits on the relationship between CUI and CUB, revealing notable contrasts with the first dataset. First, the analysis showed a non-significant moderating effect of **OTTI** on the relationship between CUI and CUB ($\beta = 0.009$, $t = 0.371$, $p = 0.711$). This indicates that OTTI does not have a notable impact on the strength of the relationship between users' intentions and their

continued use behaviour. Similarly, **CinH** also exhibited a non-significant moderating effect ($\beta = -0.021$, $t = 0.563$, $p = 0.574$), suggesting that CinH does not significantly influence the translation of CUI into CUB.

In contrast, **Neu** demonstrated a significant negative moderating effect on the relationship between CUI and CUB ($\beta = -0.099$, $t = 3.233$, $p = 0.001$). This result suggests that higher levels of neuroticism weaken the positive relationship between CUI and CUB. Unlike the first dataset, where neuroticism enhanced the alignment between intention and behaviour, this finding points to the potential for increased neuroticism to disrupt users' ability to sustain long-term adoption. **Overall Key Insights:** The second dataset highlights notable differences in the moderating role of personality traits compared to the first dataset. OTTI and CinH show no significant impact on the CUI-CUB relationship, while Neu surprisingly shifts to a negative moderating role, weakening the relationship. These results emphasise the dynamic and context-dependent influence of personality traits on the continued use of WFTs.

Chapter 7: Longitudinal Analysis and Results

7.1 Sample Description for Models 1 and 2

The approach to developing models used by Limayem *et al.* (2007) was adopted in the design of the current study, wherein antecedents of continued use behaviour lagged by one time period. This approach necessitated analysing only those participants who provided data at both time points, which affected the study's sample size. However, this methodology is essential for facilitating causal interpretation. Data were collected at two distinct time points, enabling the construction of two separate models. This design was selected to highlight the highest contrast between the two periods, thereby ensuring robust and stable estimates. A six-month temporal separation between models 1 and 2 was maintained to allow sufficient time for use behaviour to manifest, enabling changes and contrasts in user behaviour to be captured over time. This interval was deemed crucial as it would allow enough time to observe the evolution of technological use behaviour (Caruana *et al.*, 2015). Table 7-1 illustrates the final sample size and the respondents' demographics that were used for the two models (reflecting the number and analysis of participants who completed both rounds of data collection).

Table 7–1 Final sample size and demographic analysis of respondents (T1 and T2)

Demographics	T1 (n = 331)		T2 (n = 267)	
	Frequency	Percentage	Frequency	Percentage
Gender				
Female	180	54.4	160	59.9
Male	148	44.7	107	40.1
Age (years)				
18–25	66	19.9	40	15.1
26–35	162	48.9	135	50.6
36–45	98	29.6	83	30.8
46–55	5	1.6	9	3.5
Education				
Completed primary school	1	0.3	1	0.4
Some secondary	1	0.3	1	0.4
Completed secondary school	37	11.2	27	10.1
Vocational or similar	43	13	30	11.2
Some university but no degree	33	10	26	9.7
University bachelor's degree	138	41.7	125	46.8
Graduate or professional degree (MA, MSc, MBA, PhD, JD, MD, DDS)	77	23.3	56	21
Prefer not to say	1	0.3	1	0.4
Current wearable device WFT/SW brand				
Apple	133	40.2	108	40.4
Samsung	35	10.6	28	10.5
Huawei	18	5.4	18	6.7
Garmin	26	7.9	19	7.1
Fitbit	86	26	70	26.2
Xiaomi	16	4.8	14	5.2
Fossil	4	1.2	1	0.4
Other	13	3.9	9	3.4

7.2 Use of Structural Equation Modelling for Longitudinal Data

SEM and CFA are essential tools for analysing longitudinal data, particularly in the context of investigating technology users' continued use of WFT as in the current study. SEM allows for the examination of complex relationships among observed and latent variables over time, making it

possible to model the temporal dynamics of user behaviours and perceptions (Little, 2013). It also accounts for measurement error, providing more accurate and reliable estimates (Kline, 2012). CFA, on the other hand, ensures that constructs are measured consistently across different time points, which is crucial for valid longitudinal inferences (Byrne, 2016). Together, these techniques facilitate the testing of moderating and mediating effects over time, such as the influence of personality traits on continued use behaviour, offering a comprehensive understanding of the factors driving technology adoption and continued use (Ullman and Bentler, 2013).

7.3 Final Longitudinal Analysis

The current thesis employed partial least squares structural equation modelling (PLS-SEM) using SmartPLS 4.1.0.9 (Ringle and Becker, 2024) to analyse the data, following established guidelines for PLS analysis and several exemplars in IS research (Cheung *et al.*, 2019; Farivar, Abouzahra and Ghasemaghahi, 2020; Tsai *et al.*, 2021; Yan *et al.*, 2021). PLS-SEM is a powerful tool for constructing and evaluating measurement and structural models when performing hypothesis testing. Path analysis, as noted by Hair *et al.* (2017), is an effective technique for assessing the predictive validity of structural models. This method is particularly well suited for handling smaller datasets and addressing **multicollinearity** issues in complex, mediated studies, such as those conducted longitudinally. Data analysis was performed in **three stages**.

7.3.1 Measurement Model Evaluation

An estimation of both model 1 and model 2 was conducted to evaluate the psychometric properties of the study constructs at two distinct time periods (T1 and T2). Reliability and validity were assessed using Cronbach's alpha, composite reliability (ρ_a and ρ_c), and AVE, with further details on the evaluation of the measurement and structural models provided in [Appendix K](#). The

findings indicate strong reliability and validity across most of the constructs. For instance, CinH, CUI, and PEnj demonstrated excellent reliability (Cronbach's alpha > 0.9, rho_c > 0.96, and AVE > 0.83). This suggests robust internal consistency and convergent validity. However, constructs such as SotPrss and TechH, while meeting acceptable thresholds, exhibited slightly lower AVE values (0.664 and 0.679, respectively), indicating room for refinement in future studies.

7.3.2 Structural Model Evaluation

The significance of structural paths for both models was assessed using non-parametric bootstrapping with 5,000 subsamples. This approach was used to examine the relationships between constructs, allowing for robust hypothesis testing. The structural model demonstrated predictive validity, with key constructs such as EffExp and PValu showing significant impacts on CUB. The bootstrapping results further highlighted the temporal evolution of these relationships, as presented in Figure 7-1.

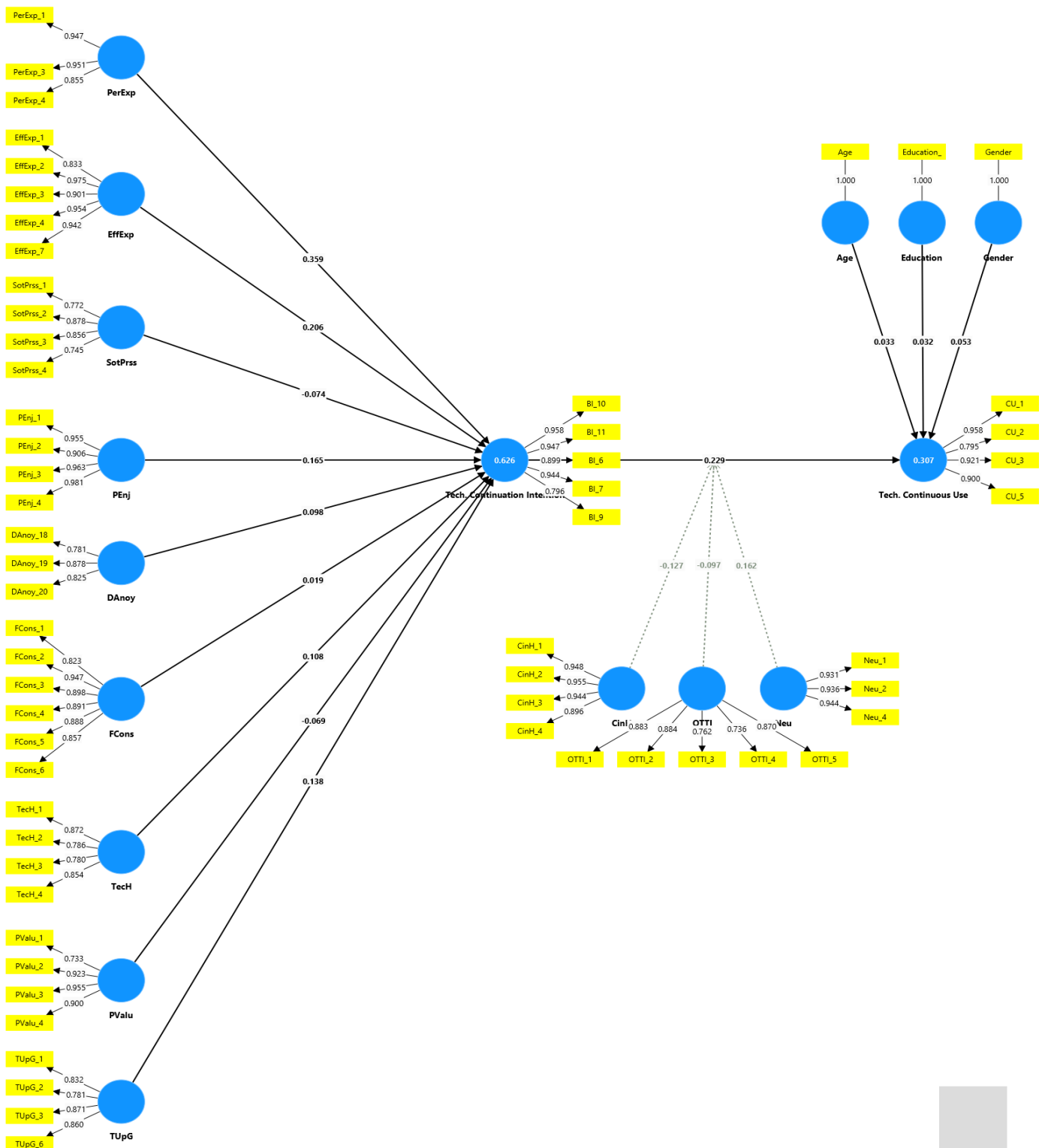


Figure 7-1 Path coefficient results

Legend: → Direct effect - - - - -> Moderating effect

7.3.3 Temporal and Measurement Invariance Testing

A modified version of the permutation approach to multigroup analysis was applied to compare models 1 and 2, assessing temporal effects. Measurement invariance over time was tested to ensure consistency in construct measurement and to validate whether observed changes in relationships reflected true temporal differences rather than measurement artefacts (Ployhart and Vandenberg, 2010). Results confirmed measurement invariance, strengthening the study's longitudinal findings (see Table 7-2).

Table 7–2 Reliability and convergent validity test results

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
CinH	0.953	0.957	0.966	0.876
CUI	0.948	0.949	0.960	0.830
CUB	0.933	0.939	0.950	0.794
DAnoy	0.771	0.776	0.868	0.687
EffExp	0.955	0.957	0.966	0.851
FCons	0.944	0.946	0.956	0.783
Neu	0.931	0.935	0.956	0.878
OTTI	0.885	0.893	0.916	0.688
PEnj	0.965	0.966	0.975	0.906
PValu	0.902	0.919	0.933	0.778
PerExp	0.906	0.908	0.942	0.844
SotPrss	0.831	0.845	0.887	0.664
TUpG	0.857	0.861	0.903	0.700
Tech	0.848	0.889	0.894	0.679

Overall, this analysis highlights the robust psychometric properties of the study constructs, the importance of the structural paths, and the temporal evolution of the relationships within the theoretical framework. The findings provide valuable insights into the continued use of WFTs, offering both theoretical and practical implications for enhancing user engagement and continued use.

7.4 Final Longitudinal Findings

7.4.1 Direct Effect

The longitudinal analysis highlights the evolving and stable factors influencing **CUI** and **CUB** for wearable fitness technologies over time as follows.

Stable Predictors of Continued Use Intention

Effort expectancy, performance expectancy, perceived enjoyment, technology upgradability, and technological habit consistently demonstrated significant positive influences on CUI across both datasets. These stable predictors highlight the importance of ease of use, as reflected in effort expectancy, and users' belief in the technology's utility for achieving their goals, as captured by performance expectancy. Perceived enjoyment underscores the role of intrinsic motivation, and technology upgradability emphasises adaptability and the relevance of keeping devices functional and up to date. In addition, technological habit demonstrates the power of routine behaviour in fostering long-term use.

Evolving Predictors

In contrast, evolving predictors, such as facilitating conditions and price value, shifted from being non-significant in the first dataset to significant in the second. This evolution indicates that users increasingly value the investment return on their devices and the external support they receive as they engage more deeply with the technology. Societal pressure, however, exhibited a diminishing influence; although it was significant during the early adoption phase, its importance declined over time as users developed stronger intrinsic motivations for continued use. Similarly, the effect of perceived device annoyance, which was significant in the first dataset, disappeared in the second, suggesting that initial frustrations fade as users adapt to the technology (see Table 7-3).

Table 7–3 Findings of the longitudinal analysis

<i>Hypotheses</i>	<i>1st Dataset p-values</i>	<i>2nd Dataset p-values</i>	<i>Findings</i>
<i>DAnoy -> Continued Use Intention</i>	0.010 (S)	0.917 (NS)	No consistent influence as it diminishes over time
<i>EffExp -> Continued Use Intention</i>	0.000 (S)	0.000 (S)	Significant positive influence over time
<i>FCons -> Continued Use Intention</i>	0.663 (NS)	0.000 (S)	Evolving significance in the 2nd dataset
<i>PEnj -> Continued Use Intention</i>	0.001 (S)	0.000 (S)	Significant positive influence over time
<i>PValu -> Continued Use Intention</i>	0.067 (NS)	0.002 (S)	Evolving significance in the 2nd dataset
<i>PerExp -> Continued Use Intention</i>	0.000 (S)	0.033 (S)	Significant positive influence over time
<i>SotPrss -> Continued Use Intention</i>	0.049 (S)	0.838 (NS)	No consistent influence as it diminishes over time
<i>TUpG -> Continued Use Intention</i>	0.002 (S)	0.000 (S)	Significant positive influence over time
<i>Tech -> Continued Use Intention</i>	0.012 (S)	0.011 (S)	Significant positive influence over time
<i>Continued Use Intention -> Continued Use Behaviour</i>	0.000 (S)	0.000 (S)	Strong mediating effect over time

Note: PerExp = performance expectancy; EffExp = effort expectancy; SotPrss = societal pressure; PE_{enj} = perceived enjoyment; DAnoy = perceived device annoyance; FCons = facilitating conditions; Tech = technology habit; PValu = price value; TUpG = technology upgradability.

7.4.2 Mediating Effect

CUI emerged as a strong and consistent predictor of CUB across both datasets. This finding confirms the critical role of CUI as a mediator, and its effectiveness in translating antecedent factors into continued behavioural outcomes. These **findings** provide valuable guidance for improving user retention strategies, focusing on enhancing intrinsic motivators, usability, and adaptability while addressing evolving user perceptions over time (see Table 7-4).

Table 7–4 Results of mediating effects following longitudinal analysis

<i>Hypotheses</i>	<i>1st Dataset</i>	<i>2nd Dataset</i>	<i>Mediation</i>
H1(a) PerExp -> R -> CUB	Partial Mediation	Full Mediation	Partial Mediation
H1(b) EffExp -> R -> CUB	No Mediation/NS	Full Mediation	No Mediation/NS
H1(c) SotPrss -> R -> CUB	No Mediation/NS	No Mediation/NS	No Mediation/NS
H1(d) PEnj -> R -> CUB	Partial Mediation	Partial Mediation	Partial Mediation
H1(e) DAnoy -> R -> CUB	No Mediation/NS	No Mediation/NS	No Mediation/NS
H1(f) FCons -> R -> CUB	No Mediation/NS	Partial Mediation	No Mediation/NS
H1(g) TechH -> R -> CUB	Partial Mediation	Partial Mediation	Partial Mediation
H1(h) PValu -> R -> CUB	Partial Mediation	Partial Mediation	Partial Mediation
H1(i) TUpG -> R -> CUB	Partial Mediation	Full Mediation	Partial Mediation

Note: PerExp = performance expectancy; EffExp = effort expectancy; SotPrss = societal pressure; PEnj = perceived enjoyment; DAnoy = perceived device annoyance; FCons = facilitating conditions; TechH = technology habit; PValu = price value; TUpG = technology upgradability; R = continued use intention; CUB = continued use behaviour.

7.4.3 Moderating Effect

The findings regarding moderating effects reveal nuanced and context-dependent roles of personality traits in shaping the relationship between the CUI and CUB of WFTs. In the first dataset, personality traits exhibit significant moderation: Neu enhances the CUI–CUB relationship, whereas OTTI and CinH weaken it, suggesting a complex interplay that challenges traditional assumptions and highlights the importance of tailoring WFT strategies to personality-driven variability. However, the second dataset presents a contrasting dynamic, with OTTI and CinH showing no significant moderating effects and Neu unexpectedly weakening the relationship. This divergence points to the variability and context-dependent nature of personality traits, emphasising the need for flexible, user-centric approaches in fostering continued WFT use.

Table 7–5 Results of moderating effects following longitudinal analysis

<i>Hypotheses</i>	<i>1st Dataset P- Values</i>	<i>2nd Dataset P- Values</i>	<i>Findings</i>
OTTI x CUI -> CUB	0.046	0.711	In the 1st dataset, OTTI significantly weakens the CUI-CUB relationship ($p < 0.05$). In the 2nd dataset, OTTI has no significant moderating effect.
CinH x CUI -> CUB	0.027	0.574	In the 1st dataset, CinH significantly weakens the CUI-CUB relationship ($p < 0.05$). In the 2nd dataset, CinH has no significant moderating effect.
Neu x CUI -> CUB	0.006	0.001	In both datasets, Neu significantly moderates the CUI-CUB relationship; however, the effect shifts, strengthening the relationship in the first dataset and weakening it in the second.

Note: OTTI = openness to technological innovativeness; CinH = conscientious in health; Neu = neuroticism; CUI= continued use intention; CUB = continued use behaviour

Overall Key Insights:

1. **Consistency Across Datasets:** Factors such as effort expectancy, performance expectancy, perceived enjoyment, technology upgradability, and technological habit remain stable drivers of continued use intention.
2. **Dynamic Factors:** Facilitating conditions and price value grow in importance over time, reflecting users' evolving perceptions and needs.
3. **Diminishing Effects:** Device annoyance and societal pressure lose significance as users become more accustomed to the technology.
4. **Importance of CUI:** Continued use intention serves as the most critical mediator, bridging predictors and continued use behaviour.
5. **Moderating Role of Personality:** The influence of personality traits on the CUI–CUB relationship varies across datasets, with Neu showing contrasting effects (i.e., positive in the

first dataset, negative in the second dataset) and OTTI and CinH displaying either weakening or non-significant roles, highlighting the dynamic and context-dependent nature of these moderating effects.

Chapter 8: Conclusions and Contributions

There has been extensive research on technology adoption, including users' purchase intentions (Chiu, Oh and Cho, 2021; Zhao *et al.*, 2021; Mehra, Rajput and Paul, 2022), related behaviours and attitudes (Talukder *et al.*, 2019; Chen *et al.*, 2021; Qasem, 2021; Suo *et al.*, 2021), and the factors influencing them; however, minimal effort has been devoted to studying continued use factors, particularly in a longitudinal setting. Most empirical studies have relied on cross-sectional or experimental designs. A longitudinal approach is essential to investigating how perceived predictors of CUB evolve over time and to distinguish between factors influencing technology adoption and those affecting post-adoption behaviour. Further, extensive research from the fields of psychology and marketing demonstrates the significant impact of personality on individual behaviours (Malouff, Thorsteinsson and Schutte, 2006; Buettner, 2017; Ali, Bowen and Deininger, 2020). Personality traits influence how customers perceive and interact with technology and feature significantly in explanations of their attitudes, continued intentions, and use of different technologies (Rupp *et al.*, 2018). However, IT/IS research has historically overlooked the role of personality traits (Wang, Ngai and Wei, 2012), particularly in the context of WFT/SW.

In this rapidly evolving landscape of technology consumption, understanding the mechanisms driving users' CUB has become increasingly important. This thesis addresses the gaps identified in the literature (as discussed in Chapter 2) by providing a comprehensive understanding of the phenomenon of consumers' continued use of technology. The current research undertook the following examination: 1) the mechanisms driving users' continued use of technology; 2) the key post-adoption factors influencing continued use; 3) the role of CUI in converting perceived factors into CUB; and 4) the interplay between consumer personality and continued use, focusing on how personality characteristics amplify the effects of CUI on CUB in relation to WFT.

8.1 Study Findings

8.1.1 Mechanisms of Users' Continued Use of Technology

The first aim of this study was to uncover the underlying mechanisms that directly drive users to continue using WFTs, focusing on identifying and explaining the constructs and processes that influence CUI and its subsequent translation into CUB. The findings reveal that CUI emerges as the central mechanism driving the continued use of WFTs, with factors such as performance expectancy, effort expectancy, perceived enjoyment, technology habit, price value, and technology upgradability playing crucial roles. These results underscore the multifaceted interplay of utility, ease of use, enjoyment, and adaptability in shaping long-term engagement with WFTs.

Following the definition of performance expectancy provided in Venkatesh *et al.* (2003) as "the degree to which an individual believes that using the system/technology will help a person to attain gains in job performance" (p. 447), this study found that users perceive WFTs as enhancing fitness and daily activities, making it a critical driver of CUI. Similarly, effort expectancy, defined by Venkatesh, Thong and Xu (2012) as "the degree of ease associated with an individual's use of a system or technology" (p. 159), was found to have a significant impact on CUI. Users place a high value on devices that provide easy access to personal data, making ease of use a major motivator for WFT adoption and continuance (Canhoto and Arp, 2017; Jarrahi, Gafinowitz and Shin, 2018). This finding aligns with Oc and Toker's (2022) conclusion that effort expectancy is critical for behavioural intentions to use sports technologies.

The findings also emphasise the role of perceived enjoyment, conceptualised as a hedonic value (Beh *et al.*, 2021), which fosters intrinsic motivation by making technology use pleasurable and fun. These results align with prior studies highlighting perceived enjoyment or playfulness as a powerful predictor of wearable technology adoption (Rheingans, Cikit and Ernst, 2016; Randriambelonoro,

Chen and Pu, 2017). In addition, technology habit, a reflection of how ingrained WFT use becomes in daily routines, further strengthens continuance intentions by establishing automatic behaviours. This is supported by previous studies, such as those by Lin, Wang and Hsu (2017), Nascimento, Oliveira and Tam (2018), and Bölen (2020), which define a habit as an automatic behavioural tendency resulting from repeated actions, emphasising its role in promoting unconscious, familiar patterns of technology use. Further, this is consistent with research by Schomakers *et al.* (2022), who demonstrate the pivotal role of habit in shaping technology usage intentions.

In following the definition of price value by Venkatesh, Thong and Xu (2012) as “the consumers' cognitive trade-off between the perceived benefits of the applications and the monetary cost for using them” (p. 161), this study highlights the relationship between price value and consumers' continued intention to use technology. The study finding is consistent with prior research findings showing that consumers perceive the balance between cost and benefits as essential in shaping their perceptions of value, encouraging continued use when devices are viewed as worthwhile investments. Further, building on the aforementioned definition of price value in Venkatesh, Thong and Xu (2012), this study underscores the relationship between price value and consumers' continued intention to use technology. The findings align with research by Mani and Chouk (2017), which indicates that consumers view the balance between cost and benefits as crucial in shaping their perceptions of value. When devices are seen as worthwhile investments, this balance encourages their continued use. Finally, building on the definition provided by Khan *et al.* (2018), this current study defines technology upgradability as the ability or tendency of technological products, such as WFTs, to be enhanced in functionality to align with users' evolving lifestyles. This includes software updates offering additional features and hardware improvements providing superior performance over earlier versions. The findings suggest that technology upgradability,

characterised by users' expectations of ongoing improvement, sustains interest by assuring the users of the evolving utility of the device.

In conclusion, these mechanisms collectively illustrate a combination of functional, experiential, and habitual drivers, providing a comprehensive understanding of the factors influencing consumers' continued use of WFTs.

Key finding 1 – CUI is the central driver of WFTs' continued use, shaped by performance expectancy, effort expectancy, enjoyment, habit, price value, and upgradability, highlighting a blend of utility, ease, and adaptability in shaping long-term engagement.

8.1.2 Post-Adoption Factors Influencing Continued Use and Evolving User Perceptions

Building on the mechanisms identified above, the second aim of this study was to explore the temporal dynamics of post-adoption behaviour, focusing on how users' perceptions and interactions with WFTs evolve. Whereas factors such as performance expectancy, perceived enjoyment, effort expectancy, technological habit, and technology upgradability remain stable drivers of CUI, others exhibit dynamic changes. For instance, facilitating conditions and price value gain prominence over time, reflecting users' growing appreciation for supportive environments and cost-effectiveness as they integrate WFTs into their daily lives.

Conversely, the study identifies the diminishing effects of societal pressure and device annoyance over time. Societal pressure, defined as the influence exerted by family, peers, and friends to encourage continued technology use (Cho, Cheng and Hung, 2009), may have a strong effect on initial adoption. However, this study found that its relevance declines as users develop internal motivations and confidence in their use of WFTs, making external pressures less significant. Similarly, device annoyance, characterised as distractions from the focal activity caused by device-

related factors (Kim, 2014; Randriambelonoro *et al.*, 2015; Coorevits and Coenen, 2016), also diminishes over time. Although device annoyance can serve as an early constraint, the study found that users often adapt to such distractions as they become more experienced with the technology or manufacturers resolve usability issues through updates.

These findings underline the dynamic nature of post-adoption factors, highlighting that while some influences remain stable and have a consistent impact, others evolve or diminish in significance. By adopting a longitudinal approach, this study provides a richer understanding of post-adoption behaviour, emphasising the temporal nature of technology engagement and the interplay between stable, dynamic, and diminishing factors. This perspective complements the first aim of the study by shifting the focus from underlying mechanisms to how these and other factors change throughout the life cycle of WFT use. Such insights emphasise the importance of addressing both persistent and transitional factors in order to design and support technologies to sustain long-term use.

Key finding 2 – The dynamic nature of factors influencing continued use of WFT includes evolving predictors such as performance expectancy and technology upgradability, consistent factors such as perceived enjoyment and technological habit, and limited-impact factors such as societal pressure and device annoyance.

8.1.3 Mediating Role of Continued Use Intention

The third aim of this study was to examine the mediating role of CUI in the relationship between perceived factors and CUB towards WFTs. This study highlights the pivotal role of CUI as a critical mechanism translating factors such as performance expectancy, perceived enjoyment, technological habit, perceived value, and technology upgradability into continued use of WFTs. These findings align with prior research, highlighting the significance of CUI as a bridge between user perception and behaviour in the context of technology use (Venkatesh, Thong and Xu, 2012).

The results demonstrate notable **temporal dynamics** in the mediating role of CUI across the two datasets examined. Performance expectancy transitioned from partial to full mediation, reflecting its increasing importance over time as users place greater emphasis on the utility of WFTs for continued engagement. Effort expectancy, which exhibited full mediation in the second dataset, highlights the growing significance of ease of use in fostering continued use intentions.

Conversely, societal pressure and device annoyance showed no mediation effects in either dataset, suggesting their minimal influence on continued use. Perceived enjoyment maintained consistent partial mediation, emphasising its persisting role in sustaining user interest and satisfaction with WFTs. Similarly, facilitating conditions evolved to partial mediation in the second dataset, stressing the increasing significance of external support, such as resources and infrastructure, in continued use behaviour. Technological habit and price value also demonstrated consistent partial mediation, reflecting their stable influence as habitual and cost–benefit factors that underpin long-term engagement. Finally, technology upgradability transitioned from partial to full mediation, highlighting its growing impact as users increasingly value adaptability and advanced features to meet their evolving needs and expectations. Hence, an important finding is:

Key finding 3 – The mediating role of CUI is pivotal in translating key factors such as performance expectancy, perceived enjoyment, technological habit, perceived value, and technology upgradability into continued use of WFTs while showcasing the evolving influence of these mediations over time.

8.1.4 Moderating Role of Personality Traits

With respect to its fourth aim, this study makes a significant contribution to the IS literature by examining the moderating role of personality characteristics in the relationship between CUI and CUB towards WFTs. Little is known about how individual differences influence the effect of CUI on CUB and this study addresses this gap by exploring how these traits strengthen or weaken the CUI–CUB relationship. Grounded in the personality traits model, which defines individual differences as tendencies to display consistent patterns of feelings, thoughts, and actions (Goldberg, 1990; Costa and McCrae, 1992), this research investigates the temporal dynamics of three psychological factors—openness to technological innovativeness (OTT), conscientiousness in health (CinH), and neuroticism (Neu)—and how they evolve over time. The findings reveal that personality traits are significant in shaping the CUI–CUB relationship, albeit in differing ways across the two datasets analysed. In the first dataset, Neu is found to enhance the CUI–CUB relationship, whereas OTTI and CinH weaken it, suggesting a complex interplay that challenges conventional assumptions and emphasises the importance of tailoring WFT strategies to personality-driven variability. Conversely, the second dataset presents a contrasting dynamic: OTTI and CinH exhibit no significant moderating effects, whereas Neu unexpectedly weakens the relationship. This difference highlights the variability and context-dependent influence of personality traits, emphasising the necessity for flexible, user-centric approaches to foster continued use of WFTs.

Moderating Role of Openness to Technological Innovativeness

In terms of OTTI, this study found that OTTI statistically significantly weakened the positive relationship between CUI and CUB in respect of the first dataset. This suggests that individuals with a high degree of openness to technological innovativeness may prioritise exploration over continued use. This finding aligns with prior research indicating that OTTI is a key factor influencing both behavioural intention (Kranthi and Asraar Ahmed, 2018) and continued use intention (Hong, Lin and

Hsieh, 2017). Furthermore, Jackson, Yi and Park (2013) emphasise that involving highly innovative individuals throughout the adoption process is critical for the successful implementation of technology. Consistent with these insights, the current study observed that individuals high in OTTI may abandon technology once its novelty diminishes, redirecting their attention to newer, more innovative alternatives. Conversely, the second dataset revealed no significant moderating effect of OTTI on the CUI–CUB relationship, showing results similar to those of previous research. For instance, Krey *et al.* (2019) found that OTTI negatively moderates the functional value–attitude relationship in smart wearable adoption, suggesting it does not consistently support continued intention to use. Similarly, Shetu, Islam and Promi (2022) reported that OTTI did not have a significant influence on the continued intention to use digital wallets.

Moderating Role of Conscientiousness in Health

Further, this study found that CinH statistically significantly weakened the positive relationship between CUI and CUB with regard to the first dataset. This suggests that individuals who are highly conscientious about their health may critically assess WFTs and potentially discontinue their use if the devices fail to meet their high standards or expectations for supporting health-related goals. This finding aligns with prior research that indicates that conscientiousness has a significant influence on the continued intention to use electronic health systems (Alsyouf *et al.*, 2022) and serves as a positive predictor of the perceived usefulness of fitness apps (Alshawmar, Tulu and Hall-Phillips, 2022). Conversely, the second dataset revealed no significant moderating effect of CinH on the CUI–CUB relationship. Supporting this, previous studies have noted that conscientiousness-related traits may not always exhibit a direct influence; for instance, no significant impact was reported on the social sustainability of the Metaverse (Arpaci *et al.*, 2022). These findings challenge assumptions about the uniform role of conscientiousness in health-related technology use and highlight its complexity in influencing technology continuance.

Moderating Role of Neuroticism

The findings indicate that neuroticism statistically significantly strengthened the positive relationship between CUI and CUB in respect of the first dataset. This suggests that individuals with higher levels of neuroticism, often characterised by emotional instability and heightened sensitivity to stress (Costa and McCrae, 1992), may rely on WFTs as a coping mechanism to alleviate their anxieties or manage stress. Neurotic individuals are also known to have negative perceptions when interacting with their environment (Carver and Connor-Smith, 2010). This finding aligns with prior research indicating that individuals with high levels of neuroticism tend to experience less stable emotions and often view tasks negatively, especially those that induce stress (Ismail *et al.*, 2023). In contrast, analysis of the second dataset revealed that neuroticism statistically significantly weakened the CUI–CUB relationship. This finding highlights the complex and context-dependent nature of the influence of neuroticism on continued use behaviour. Although neurotic individuals may initially find value in using WFTs to manage their health-related concerns, prolonged use may amplify their dissatisfaction or frustration, particularly if the devices fail to meet their emotional needs or exacerbate feelings of stress. This dynamic may stem from neurotic individuals' heightened sensitivity to perceived shortcomings in technology regarding its usefulness (Alshawmar, Tulu and Hall-Phillips, 2022).

Hence, the key finding is as follows:

Key finding 4 – The moderating role of personality traits in the relationship between CUI and CUB is dynamic, with OTTI and CinH either weakening or showing no significant impact and Neu exhibiting contrasting effects across the two datasets examined, highlighting the importance of considering personality-driven differences to enhance continued use of WFT.

8.2 Contributions of the Study

This study presents several theoretical and managerial contributions to the literature on the adoption and continued use of technology.

8.2.1 Theoretical Contributions

This research makes substantial theoretical contributions to the IS field by advancing the understanding of consumers' continued use behaviour with a focus on WFTs. The study addresses critical gaps in the literature by adopting a longitudinal approach, offering a nuanced understanding of how user perceptions and behaviours, as well as influencing factors, evolve over time.

In response to research gap 1, this study examined the phenomenon of consumer CUB towards WFT through a longitudinal approach, investigating how perceived predictors of CUB evolve over time. The majority of prior studies in IS research have employed cross-sectional methodologies (e.g., Talukder *et al.*, 2020), which provide only static snapshots of user behaviour and fail to capture the temporal evolution of user perceptions and engagement. A significant contribution of the current research is its longitudinal analysis of post-adoption factors influencing CUB. By adopting a longitudinal design, this study addresses the limitations of cross-sectional approaches, offering deeper insights into how user behaviours and attitudes, as well as influencing factors, shift dynamically over time (Venkatesh, Thong and Xu, 2012). The findings reveal three distinct categories of factors influencing CUB: stable, dynamic, and diminishing factors. Stable factors, such as performance expectancy and technological habit, consistently drive CUB across time points, affirming their foundational role in continued user engagement. Dynamic factors, including facilitating conditions and price value, grow significantly as users gain familiarity with the technology, reflecting an evolving reliance on support structures and cost–benefit evaluations. This aligns with prior literature; for instance, Sergueeva, Shaw and Lee (2020) found that although price value was

not significant in predicting initial use intention, facilitating conditions played a significant role in supporting technology usage. These dynamics highlight the transition of user priorities from initial adoption drivers to continuance considerations shaped by accumulated experience and ongoing utility.

Conversely, diminishing factors, such as societal pressure and device annoyance, highlight the reduced impact of external influences and any initial frustrations over time. This finding aligns with prior literature, whereby Yan *et al.* (2021) observed that social norms are not significant predictors of health app users' intentions. However, contrasting evidence exists; for example, studies have shown that social norms have a significant impact on continued use intention in contexts such as online gaming (Chang, Liu and Chen, 2014). These results challenge traditional assumptions that societal pressure and novelty effects sustain long-term engagement. Instead, they underscore the critical role of intrinsic motivators, such as perceived enjoyment and adaptive features, in fostering continued use.

By capturing temporal dynamics, this study not only provides a nuanced understanding of user retention but also addresses a significant gap in the IS literature, which has often overlooked the evolving nature of post-adoption behaviour. The results emphasise the importance of adopting longitudinal methodologies to investigate the dynamic interplay of predictors over time (Bhattacharjee and Premkumar, 2004). Furthermore, this research extends theoretical frameworks, UTAUT2, for example, by demonstrating how constructs, such as facilitating conditions, gain importance post adoption. This finding suggests that existing models should incorporate temporal dynamics to account for the shifting weight of predictors as users transition from initial adoption to continued use (Venkatesh, Thong and Xu, 2012).

In summary, the longitudinal approach employed in this study advances the understanding of post-adoption behaviour by identifying the evolving roles of stable, dynamic, and diminishing factors. This contribution addresses a critical limitation of cross-sectional studies and provides a robust theoretical foundation for future research on sustained technology engagement.

In response to research gap 2, this study refines and extends the UTAUT2 framework (Venkatesh, Thong and Xu, 2012), to better explore CUB in the context of WFT. The research introduces novel constructs and reconfigures existing ones to capture the unique benefits and challenges users face with WFTs. Specifically, it introduces technology upgradability and separates the original construct of hedonic motivation into two distinct dimensions: perceived enjoyment and perceived device annoyance. These refinements address aspects previously unexamined within the UTAUT2 framework.

Building on the definition presented by Khan *et al.* (2018), this research study defines technology upgradability as the ability or tendency of technological products, such as WFTs, to be enhanced in functionality to align with users' evolving lifestyles. This includes software programs offering added features over earlier versions and hardware improvements providing superior performance compared to prior models. By reflecting the rapid pace of innovation, this construct underscores the critical role of adaptability and future-proofing in sustaining continued use. Unlike earlier research that explored upgradability primarily in cloud computing (Csernai *et al.*, 2013) or consumer electronics (Agrawal, Atasu and Ülkü, 2016), this study situates it within the context of health-focused wearable devices, emphasising its importance in maintaining user interest and relevance. Continuous improvements in WFTs not only enhance their usability but also ensure alignment with users' shifting expectations and fitness goals, thereby promoting long-term use.

Perceived device annoyance is a critical factor influencing the use of WFTs, as it goes beyond cognition-oriented rational models to encompass emotive concepts (Ortiz de Guinea and Markus, 2009). This construct captures the negative affective responses users experience due to excessive notifications, interruptions, or intrusive features. These distractions from focal activities have been identified as significant barriers to the use of wearables (Kim, 2014; Randriambelonoro *et al.*, 2015; Coorevits and Coenen, 2016). By integrating this dimension, the current study addresses the duality of hedonic motivation, which has traditionally been conceptualised only in positive terms. This approach provides a more balanced understanding of user experiences, encompassing both the benefits and potential drawbacks of WFT engagement. The study also refines and validates core constructs of the UTAUT2 model, such as technology habit and societal pressure, to better align with the specific affordances and challenges of WFTs. For example, societal pressure has been reconceptualised to include the influence of health-related social norms, such as body image expectations (Yim and Park, 2019) and peer comparisons prevalent in fitness communities. These refinements not only enhance the explanatory power of the UTAUT2 framework but also broaden its applicability to a wider range of consumer health technologies.

Through empirical validation via a longitudinal study, this research demonstrates how effective the extended UTAUT2 framework is in capturing the complexities of CUB in dynamic and rapidly evolving technological contexts. By accounting for both positive and negative user experiences, this study contributes to a more nuanced theoretical understanding of consumer engagement with WFTs.

In response to research gap 3, this study contributes to the growing body of knowledge on individual differences in technology use by examining how personality traits moderate the relationship between CUI and CUB. Drawing on the FFM, the study focuses on three traits: openness to technological innovativeness (OTTI), conscientiousness in health (CinH), and neuroticism (Neu). These traits were selected for their relevance in predicting user engagement with WFTs. OTTI was found to amplify the effects of CUI on CUB as individuals with a high degree of openness are more likely to embrace novel features and updates, thereby maintaining long-term engagement. This aligns with prior research indicating that openness fosters adaptability and curiosity in technology adoption contexts (Breil *et al.*, 2019). CinH emerged as a critical factor for continued use, with highly conscientious users demonstrating greater persistence in leveraging WFTs to achieve their health-related goals. This finding underscores the role of goal orientation and self-discipline in shaping consistent technology usage behaviours. Users with high CinH are motivated to maintain their health and fitness routines (Alshawmar, Tulu and Hall-Phillips, 2022), and this motivation is directly supported by the continuous use of WFTs. Consequently, designing features that align with health-conscious objectives, such as goal tracking and personalised fitness insights, is essential to ensuring long-term engagement.

Conversely, Neu presented a more complex influence. Although neurotic individuals may initially exhibit heightened use due to anxiety-driven behaviours (Sergueeva, Shaw and Lee, 2020), their long-term engagement is often undermined by dissatisfaction or criticism of the technology's limitations. This duality underscores the need for personalised interventions to address the specific concerns of neurotic users, such as enhancing the user experience and attending to perceived shortcomings.

By integrating personality traits as moderators, this study advances the theoretical understanding of how individual differences shape technology continuance. It responds to calls in the literature for incorporating psychological constructs into IS models, particularly in consumer technology contexts. Furthermore, the findings emphasise the importance of tailoring technology design and marketing strategies to accommodate diverse personality profiles, ultimately enhancing user retention and satisfaction. Table 8-1 presents a summary of the theoretical contributions of this study.

Table 8–1 Summary of theoretical contributions

<i>Literature</i>	<i>Contributions</i>
<i>Technology adoption and continued use</i>	Investigating how perceived predictors of CUB evolve over time • Applying a longitudinal framework to reveal temporal changes in post-adoption factors. • Identifying stable (e.g., performance expectancy), dynamic (e.g., facilitating conditions), and diminishing (e.g., societal norms) factors.
	Refining and extending the UTAUT2 model • Adding new constructs to UTAUT2, including perceived device annoyance and technology upgradability. • Positioning technology upgradability as key for adaptability and continued engagement. • Providing a comprehensive framework for understanding continued technology use in consumer and health contexts.
	Investigating the moderating role of personality traits • Applying a new moderation mechanism, personality traits (OTTI, CinH, and Neu), between CUI and CUB. • Identifying that OTTI fosters curiosity and adaptability, CinH drives goal-oriented engagement, and Neu shows mixed effects on continued use. • Emphasising the importance of tailoring technology design and marketing strategies to user personality profiles for improved engagement.

8.2.2 Contextual Contributions

Contextually, this study responds to calls for research on factors influencing the continued use of technology, focusing on benefits gained through continued use rather than initial adoption alone. As advanced devices, WFTs can reduce abandonment rates and foster continued engagement. By examining post-adoption factors longitudinally, unlike most studies, which rely on cross-sectional or experimental designs (e.g., Hong, Lin and Hsieh, 2017; Dehghani, Kim and Dangelico, 2018; Nascimento, Oliveira and Tam, 2018; Gupta *et al.*, 2021; Siepmann and Kowalczyk, 2021), this current research addresses the temporal effects of perceived factors and the mediating role of CUI in shaping CUB. Unlike prior studies that focused on organisational contexts such as m-commerce, m-learning, e-banking, and healthcare (e.g., Tarhini *et al.*, 2019; Chao, 2019; Mojarro Aliaño *et al.*, 2019; Farah, Hasni and Abbas, 2018; and Quaasar, Hoque and Bao, 2018), this study examines individual consumer behaviour. It explores technological/utilitarian, affective/hedonic, emotional, and social factors critical for personal health and fitness management as key outcomes of WFT usage.

A notable contribution of this study is the inclusion of psychological traits (i.e., OTTI, CinH, and Neu) as moderators. By replacing traditional moderators, this study addresses gaps in the literature (Tamilmani *et al.*, 2021) and enhances the applicability of UTAUT2 across various contexts. This integration provides a nuanced understanding of how personality traits influence technology adoption and continued use, contributing significantly to theory. This study also emphasises technology upgradability, a relatively unexplored concept in the IS literature, particularly for measuring long-term user engagement. Although recent studies have highlighted improved functionality, for instance, in the circular economy (Vimal *et al.*, 2021), this current research isolates technology upgradability to offer actionable insights for manufacturers and marketers. By identifying these critical determinants of technology adoption and continued use, this research provides

practical guidance to address the continued use of devices and enhance consumer retention. Situated within its specific context, this study offers valuable localised insights that advance theoretical understanding and practical applications in WFT (discussed in dedicated sections).

8.2.3 Empirical Contributions

This thesis extends the UTAUT2 model (Venkatesh, Thong and Xu, 2012) by examining its applicability in the context of long-term WFT usage. UTAUT2 emphasises core user perceptions, such as performance expectancy and effort expectancy, in predicting technology adoption. The study's findings also support the continued relevance of facilitating conditions and highlight the enduring significance of both perceived enjoyment and perceived device annoyance in WFT use. This aligns with the hedonic motivation aspect of UTAUT2, suggesting that users find WFTs intrinsically pleasurable to use (Venkatesh, Thong and Xu, 2012). In addition, the development of a technology habit over time strengthens continued WFT engagement, reflecting the model's emphasis on habit formation (Wang and Lin, 2021).

However, the study also reveals interesting nuances in the influence of other UTAUT2 constructs. Although social influence (societal pressure) is a prominent factor in technology adoption in general, it appears less significant for the continued use of WFTs. This suggests that users might be driven more by personal fitness goals and enjoyment than by social pressure to wear a WFT.

This research refines the understanding of UTAUT2 within the specific domain of WFT use. While core constructs, such as facilitating conditions and hedonic motivation (perceived enjoyment and perceived device annoyance) remain significant, social influence (societal pressure) appears to have less of an impact. The increasing significance of performance expectancy and effort expectancy over time suggests a shift in user focus towards goal achievement and the perceived ease of using a WFT to get there. These findings provide valuable context for future research on

WFT user behaviour and could be used to inform design and marketing strategies for this growing technology sector.

To conclude, this thesis provides a comprehensive framework that extends the UTAUT2 model by incorporating longitudinal analysis, new constructs, and external theories. It is suggested that IT device/application developers consider both the original UTAUT2 attributes and the additional ones introduced in this research. By doing so, developers could improve existing devices and applications and design new ones that better meet the needs of current and future consumers, ensuring higher adoption and continued use by taking their personality characteristics into account.

8.2.4 Managerial Implications

Implications Related to Strategies to Foster Continued Use

Understanding the factors influencing the continued use of technology is crucial for retaining the users and sustaining their engagement. This research identifies personality traits associated with a positive attitude towards the continued use of WFT and those likely to engender resistance. These insights could enable managers to refine existing technologies and optimise their design to meet user needs. For instance, focusing on particular factors or recognising that certain personality types may have a negative attitude towards continued IT use would allow manufacturers, marketers, and developers to be more proactive in addressing potential barriers and fostering continued engagement. Consequently, this thesis offers valuable managerial implications for companies in the technology industry, particularly in the WFT sector, to enhance user engagement and promote the long-term use of technological devices. By understanding the interplay between user perceptions, personality traits, and evolving behaviours, stakeholders can create more effective strategies to ensure consumer retention.

The findings suggest that the drivers of continued technology use can be categorised into stable, dynamic, and diminishing factors, each requiring distinct managerial strategies. **Stable drivers**, such as performance expectancy, effort expectancy, perceived enjoyment, technology upgradability, and technological habit, remain consistent predictors of CUI. Managers could prioritise enhancing these factors by focusing on superior utility and creating enjoyable user experiences (UX), as they align with users' intrinsic motivations for continued engagement. This underlines the critical role of UX in the design of wearables. To foster continued use, WFTs should be enjoyable to wear and interact with, incorporating features that gamify fitness goals and offer positive reinforcement of user progress (Amo *et al.*, 2020). Examples include adding virtual badges for milestone achievements or personalised challenges tailored to individual fitness levels (Kim, Cho and Kim, 2023). This approach aligns with recent research emphasising the emotional aspects of long-term mobile app usage, particularly the feeling of enjoyment (Dirin, Nieminen and Laine, 2023).

The findings further identify the increasing significance of performance expectancy and effort expectancy over time, which suggests a user focus shift towards achieving fitness goals. Managers could leverage this by emphasising goal-setting functionalities within WFT applications and providing clear data visualisation tools to track progress. It is possible to imagine users setting personalised goals for weekly step counts or distance walked, with the WFT app offering easy-to-understand charts and graphs to monitor their progress against their fitness plans (Yao, 2024). The growing importance of technology upgradability indicates a user desire for WFTs that adapt and offer new features over time. This aligns with the concept of "future-oriented design", whereby technology is designed to be modular and upgradable to meet evolving user needs. WFTs with modular components or software updates that unlock new functionalities can address this by providing users with a sense of continued value (Skulimowski and Köhler, 2023).

Dynamic drivers, such as price value and facilitating conditions, gain importance over time, reflecting users' evolving expectations. For instance, price value reflects the evolving perceptions of users regarding the cost–benefit balance of WFTs. Over time, users become more attuned to the long-term value offered by the technology, which necessitates pricing strategies that resonate with their ongoing expectations. It is suggested that managers adopt flexible and user-centric pricing models, such as subscription plans, loyalty discounts, or bundling additional value-added services. These approaches not only reinforce the perceived worth of the product but also build long-term customer relationships and continued engagement with WFTs. Regarding facilitating conditions, managers should ensure that WFTs are supported by robust customer service systems and infrastructure to integrate seamlessly into users' routines and ecosystems (M. S. Rahman *et al.*, 2022). This ensures that WFTs align with users' daily habits and reduces the friction of adoption, making the technology more convenient and accessible. Moreover, incorporating features that resonate with consumers' unique personalities and preferences can create more engaging and personalised experiences, encouraging continued usage and fostering brand loyalty (Anisimova, Weiss and Mavondo, 2019). In addition to offering customisable interfaces, adaptive fitness plans (Yao, 2024) or compatibility with other devices and platforms can cater to individual preferences, enhancing the perceived value of the technology. These efforts not only increase user satisfaction but also strengthen the emotional connection between users and the brand, ultimately driving continued use of technology.

Finally, the findings highlight that **diminishing drivers**, such as device annoyance and societal pressure, underline the importance of reducing initial adoption barriers in order to ensure long-term use. For instance, device annoyance is a significant obstacle to the continued use of technology (Siepmann and Kowalczyk, 2021). Implementing intuitive designs, smooth onboarding processes, and proactive troubleshooting can be effective in alleviating early frustrations and enhancing user

satisfaction. In addition, as users become more familiar with the technology, marketing strategies could shift from leveraging social influences, such as celebrity endorsements, to emphasising personalised benefits and promoting user autonomy. For instance, highlighting real user success stories, such as individuals who have significantly improved their health through wearable technology, can resonate more deeply with potential users. These approaches are more effective in fostering the continued use of technology over time.

Implications Related to Enhancing Consumer Engagement Through Personalisation

The study's findings regarding personality traits provide valuable insights for targeted marketing and personalised user engagement strategies. WFTs should be marketed to individuals who are highly open to technology innovation (OTTI) and conscientious about health (CinH). The diminishing influence of neuroticism over time also suggests that initial anxieties about using WFTs can be alleviated through marketing campaigns emphasising their user-friendly nature and promoting supportive online communities (Abdur Rafay and Mustafa, 2023).

Furthermore, the moderating effects of personality traits on the relationship between CUI and CUB highlight the importance of personalisation. Feature-rich updates and customisation options can enhance satisfaction for users who are open to new technologies, while addressing neurotic users' concerns through empathetic customer support, intuitive designs, and robust security features that are able to foster trust and long-term engagement. These insights underline the need for designers and companies to integrate personality traits and personalisation into their strategies, enabling tailored experiences that resonate deeply with individual users. By aligning technology features and support with users' psychological profiles, companies and designers can build stronger connections and drive sustained adoption.

8.3 Limitations and Suggestions for Future Research

The current study provides valuable insights into the continued use of WFTs by employing a longitudinal approach to examine the factors influencing users' continuance intention and subsequent continued use behaviour. The study also explored the moderating role of users' psychological traits, including general personality and technology-specific characteristics, in the long-term use of technology. Despite these contributions, several limitations warrant consideration and offer opportunities for future research. This section outlines these limitations and proposes directions for future research.

8.3.1 Limitations and Future Research Directions Regarding the Mediating Mechanism

This study highlights the critical mediating role of CUI in translating perceived factors into CUB towards WFT.

Limitations: Although the study identifies the mediating effect of CUI, it does not account for potential alternative or additional mediators that could contribute to a more nuanced understanding of the relationship between perceived factors and CUB. Further, the study assumes a linear causal relationship through CUI, which may oversimplify the dynamic and iterative nature of user behaviour.

Future research directions: To address the limitation identified above, future research could explore additional mediating variables, such as user satisfaction, trust in the technology, or emotional attachment (Pang and Zhang, 2024), to uncover alternative pathways that might influence CUB. Incorporating these mediators would provide a more comprehensive understanding of the mechanisms driving sustained technology use. Future studies could also investigate non-linear

relationships (Schmitz, Teng and Webb, 2016) and feedback loops (Zakariah, Hosany and Cappellini, 2021) in the mediating mechanism of CUI.

8.3.2 Limitations and Future Research Directions Regarding the Moderating Mechanism

The study highlights the significant role of three specific personality traits (OTTI, CinH, and Neu) as moderators influencing continued use intentions and behaviours towards WFT.

Limitations: As stated above, the well-known Five-Factor Model of personality, also known as the Big Five (Goldberg, 1990; Costa and McCrae, 1992), has been extensively applied to conceptualise personality through five superordinate constructs: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (McCrae and Costa, 1987; Costa and McCrae, 1992). However, the current research prioritised internal psychological traits over external social factors and, consequently, strategically omitted two traits, agreeableness and extraversion, from its analysis. This decision was made in order to focus on traits with a direct theoretical linkage to health behaviour and technological adoption, which may have constrained the broader understanding of personality influences.

Future research directions: Future research could examine the influence of the two traits, agreeableness and extraversion, alone or the complete FFM to assess their potential moderating roles in strengthening or weakening the relationship between CUI and CUB. This would provide a more comprehensive understanding of how personality traits influence post-adoption behaviours in the WFT context. Moreover, previous research suggests that certain personality traits correlate with technology-related skills (Carlos Barrera, 2021). Future investigations could explore how these traits influence the continued use of technological devices, particularly in contexts in which skill development and technological competence play critical roles. Expanding the scope to include

these additional dimensions would offer a richer and more nuanced perspective on the interplay between personality and continued technology-related behaviours.

8.3.3 Limitations and Future Directions Regarding Context and Methodology

This thesis employed a unique longitudinal approach to examine the evolving dynamics of users' continued intentions and behaviours towards technology use over time.

Limitations: The current study focused exclusively on the WFT context from the users' perspective, which may limit the generalisability of the findings to other types of technology or contexts. Furthermore, this research employed a survey-based methodology to capture the dynamics of consumer continued intentions and use behaviour over time, as well as the psychological role of personality traits. While this approach provided valuable insights, it also presents an opportunity to explore other methodological designs that could offer complementary perspectives.

Future research directions: To enhance the generalisability of the research findings, future research could investigate whether the determinants of continued use identified are applicable to other categories of wearable devices, such as medical wearables, AR headsets, or smart glasses. Such studies could determine whether the insights derived from this study are unique to fitness devices or extend to broader wearable technology contexts. In addition, within the WFT domain, future research could explore variations in continued use determinants by comparing different brands, models, or devices with varying feature sets. This approach could provide more granular insights into how device-specific attributes influence continued use behaviour. Other contextual factors, such as workplace wellness programmes, community-driven fitness initiatives, or social fitness challenges, may also play a role in shaping long-term engagement with wearable devices and should be considered in future investigations. Furthermore, employing alternative methodological approaches, such as in-depth qualitative interviews or controlled experimental designs, could uncover nuanced insights into the contextual and psychological factors influencing

consumer behaviour. These methods might reveal aspects of technology use that are difficult to capture through quantitative surveys alone, such as emotional connections to devices or situational influences on usage patterns. By addressing these directions, future research could build on the current study to provide a more comprehensive understanding of the factors driving the continued use of wearable technologies in diverse contexts and populations.

Limitations: As highlighted earlier, this study relies on self-reported data, which are inherently subject to biases such as social desirability bias and recall inaccuracies (Podsakoff *et al.*, 2003). Participants may overstate their technology use or report intentions that do not align with their actual behaviour, with the potential to affect the accuracy of the findings.

Future research directions: Although steps were taken to ensure data reliability, such as ensuring anonymity and providing clear instructions, future studies could incorporate objective measures. For example, device usage logs, app analytics, or wearable-generated data could complement self-reported responses, providing a more comprehensive and accurate understanding of technology usage patterns. Such approaches would offer a more robust triangulation of data sources.

Limitations: The study sample may not fully represent the broader population interested in WFTs. Quantitative and longitudinal studies often require stratified random sampling of dedicated participants, which can inadvertently favour those who are more engaged with technology or are more health conscious compared to the general population. This specificity limits the generalisability of the findings (Oppenheimer, Meyvis and Davidenko, 2009). Furthermore, cultural and socioeconomic differences, which can have a significant influence on technology adoption and continued use behaviours, were not explicitly addressed in this study.

Future research directions: To address the limitation of sample specificity, future studies could explore diverse populations across different regions, age groups, and socioeconomic backgrounds (Ridgers *et al.*, 2021). Cross-cultural research could provide valuable insights into how cultural dimensions, such as individualism versus collectivism (Izogo *et al.*, 2022), influence continued behaviour towards technology. Investigating how cultural and socioeconomic factors interact with psychological and behavioural determinants could also further broaden understanding. Comparative studies across high- and low-income regions or analyses of cultural values regarding technology adoption would enhance the external validity of the findings and provide a more comprehensive understanding of user behaviour in various contexts.

Limitations: The current study concerns the measurement of CUB. The items used to assess CUB were adapted from Venkatesh, Thong, and Xu (2012), whose scale is well-established in post-adoption IS research. These items are theoretically grounded and widely accepted for evaluating user continuance in general technology contexts; [see Table 4-2 for measurement items](#). However, in the context of WFT, the items primarily reflect future behavioural intentions. For instance, intentions to continue using the device rather than direct assessments of actual usage patterns or behaviours over time. This presents a potential misalignment with the study's conceptualisation of CUB as real-world, repeated usage over time.

Future research directions: Although this approach was appropriate given the self-report nature of the survey, it may not fully capture the behavioural depth involved in continued WFT use. To address this, future research could incorporate objective behavioural data, such as device usage logs, fitness app activity records or backend analytics from wearable platforms. These methods would allow researchers to capture more accurate and temporally grounded behavioural data. Additionally, future studies may adopt a multidimensional approach to measuring CUB,

incorporating behavioural dimensions such as frequency of use, session duration and type of engagement.

8.4 Conclusion

A review of the existing literature on users' continued use of technology was conducted and revealed three research gaps. Based on the research gaps identified, the research objectives for this study were to:

- a) Understand the mechanisms of users' continued use of technology in the context of WFT (i.e., smartwatches).
- b) Understand post-adoption factors influencing continued technology use and how user perceptions and behaviour evolve over time.
- c) Understand the role of continued use intention towards WFT as a key mechanism for converting perceived factors into continued use behaviour.
- d) Understand the interplay between consumer personality traits and the continued use of WFT by evaluating how personality characteristics enhance the impact of continued use intention on behaviour.

To accomplish the above-stated objectives, research hypotheses were proposed to test:

- a) The direct relationships between perceived factors and the continued use intention of WFT;
- b) The mediating effect of CUI between perceived factors and CUB; and
- c) The moderating effects of users' psychological traits on their continued use intentions and continued use behaviour towards WFT.

Furthermore, building on multiple theoretical perspectives, specifically the extended UTAUT2 model (Venkatesh, Thong and Xu, 2012) and the personality traits model (Terracciano and Costa, 2004), a research model was developed to test the proposed hypotheses. A quantitative methodological approach was employed, involving data collection through an online survey conducted longitudinally

at two-time points (T1 and T2), six months apart, with responses from current users of WFT (331 respondents at T1 and 267 respondents at T2). The data were then analysed quantitatively, encompassing data coding, preliminary examination, and validation of the research model through EFA and CFA. SEM was subsequently used to test the proposed hypotheses.

Next, notable findings were obtained for each of the stated research objectives. The first research aim focused on uncovering the underlying mechanisms that directly drive users to continue using WFTs, aiming to identify and explain the constructs and processes that influence CUI and its subsequent translation into CUB. The second aim explored the post-adoption factors influencing continued technology use and user perceptions and behaviour evolution over time. The third research objective examined the role of CUI as a key mechanism for converting perceived factors into CUB. The fourth objective, which investigated the interplay between consumer personality traits and the continued use of WFTs, specifically evaluated how personality characteristics enhance the impact of CUI on CUB.

Lastly, this study highlighted its theoretical contributions to the technology adoption literature, particularly within the domain of continued use. It also provided a contextual contribution by examining the phenomenon of users' continued use of technology within the specific context of WFTs. Managerial implications were also discussed, focusing on strategies to foster continued use and enhance consumer engagement through personalisation. The study concluded by proposing future research directions based on its limitations, offering a pathway for further exploration in this area.

I have chosen to finish this thesis with the following quotation:

“We're changing the world with technology.”

Bill Gates

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Chapter 9: Appendices

9.1 Appendix A: Ethical Approval Application Form and Participant Information Sheet

Ethical Approval Application Form

Ethics ETH2122-1095: Ms Rasha Elsayy

Date Created	11 Apr 2022
Date Submitted	10 Oct 2022
Date of last resubmission	08 Dec 2022
Academic Staff	Ms Rasha Elsayy
Category	Professional Services Staff
Supervisor	Dr Maged Ali
Project	Continued usage of wearable fitness technology: An extended UTAUT2 model perspective
Faculty	Social Sciences
Department	Essex Business School
Current status	Signed off under Annex B

Ethics application

Project Overview

Title of project

Continued usage of wearable fitness technology: An extended UTAUT2 model perspective

Do you object to the title of your project being published?

No

Applicant(s)

[Ms Rasha Elsayy](#)

How would you like to submit your application?

Supervisor(s)

[Dr Maged Ali](#)

[Dr Atika Kemal](#)

Proposed start date of research

23 Dec 2022

Expected end date

20 Feb 2023

Will this project be externally funded?

No

Will the research involve human participants?

Yes

Will the research use collected or generated personal data?

Yes

Will the research involve the use of animals?

No

Will any of the research take place outside the UK?

No

Project details**Summary of the project**

1. the purpose of the study is to identify the key determinants influencing the continued use of WFTs through analysis
2. An online questionnaire designed in Qualtrics and prolific will be used to record the responses of the participants longitudinally (at two points in time) to find out the significant changes in user behaviour and perceptions over time.
3. Depending on the results of the online survey, insights will be drawn to understand the phenomenon of consumer continuance use behaviour of technology.

Participant details**Who are the potential participants?**

Data will be collected from (potential participants) existing wearable technology users (i.e., smartwatches).

How will they be recruited?

For survey distribution, participants will be recruited online using the Qualtrics and Prolific platforms.

Recruiting materials**Will participants be paid or reimbursed? Yes****If yes, please provide details and justification for this payment.**

Participants will be recruited online using a third-party platform, "Prolific". They endorse the principle of "ethical rewards" and believe fair pay leads to better data quality. Therefore, participants get paid a minimum reward rate of £6.00 per hour (when researchers create their study, they will figure out recommended payment levels).

How much will the participants be paid?

£ 3

Could potential participants be considered vulnerable?

No

If yes, please explain how the participants could be considered vulnerable and why vulnerable participants are necessary for the research.

Could potential participants be considered to feel obliged to take part in the research?

No

If yes, please explain how the participants could feel obliged and how any possibility for coercion will be addressed.

Will the research involve individuals below the age of 18 or individuals of 18 years and over with a limited capacity to give informed consent?

No

Is a Disclosure and Barring Service (DBS) Check required?

No

If yes, has the DBS check been completed?

If your project involves children or vulnerable adults but does not require a DBS check, please explain why.

Informed consent

How will consent be obtained? Written

If consent will be obtained in writing, please upload the written consent form for review and approval.

If consent will be obtained orally, please explain why.

Please upload a copy of the script that will be used to obtain oral consent.

If no script is available to upload, please explain why.

Who will be obtaining and recording consent?

The researcher will be obtaining consent.

Please indicate at what stage in the data collection process consent will be obtained.

The consent process will be obtained before collecting the data (in the first questionnaire).

If informed consent will not be obtained, explain why.

Please upload a participant information sheet.

Have you reviewed the information provided by the REO on participant information and consent? Yes

Confidentiality and anonymity

Will you be maintaining the confidentiality and anonymity of participants whose personal data will be used in your research? Yes

If yes, describe the arrangements for maintaining anonymity and confidentiality. Participants will not be asked to provide their names, but they may be asked to provide some demographic information for analysis purposes. Data collected through this questionnaire will be aggregated and will not be individually identifiable in any reports or publications from this research.

If you are not maintaining anonymity and confidentiality, please explain your reasons for not doing so.

Data access, storage and security

Describe the arrangements for storing and maintaining the security of any personal data collected as part of the project.

All information collected will be kept securely on a password-protected computer and will only be accessible by the researcher and the supervisors. However, this research forms part of my studies at the University of Essex and may be subject to scrutiny by other University staff in determining the outcome of my degree.

Please provide details of all those who will have access to the data.

As a PGR project, this research data will be retained for a period of ten years after the completion of the project. The data will be electronically destroyed at the end of that period. However, the University's Research Data Management Policy requires that research data be made available for access and re-use where legally, ethically, and commercially appropriate, taking note of any relevant safeguards.

Data Sharing

Do you intend to share or archive data generated from this project once it is complete?

If yes, please describe briefly.

Please indicate the means by which you intend to share/archive your data:

If you chose other, please provide more details.

If you do not intend to share data, please provide specific reasons why the data will not be made available.

Risk and risk management

Risk Assessment documents

Are there any potential risks (e.g. physical, psychological, social, legal or economic) to participants or subjects associated with the proposed research? No

If yes, please provide full details and explain what risk management procedures will be put in place to minimise the risks.

Are there any potential risks (e.g. physical, psychological, social, legal or economic) to the researchers working on the proposed research? No

If yes, please provide full details and explain what risk management procedures will be put in place to minimise the risks.

Are there any potential reputational risks to the University as a consequence of undertaking the proposed research?
No

If yes, please provide full details and explain what risk management procedures will be put in place to minimise the risks.

Are there any other ethical issues that have not been addressed which you would wish to bring to the attention of the reviewer(s) of your application?

Other documents

Attached files

Rasha Elsayy UPDATED Research proposal OCT 2022 .docx

Rasha Elsayy Research Invitation Letter OCT 2022UPDATED.docx

Consent form for online questionnaire OCT2022 UPDATED.docx

Participant Information Sheet OCT2022.docx

UPDATED Draft Questionnaire 07_Dec_2022.docx

Working Title

"Understanding Consumers' Continuance Use of Technology: A Longitudinal Study on the Moderating Role of Personality Traits"

Research Objectives

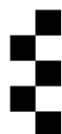
1. understand the mechanisms of consumer continuance use of technology in the context of wearable fitness technology (i.e., smartwatches);
2. understand the key post-adoption factors that influence the continued use of technology;
3. understand how user perceptions and technology use behaviour change over time (after the initial adoption);
4. understand the interplay of consumer personality and the continuance use of technological devices by investigating the role of personality characteristics in increasing the effects of continued usage intention on consumer continued behaviour to use WFT.
5. provide a deeper understanding of the role of consumer continued intention to use WFT serves as a fundamental mechanism that explains the conversion of perceived factors into continued technology use behaviour (CUB);
6. derive recommendations and explicit managerial guidance on how continued IT usage behaviour can be influenced effectively based on the results of this study.

Research Questions

What are the determinants that affect consumers' decision to continue using IT (wearable technology), which are affected by technological/utilitarian, affective/hedonic, emotional, and social factors? To what extent can personality traits (user-specific personal characteristics) predict consumers' continued usage intention and continued use behaviour of WFT/SW?

Proposed Methodology

Data collection Method- Online survey; Sampling method- Purposive sampling (custom allowlist); Sample – recent users of wearable fitness devices (Smartwatches) 18 years of age and above.



University of Essex



Participant Information Sheet for Research Project: [Rasha's thesis PIS]

Dear participant,

I, Rasha Elsayy, am currently carrying out a piece of research entitled "Adoption and use of technology" under the supervision of Dr Maged Ali. The study is being undertaken as part of my doctoral study.

We are investigating the adoption and use of technology (you will be asked about the usage of your wearable fitness devices, i.e., smartwatches). Further, it will examine the effect of personality traits. You have been invited to participate in this study as you are eligible based on the previous short survey (owning a Fitness Smartwatch for over 3 weeks).

This is the FIRST Part of a longitudinal study (two-part study), which will be approximately six months apart.

This information sheet provides you with information about the study and your rights as a participant.

What does taking part in the research involve?

The research will involve undertaking an online questionnaire survey to collect data from existing wearable technology users (i.e., smartwatches) within six months (data to be collected at two points in time). Participants will be asked about factors influencing their adoption and use of technology and related personality characteristics.

Do I have to take part?

Naturally, there is no obligation to take part in the study. It's entirely up to you. If you do decide to take part, you will be given this information sheet to keep and be asked to give consent to take part. If publications or reports have already been disseminated, these cannot be withdrawn; however, these will only contain anonymised or aggregated data. If you wish to withdraw from the study at any time, please contact the researcher at the details below.

Will my taking part in this study be kept confidential?

All information collected will be kept securely on a password-protected computer and will only be accessible by the researcher and the supervisors. However, this research forms part of my studies at the University of Essex and may be subject to scrutiny by other University staff in determining the outcome of my degree.

You will not be asked to provide your name, but you may be asked to provide some demographic information for analysis purposes. Data collected through this questionnaire will be aggregated, and you will not be individually identifiable in any reports or publications from this research.

As a PGR project, this research data will be retained for a period of ten years after the completion of the project. The data will be electronically destroyed at the end of that period. However, the University's Research Data Management Policy requires that research data are made available for access and re-use where legally, ethically and commercially appropriate, taking note of any relevant safeguards.

Are there any possible disadvantages or risks of taking part?

Taking part in this research will not have any possible disadvantages or risks, and it will only take around 20min to answer the online questionnaire's questions over six months (at two points of time).

What are the possible benefits of taking part?

Any specific benefits cannot be guaranteed. However, possible benefits of taking part in this study are that a participant might learn more about a condition that affects you, and make a difference by helping to improve quality of life, now and for future generations or take an active role in your health/lifestyle.

What is the legal basis for using the data, and who is the Data Controller?

The legal basis for processing the data collected from this project is informed consent. The Data Controller for this project is the University of Essex, and the contact is the University Information Assurance Manager (dpo@essex.ac.uk).

What should I do if I want to take part?

Please contact the researcher using the details below by 31st October 2022.

Who is funding the research?

The researcher receives no direct funding for this study.

What will happen to the results of the research study?

The research results will be submitted (as part of the thesis) in partial fulfilment of the doctoral degree programme. They might be published as journal articles or used as conference papers/presentations.

Also, a kind reminder that any results will be anonymised and that participants will not be identifiable (deposited in electronic format, as I have guaranteed earlier in this PIS. A copy of the study findings will be available to any participant upon request (please contact the researcher at the details below to apply).

Who has reviewed the study?

I have applied for ethical approval to undertake this study. My application was reviewed and approved by the Social Sciences Ethics Sub-Committee at the University of Essex.

What happens if something goes wrong?

If you are harmed by taking part in this research project, there are no special compensation arrangements. Regardless of this, if you wish to complain or have any concerns about any aspect of the way you have been treated during the course of this study, then you should immediately inform the student and/or their supervisor (details below). If you are not satisfied with the response, you may contact the Essex Business School Research Ethics Officer, Dr Casper Hoedemaekers (choedem@essex.ac.uk) or Sarah Manning-Press (sarahm@essex.ac.uk), who will advise you further.

Name of the Researcher/Research Team Members

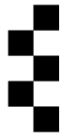
We would be very grateful for your participation in this study. If you need to contact us in future, please contact me (re20334@essex.ac.uk) or Dr Maged Ali (maali@essex.ac.uk). You can also contact us in writing at EBS, University of Essex, Colchester CO4 3SQ.

You are welcome to ask questions at any point.

Yours,

Rasha Elsayy

9.2 Appendix B: First Page of the Online Questionnaire



University of Essex



for the FIRST page of the online questionnaire

"Adoption and use of technology"

Dear participant,

This questionnaire investigates the adoption and use of technology (you will be asked about the usage of your wearable fitness devices, i.e., smartwatches). Further, it will examine the effect of personality traits. You have been invited to participate in this study as you are eligible based on the previous short survey (owning a Fitness Smartwatch for over 3 weeks). The study is being undertaken as part of my doctoral study.

This is the FIRST part of a longitudinal study (two-part study), which will be approximately six months apart.

This research is being carried out by Rasha Elsayy under the supervision of Dr Maged Ali.

You will not be asked to provide your name, but you may be asked to provide some demographic information for analysis purposes. Data collected through this questionnaire will be aggregated, and you will not be individually identifiable in any reports or publications from this research. All information collected will be kept securely and will only be accessible by the researcher and the supervisor.

For more information about your rights as a participant in this research, please download a copy of the participant information sheet, which can be found at this link: https://corexmswgj2pb8crj2mx.qualtrics.com/jfe/form/SV_414Qrf8ZZHAyvps

We would be very grateful for your participation in this study. If you need to contact us in future, please contact me at re20334@essex.ac.uk or Dr Maged Ali at maaali@essex.ac.uk. You can also contact us in writing at EBS, University of Essex, Colchester CO4 3SQ.

Yours,

Rasha Elsayy

Statement of Consent

By submitting a completed version of this questionnaire, you are consenting to the following:

- I agree to participate in the research project " Adoption and use of technology", which is being carried out by *Rasha Elsayy*.
 - This agreement has been given voluntarily and without coercion.
 - I have been given full information about the study and the researcher's contact details.
 - I have read and understood the information provided above.
 - I agree to have my anonymised data shared on publicly accessible repositories.
 - I agree to be contacted in the future by the researchers (using the Prolific ID).
 - I confirm that I am aged 18 or above.
-

Text for the LAST page of the online questionnaire

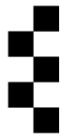
Thank you for your participation in this study, " Adoption and Use of Technology".

You are reminded that by submitting a completed version of this questionnaire, you are agreeing to participate in this research.

If you have any queries, please contact me at re20334@essex.ac.uk or Dr Maged Ali at maaali@essex.ac.uk. You can also contact us in writing at EBS, University of Essex, Colchester CO4 3SQ.

Yours,
Rasha Elsayy

9.3 Appendix C: Research Recruitment/Invitation Letter



University of Essex



Dear Sir/Madam,

Re: Invitation to Participate in Essex Business School Research Project

I am writing to invite you to participate in a research project entitled "Adoption and Use of Technology".

This research aims to investigate the adoption and use of technology (you will be asked about the usage of your wearable fitness devices, i.e., smartwatches). Further, it will examine the effect of personality traits. You have been invited to participate in this study as you are eligible based on the previous short survey (owning a Fitness Smartwatch for over 3 weeks).

This is the FIRST part of a longitudinal (two-part study) study, which will be approximately six months apart.

The research forms part of my doctoral study and is being undertaken under the supervision of Dr Maged Ali at Essex Business School.

The research will involve undertaking an online questionnaire survey to collect data from existing wearable technology users within six months (data to be collected at 2 points of time, two surveys). All data collected will be treated in the strictest confidence.

I have attached an **information sheet** which provides further details about what participation in the research would entail and how anonymity and confidentiality will be managed.

Your participation and support will be highly appreciated. For further information, you can directly contact the researcher or the supervisor via the emails shown below.

Thank you very much for your attention and consideration.

Yours faithfully,

Researcher(s)	Contact details
Researcher Rasha Elsayy	re20334@essex.ac.uk
Supervisor Dr Maged Ali	maaali@essex.ac.uk

9.4 Appendix D: Questionnaire

Final Questionnaire

About the Research

This study is about the adoption and use of technology. You will be asked about the usage of your wearable fitness devices, i.e., smartwatches.). Further, it will examine the effect of personality traits. You have been invited to participate in this study as you are eligible based on the previous short survey (owning a Fitness Smartwatch for over 3 weeks).

This is the FIRST part of a two-part study. You will receive a bonus reward after completing both studies. The studies are approximately six months apart.

The study is being undertaken as part of my doctoral study, and Rasha Elsaywy is carrying it out under the supervision of Dr Maged Ali.

9.4.1 Consent Question

Dear participant,

You have been invited to participate in this study as you are eligible based on the previous short survey (owning a Fitness Smartwatch for over 3 weeks).

This is the FIRST Part of a longitudinal study (two-part study), which will be approximately six months apart.

Please read all questions CAREFULLY to avoid rejection.

This study is about the adoption and use of technology. You will be asked about your usage and your personality traits.

I, Rasha Elsaywy, carry out this research as part of my doctoral study under the supervision of Dr Maged Ali.

You will NOT be asked to provide your name, but you may be asked to provide some demographic information for analysis purposes. Data collected through this questionnaire will be aggregated, and you will not be individually identifiable in any reports or publications from this research. All information collected will be kept securely and will only be accessible by the researcher and the supervisor. If you need to contact us in future, please contact me through Prolific.

For more information about your rights as a participant in this research, please download a copy of the participant information sheet, which can be found at this link

<https://d.docs.live.net/35553586b7cb8a9f/Desktop/Ethical%20approval%20SEP%202022/done%20>

[and%20ready%20for%20submission%20Nshallah/Participant%20Information%20Sheet%20OCT2022.docx](#)

We would be very grateful for your participation in this study. If you need to contact us in future, please contact me at re20334@essex.ac.uk or Dr Maged Ali at maaali@essex.ac.uk. You can also contact us in writing at EBS, University of Essex, Colchester CO4 3SQ.

Consent form

By submitting a completed version of this questionnaire, you are consenting to the following:

- I agree to participate in the research project " Adoption and use of technology", which is being carried out by Rasha Elsayy.
- This agreement has been given voluntarily and without coercion.
- I have been given full information about the study and the researcher's contact details.
- I have read and understood the information provided above.
- I agree to have my anonymised data shared on publicly accessible repositories.
- I agree to be contacted by the researchers in the future (using the Prolific ID).
- I confirm that I am aged 18 or above.

Consent

- 1- Yes, I do consent
- 2- No, I do not consent

9.4.2 Controlled Questions

Age: (Please type in numbers) _____ Gender: Male [☐] Female [☐]

Highest completed level of education: Some primary [☐] Completed primary school [☐] Some secondary

[☐] Completed secondary school [☐] Vocational or similar [☐] Some university but no degree [☐]

University bachelor's degree [☐] Graduate or Professional degree (MA, MS, MBA, PhD, JD, MD, DDS)

9.4.3 Questionnaire Statements

Table 9–1 Questionnaire items used in my thesis

Item	Questions/Statements	Strongly disagree 1	Somewhat disagree 2	Neither 3	Somewhat agree 4	Strongly agree 5
Performance Expectancy (PerExp)						
PerExp1	I find that my Wearable Fitness Technology (WFT) device ...	☐	☐	☐	☐	☐
	- Useful in my daily life.					
PerExp2	- Using it helps accomplish things more quickly	☐	☐	☐	☐	☐
PerExp3	- Using WFT improves the quality of my daily health/fitness activities	☐	☐	☐	☐	☐
PerExp4	- Using WFT provides the data/information I need (which important to me)	☐	☐	☐	☐	☐
Effort Expectancy (EffExp)						
EffExp1	I believe that while using Wearable Fitness Technology (WFT) devices ...	☐	☐	☐	☐	☐
	- I can learn how to use new electronic devices (i.e., smartwatches) very quickly					
EffExp2	- I find WFT devices easy to use	☐	☐	☐	☐	☐
EffExp3	- It is easy to get hold of the data provided by WFT	☐	☐	☐	☐	☐
EffExp4	- I can make good use of WFT and the data provided	☐	☐	☐	☐	☐
EffExp5	- It is easy for me to become skillful at using WFT devices.	☐	☐	☐	☐	☐
Societal Pressure (SotPrss)						
SotPrss1	About using Wearable Fitness Technology (WFT) ...	☐	☐	☐	☐	☐
	- My family members think that I should use the chosen WFT device to enhance my body image					
SotPrss2	- My peers think that I should use the chosen WFT device to enhance my body image	☐	☐	☐	☐	☐
SotPrss3	- My friends think that I should use the chosen WFT device to enhance my body image	☐	☐	☐	☐	☐

SotPrss4 - As a whole, the use of the chosen WFT device is a trend which I will follow. ☐ ☐ ☐ ☐ ☐

Perceived Enjoyment (PEnj)

PEnj1 I believe that using wearable fitness devices ... ☐ ☐ ☐ ☐ ☐

- is truly fun

PEnj2 - is enjoyable ☐ ☐ ☐ ☐ ☐

PEnj3 - gives me pleasure ☐ ☐ ☐ ☐ ☐

PEnj4 - makes me feel good. ☐ ☐ ☐ ☐ ☐

Price Value (PValu)

PValu1 My current Wearable Fitness Technology (WFT) device is ... ☐ ☐ ☐ ☐ ☐

- Reasonably priced

PValu2 - A good investment compared to the price paid for them ☐ ☐ ☐ ☐ ☐

PValu3 - At the current price, WFT devices provide a good value/performance ratio ☐ ☐ ☐ ☐ ☐

PValu4 - Affordable, and I am willing to pay the current price given its features ☐ ☐ ☐ ☐ ☐

Facilitating Conditions (FCon)

FCons1 In my opinion, that ☐ ☐ ☐ ☐ ☐

- I have the resources necessary to use WFT/SW (financial and technological)

FCons2 - I have the knowledge necessary to use WFT/SW ☐ ☐ ☐ ☐ ☐

FCons3 - WFT/SW is compatible with other technologies I use ☐ ☐ ☐ ☐ ☐

FCons4 - I can get help from others when I have difficulties using WFT (i.e., smartwatch) ☐ ☐ ☐ ☐ ☐

FCons5 - Guidance will be available to me in the use of WFT devices (i.e., user manual, website, forums, live chats...etc.). ☐ ☐ ☐ ☐ ☐

Technology Habit (Tech)

TechH1 I believe that ... ☐ ☐ ☐ ☐ ☐

- The use of WFT devices has become a habit for me

TechH2 - I am addicted to using WFT devices ☐ ☐ ☐ ☐ ☐

TechH3 - I must use WFT devices (Without them, I feel uncomfortable) ☐ ☐ ☐ ☐ ☐

CUB5 - Overall, I will continue using WFT than use any alternative means. ○ ○ ○ ○ ○

Openness to Technology Innovativeness (OTTI)

OTTI1	I see myself as someone who...					
	- likes to be around unconventional people who dare to try new things	☐	☐	☐	☐	☐
OTTI2	- is curious about how things work	☐	☐	☐	☐	☐
OTTI3	- likes to experiment with new ways of doing things	☐	☐	☐	☐	☐
OTTI4	- likes to search for information about new products or technologies	☐	☐	☐	☐	☐
OTTI5	- is often seek out information about new products.	☐	☐	☐	☐	☐

Conscientiousness in Health (CinH)

CinH1	see myself as someone...	☐	☐	☐	☐	☐
	- who is very self-conscious about my health					
CinH2	- who is alert to changes in my health	☐	☐	☐	☐	☐
CinH3	- likes to experiment with new ways of doing things	☐	☐	☐	☐	☐
CinH4	- takes responsibility for the state of my health	☐	☐	☐	☐	☐
CinH5	- It's important that you pay attention to this study;	☐	☐	☐	☐	☐
	please select strongly agree .					

Neuroticism (Neu)

Neu1	I see myself as someone who...	☐	☐	☐	☐	☐
	- is easily worry about things					
Neu2	- is easily disturbed	☐	☐	☐	☐	☐
Neu3	- gets upset easily.	☐	☐	☐	☐	☐

Tech. Upgradability (TUpG)

Item	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
TUpG1	I believe that my wearable fitness device ...				
TUpG2					
TUpG3					
TUpG4					

Thank you for your time & help.

9.5 Appendix E Harman's Single Factor in SPSS (1st Dataset)

Table 9–2 Total Variance Explained, 1st Dataset

Factor	Total Variance Explained					
	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	17.584	29.306	29.306	17.014	28.356	28.356
2	4.862	8.104	37.410			
3	3.818	6.363	43.773			
4	3.275	5.459	49.231			
5	3.111	5.185	54.416			
6	2.610	4.350	58.766			
7	2.443	4.072	62.838			
8	2.011	3.352	66.190			
9	1.891	3.152	69.341			
10	1.588	2.646	71.987			
11	1.444	2.407	74.395			
12	1.322	2.203	76.597			
13	1.173	1.956	78.553			
14	.997	1.662	80.216			
15	.794	1.323	81.538			
16	.711	1.186	82.724			
17	.615	1.024	83.748			
18	.610	1.017	84.766			
19	.585	.975	85.741			
20	.554	.924	86.665			
21	.543	.905	87.569			
22	.463	.772	88.341			
23	.427	.712	89.053			
24	.413	.688	89.741			
25	.397	.661	90.402			
26	.374	.623	91.026			
27	.347	.579	91.605			
28	.340	.566	92.171			
29	.310	.516	92.687			
30	.291	.485	93.172			

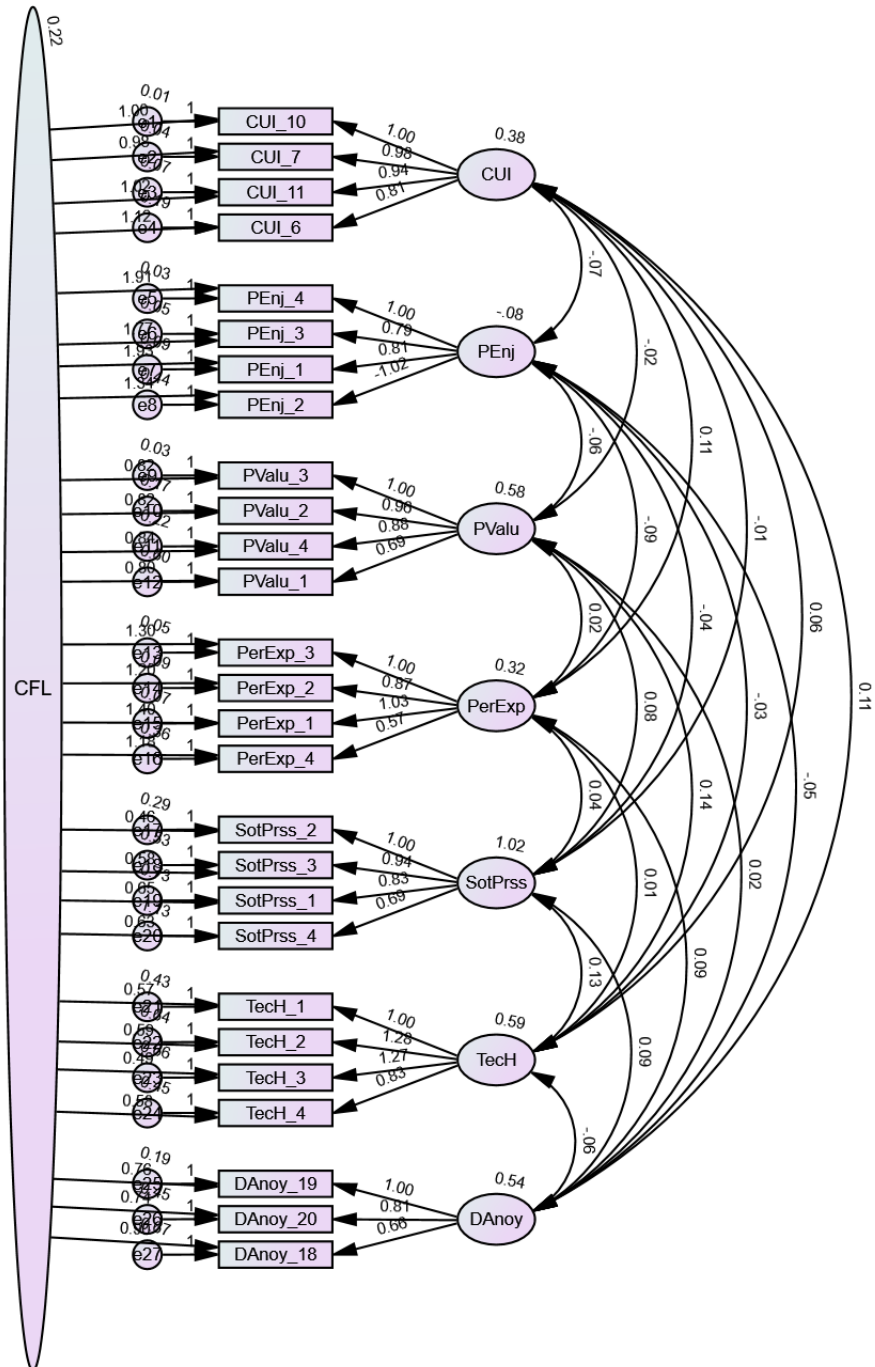
31	.288	.481	93.652			
32	.268	.447	94.099			
33	.258	.429	94.528			
34	.235	.392	94.920			
35	.231	.385	95.306			
36	.219	.364	95.670			
37	.209	.348	96.018			
38	.204	.340	96.358			
39	.198	.330	96.688			
40	.184	.307	96.994			
41	.174	.290	97.284			
42	.159	.265	97.550			
43	.154	.256	97.806			
44	.149	.248	98.054			
45	.132	.221	98.274			
46	.126	.211	98.485			
47	.116	.193	98.677			
48	.110	.183	98.860			
49	.093	.156	99.015			
50	.083	.139	99.154			
51	.074	.124	99.278			
52	.072	.120	99.397			
53	.068	.114	99.511			
54	.061	.101	99.613			
55	.054	.089	99.702			
56	.051	.085	99.786			
57	.047	.079	99.865			
58	.032	.054	99.919			
59	.026	.043	99.962			
60	.023	.038	100.000			

Extraction Method: Principal Axis Factoring.

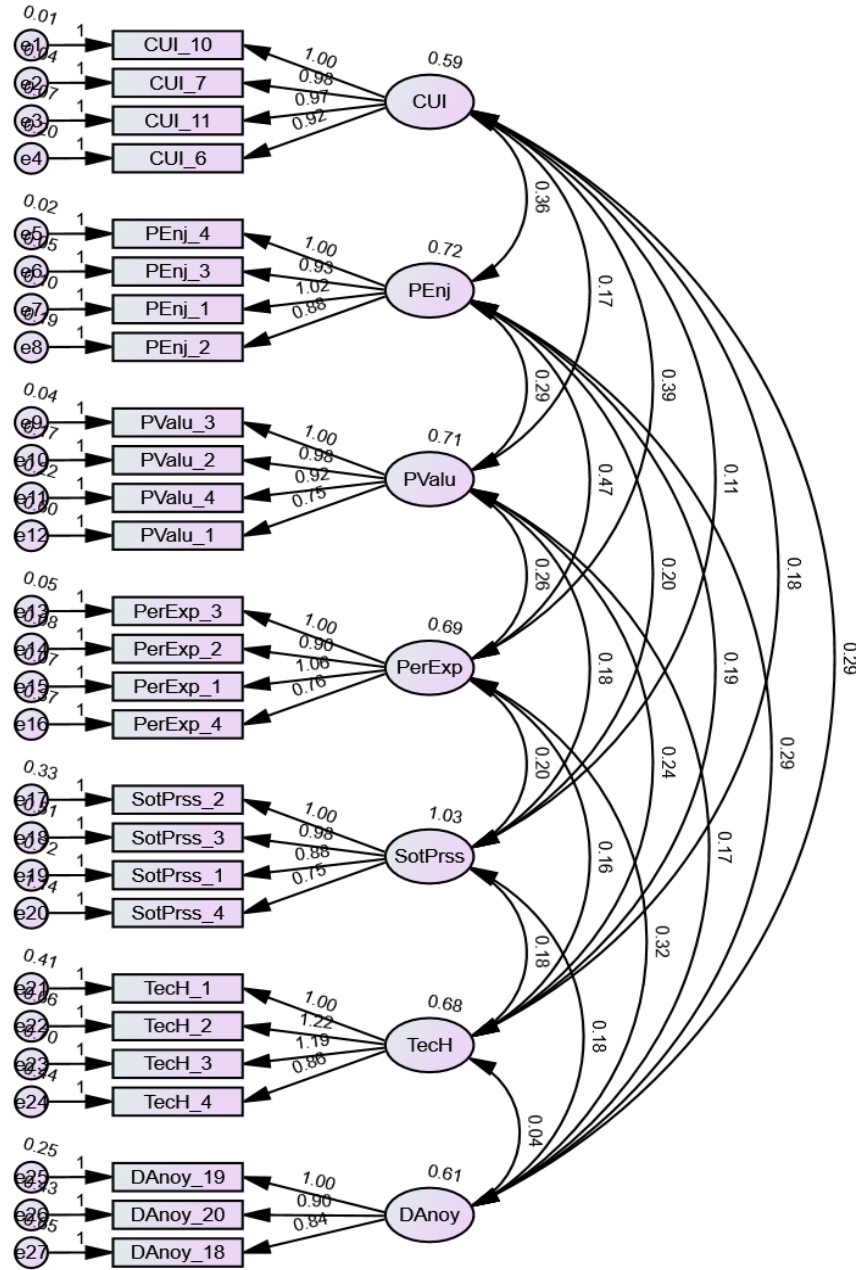
9.6 Appendix F Common Method Bias (CMB) in AMOS (1st Dataset)

9.6.1 Group 1 With and Without common latent factor (CLF)

With CLF



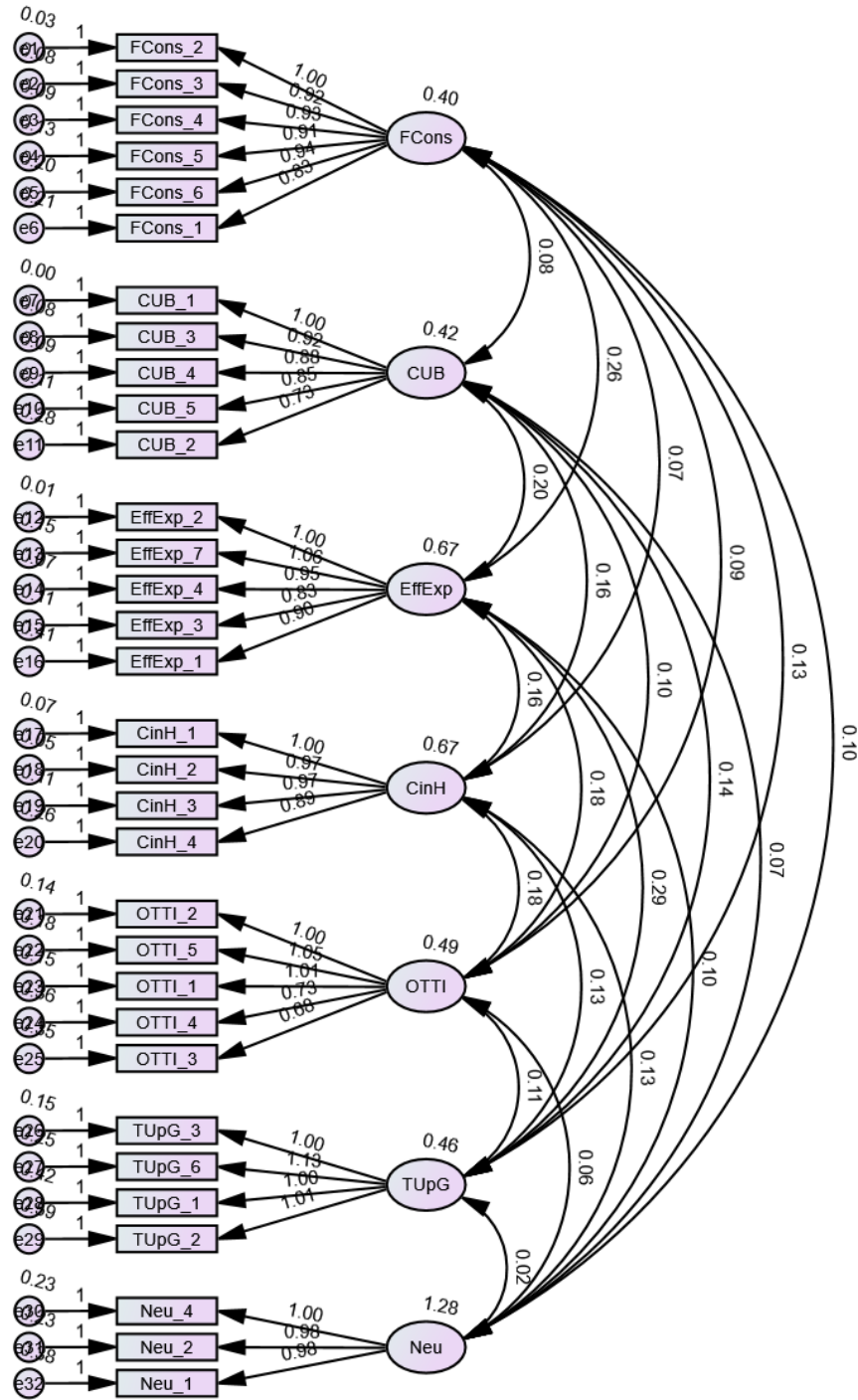
Without CLF





Without CLF

Figure 9-2 CMB in AMOS for Group 2 without CLF



9.7 Appendix G: Collinearity Statistics (variance inflation factor 'VIF') – Inner Model- List

	VIF
Age -> Continued Use Behaviour	1.061
CinH -> Continued Use Behaviour	1.314
Continued Usage Intention -> Continued Use Behaviour	1.280
DAnoy -> Continued Usage Intention	1.490
Education -> Continued Use Behaviour	1.066
EffExp -> Continued Usage Intention	2.327
FCons -> Continued Usage Intention	1.458
Gender -> Continued Use Behaviour	1.099
Neu -> Continued Use Behaviour	1.078
OTTI -> Continued Use Behaviour	1.328
PEnj -> Continued Usage Intention	2.318
PValu -> Continued Usage Intention	1.396
PerExp -> Continued Usage Intention	2.436
SotPrss -> Continued Usage Intention	1.136
TUpG -> Continued Usage Intention	1.595
Tech -> Continued Usage Intention	1.232
OTTI x Continued Usage Intention -> Continued Use Behaviour	1.272
CinH x Continued Usage Intention -> Continued Use Behaviour	1.267
Neu x Continued Usage Intention -> Continued Use Behaviour	1.059

9.8 Appendix H Harman's Single Factor in SPSS (2nd Dataset)

Table 9–3 Total Variance Explained, 2nd Dataset

Factor	Total Variance Explained					
	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	15.843	26.406	26.406	15.243	25.405	25.405
2	4.627	7.711	34.117			
3	4.344	7.240	41.357			
4	3.751	6.251	47.608			
5	3.543	5.905	53.513			
6	3.377	5.628	59.141			
7	3.066	5.111	64.252			
8	2.717	4.529	68.781			
9	2.319	3.865	72.646			
10	2.036	3.393	76.039			
11	1.873	3.122	79.161			
12	1.786	2.977	82.138			
13	1.361	2.269	84.406			
14	.789	1.315	85.721			
15	.626	1.043	86.765			
16	.521	.869	87.634			
17	.507	.845	88.479			
18	.410	.684	89.163			
19	.387	.645	89.807			
20	.365	.608	90.415			
21	.320	.533	90.948			
22	.307	.512	91.460			
23	.285	.475	91.936			
24	.257	.428	92.363			
25	.244	.406	92.769			
26	.239	.399	93.168			
27	.229	.382	93.550			
28	.219	.365	93.915			
29	.209	.349	94.264			
30	.200	.334	94.598			

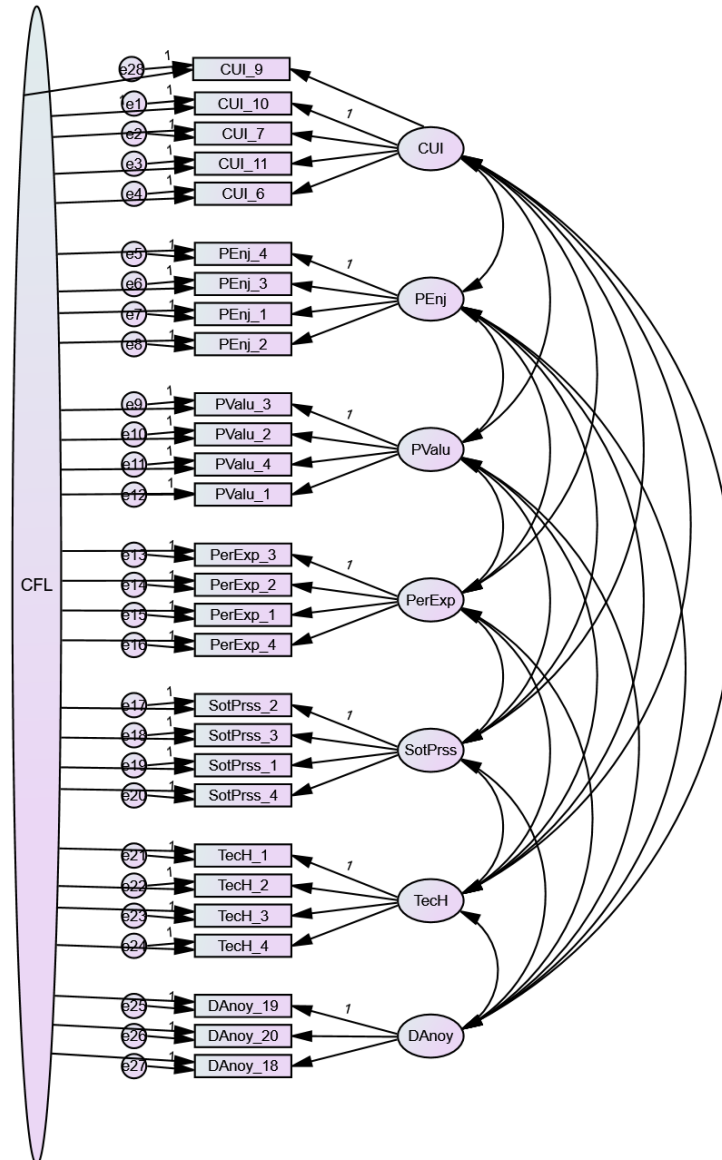
31	.191	.319	94.917			
32	.177	.295	95.212			
33	.172	.286	95.498			
34	.169	.282	95.780			
35	.162	.271	96.051			
36	.154	.257	96.308			
37	.148	.247	96.555			
38	.144	.241	96.796			
39	.137	.228	97.024			
40	.129	.216	97.240			
41	.126	.211	97.451			
42	.122	.203	97.654			
43	.117	.195	97.849			
44	.112	.186	98.035			
45	.105	.176	98.211			
46	.105	.174	98.385			
47	.098	.164	98.549			
48	.096	.160	98.709			
49	.092	.154	98.863			
50	.089	.148	99.011			
51	.078	.130	99.141			
52	.076	.126	99.267			
53	.073	.122	99.389			
54	.067	.112	99.501			
55	.061	.102	99.603			
56	.055	.092	99.695			
57	.054	.090	99.785			
58	.046	.077	99.862			
59	.042	.070	99.933			
60	.040	.067	100.000			

Extraction Method: Principal Axis Factoring.

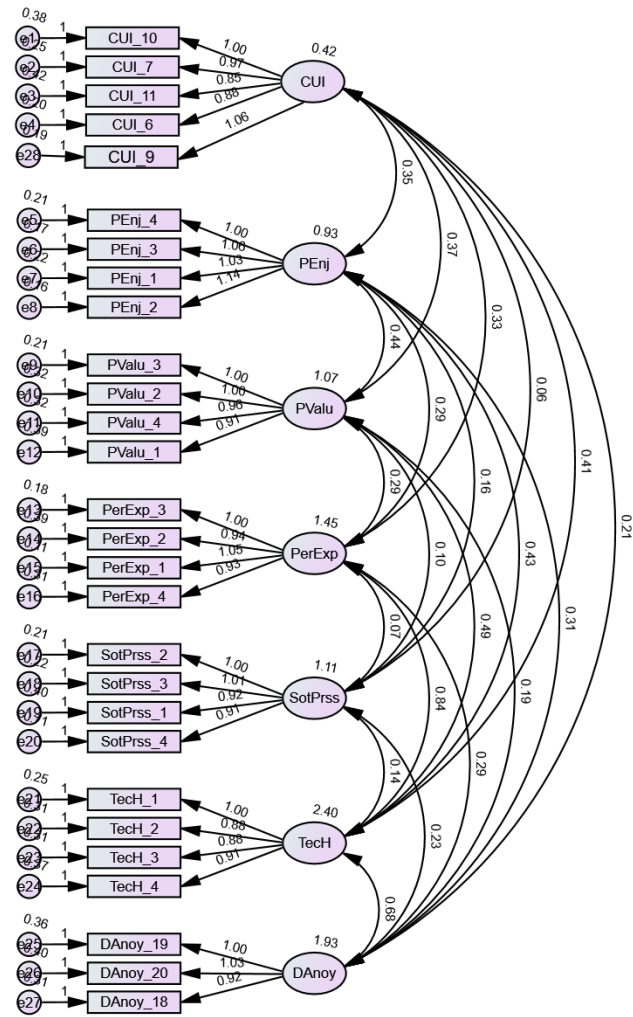
9.9 Appendix I Common Method Bias (CMB) in AMOS (2nd Dataset)

Group 1 With and without common latent factor (CLF)

With CLF

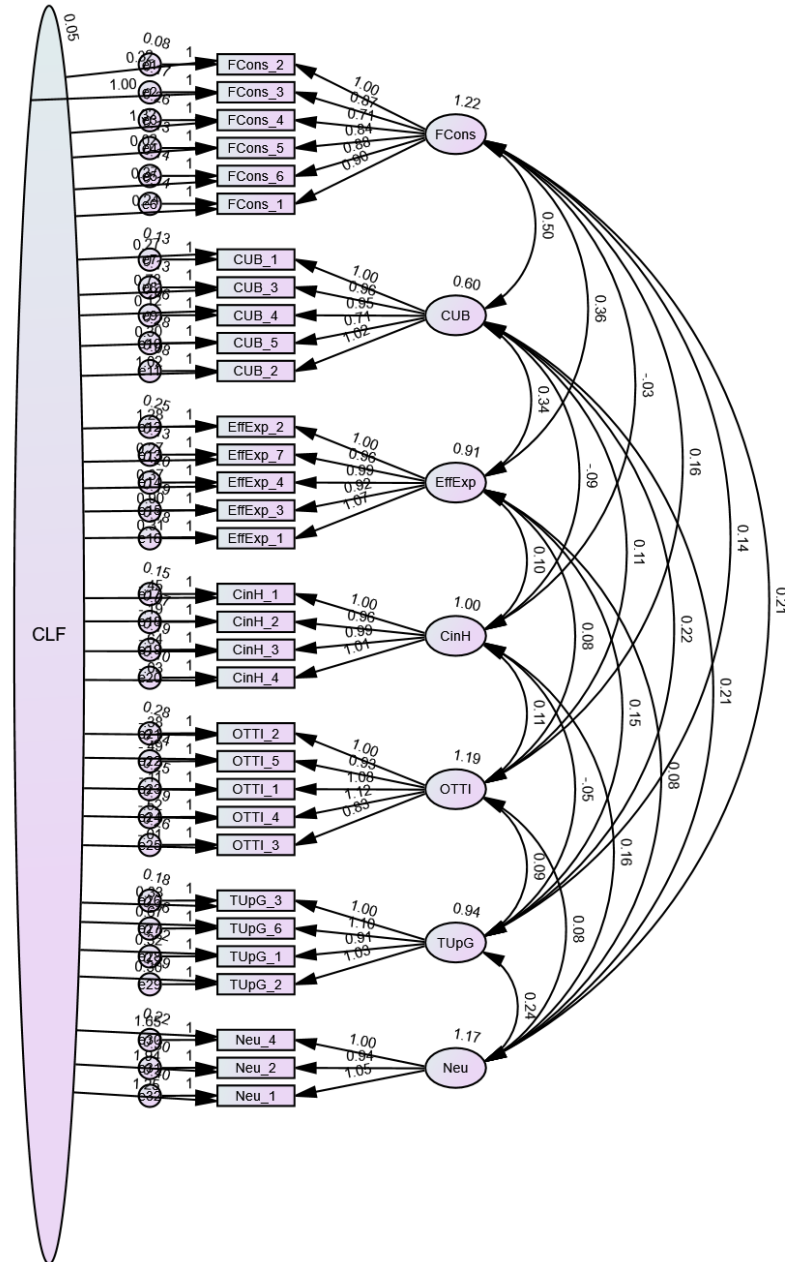


Without CLF

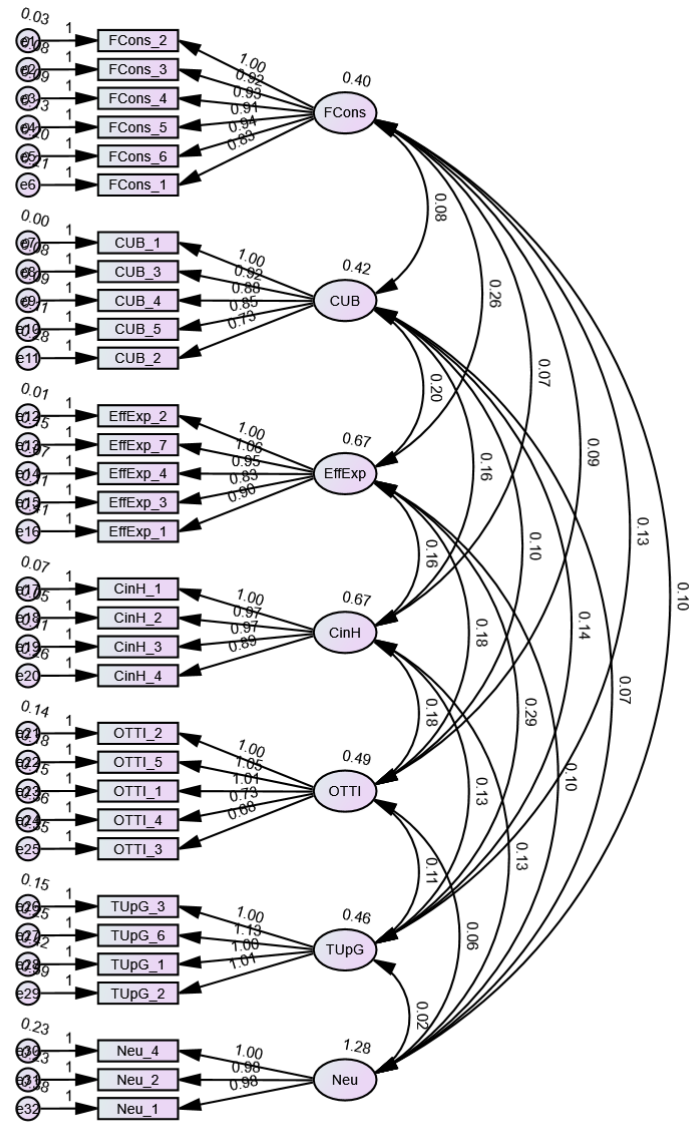


Group 2 With and without common latent factor (CLF)

With CLF



Without CLF



9.10 Appendix J: Collinearity Statistics (variance inflation factor 'VIF') – Inner Model- List

	VIF
Age -> Continued Use Behaviour	1.051
CinH -> Continued Use Behaviour	1.073
Continued Usage Intention -> Continued Use Behaviour	2.586
DAnoy -> Continued Usage Intention	1.161
Education -> Continued Use Behaviour	1.023
EffExp -> Continued Usage Intention	1.249
FCons -> Continued Usage Intention	1.312
Gender -> Continued Use Behaviour	1.119
Neu -> Continued Use Behaviour	1.199
OTTI -> Continued Use Behaviour	1.133
PEnj -> Continued Usage Intention	1.368
PValu -> Continued Usage Intention	1.403
PerExp -> Continued Usage Intention	1.322
SotPrss -> Continued Usage Intention	1.041
TUpG -> Continued Usage Intention	1.097
Tech -> Continued Usage Intention	1.393
OTTI x Continued Usage Intention -> Continued Use Behaviour	1.426
CinH x Continued Usage Intention -> Continued Use Behaviour	1.318
Neu x Continued Usage Intention -> Continued Use Behaviour	2.494

9.11 Appendix K Details and Tables on the Evaluations of the Measurement and Structural Models

Table 9–4 Descriptive Statistics and Discriminant Validity (Fornell-Larcker Criterion) for **Model 1 (1st dataset)**

	MEAN	SD	CUI	CUB	DAnoy	EffExp	FCons	PEnj	PValu	PerExp	SotPrss	TUpG	Tech
CUI	0.231	0.056	0.911										
CUB			0.370	0.891									
DAnoy	0.022	0.010	0.473	0.128	0.829								
EffExp	0.047	0.017	0.660	0.373	0.516	0.922							
FCons	0.005	0.011	0.380	0.174	0.296	0.487	0.885						
PEnj	0.038	0.015	0.637	0.410	0.424	0.589	0.374	0.952					
PValu	-0.016	0.010	0.287	0.123	0.223	0.351	0.379	0.431	0.882				
PerExp	0.082	0.023	0.711	0.450	0.449	0.652	0.360	0.690	0.362	0.919			
SotPrss	-0.015	0.010	0.140	-0.013	0.212	0.153	0.076	0.250	0.224	0.244	0.815		
TUpG	0.031	0.013	0.548	0.287	0.399	0.498	0.280	0.534	0.244	0.535	0.207	0.837	
Tech	0.026	0.012	0.280	0.180	0.067	0.272	0.318	0.270	0.330	0.208	0.164	0.136	0.824

Note: Bold values on the diagonal are the square root of AVE values.

Table 9–5 Descriptive Statistics and Discriminant Validity (Fornell-Larcker Criterion) for **Model 2 (2nd dataset)**

	MEAN	SD	CUI	CUB	DAnoy	EffExp	FCons	PEnj	PValu	PerExp	SotPrss	TUpG	Tech
CUI	0.663	0.055	0.814										
CUB			0.801	0.907									
DAnoy	0.003	0.029	0.209	0.182	0.945								
EffExp	0.175	0.034	0.529	0.467	0.108	0.925							
FCons	0.171	0.038	0.543	0.587	0.127	0.346	0.931						
PEnj	0.136	0.032	0.508	0.533	0.218	0.292	0.339	0.939					
PValu	0.096	0.032	0.495	0.491	0.125	0.306	0.358	0.414	0.907				
PerExp	0.064	0.031	0.383	0.383	0.168	0.258	0.263	0.239	0.213	0.954			
SotPrss	0.010	0.028	0.086	0.120	0.138	0.050	-0.004	0.141	0.094	0.057	0.891		
TUpG	0.098	0.028	0.318	0.298	0.180	0.170	0.145	0.130	0.235	0.109	0.041	0.929	
Tech	0.080	0.031	0.373	0.384	0.301	0.153	0.199	0.277	0.293	0.433	0.089	0.126	0.949

Note: Bold values on the diagonal are the square root of AVE values.