EXPERIENCE FIRST: INVESTIGATING SMART WEARABLE TECHNOLOGY ACCEPTANCE AMONG ELDERLY CITIZENS WITH Smart Wearables Technology Acceptance Model (SWTAM)

BY

CHAI WEI YANG

DISSERTATION SUBMITTED IN FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF SCIENCE IN
INFORMATION SYSTEMS

SUNWAY UNIVERSITY

MALAYSIA

2024

ORIGINAL LITERARY WORK DECLARATION

Name of Candidate : CHAI WEI YANG

IC /Passport No : 970312-38-5251

Student ID : 16080483

Name of Degree : MSc Information Systems

Title of Project Paper/Research Report/Dissertation/Thesis ("this Work"): Experience First: Investigating Smart Wearable Technology Acceptance Among Elderly Citizen in Malaysia

I do solemnly and sincerely declare that:

1. I am the sole author/writer of this Work;

2. This Work is original;

3. Any use of any work in which copyright exists was done by way of fair dealing and for permitted purposes and any excerpt or extract from, or reference to or reproduction of any copyright work has been disclosed expressly and sufficiently and the title of the Work and its authorship have been acknowledged in this Work;

4. I do not have any actual knowledge nor do I ought reasonably to know that the making of this work constitutes an infringement of any copyright work;

5. I hereby assign all and every right in the copyright to this Work to the Sunway University (SunU), who henceforth shall be owner of the copyright in this Work and that any reproduction or use in any form or by any means whatsoever is prohibited without the written consent of Sunway University having been first had and obtained;

6. I am fully aware that if in the course of making this Work I have infringed any copyright whether intentionally or otherwise, I may be subject to legal action or any other action as may be determined by Sunway University.

Candidate's Signature Date: 15/05/2024

Subscribed and solemnly declared before,

Witness's Signature Date: 15/05/2024

Name : Angela Lee Siew Hoong

Designation : Prof. Dr.

**Witness will be the supervisor*

(This form to be attached together with the final hardbound thesis)

Acknowledgement

Words cannot express my gratitude to Sunway University Scholarship for sponsoring the fund throughout my study. This endeavor would not have been possible without the generous support from Sunway University Scholarship, who financed my research. I also could not have undertaken this journey without my supervisors, Prof. Dr Angela Lee Siew Hoong, Assoc. Prof. Dr Ooi Pei Boon, and Assoc. Prof. Ir Abdul Aziz Omar, who generously provided knowledge and expertise. I am also grateful to my classmates' late-night feedback sessions, and moral support. A big thanks to the librarians, research assistants, and study participants from the university, who impacted and inspired me. Lastly, I would be remiss in not mentioning my family, especially my parents. Their belief in me has kept my spirits and motivation high during this process.

EXPERIENCE FIRST: INVESTIGATING SMART WEARABLE TECHNOLOGY ACCEPTANCE AMONG ELDERLY CITIZENS

Abstract

As the population ages, there is a greater demand for health care services and support, especially through smart wearable technology to monitor the elderly's health at the same time resolving the psychological, psychosocial, and mobility inadequacies. This study looked at the aspects that may have helped older people embrace smart wearable technologies to expedite and promote the use of smart wearable technology. After consulting the earlier related studies, a structural equation modeling-based model of smart wearables acceptance for elderly citizens will be developed. This model will include an extra construct—individual context—by including elements such as anxiety and self-efficacy. This study mainly focused on developing countries, which is Malaysia in this case, as the available studies for acceptance of smart wearable technology are still lacking in our country. The population of this study is mainly older adults with basic knowledge of Smart Wearable Technology or users of the technology. In the data collection phase, 300 datasets were collected, and 266 examples were used for model validation after data filtering in the data processing phase. The validity and reliability of the constructs in the model were assessed through the method of partial least squares. In the assumption testing, normality and common method variance were applied. For further assessment, convergent validity, discriminant validity, internal consistency reliability, and indicator reliability (outer loadings) were all used to evaluate the measuring model. Difficulties with collinearity, path coefficients, confidence intervals, and effect size (f^2) were also evaluated for the structural model's validation. The findings of this study identified a few factors that significantly impact older people's desire to employ smart wearable technology in both positive and negative ways, where external factors seem to be more having a significant effect on perceived usefulness when comparing with perceived ease of use. Furthermore, perceived values are the better factors to be explored in influencing the decisions of the elderly.

Keywords— Elderly, Healthcare, Elderly care, Smart home, Smart Wearable Technology

(252 words)

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AVE	Average Variance Extracted
BCI LL/UL	Bias Correct Interval Lower Limit / Upper Limit
BI	Behavioral Intentions
CA	Computer Anxiety
CB-SEM	Covariance-Based Structural Equation Modelling
CMV	Common Method Variance
COM	Compatibility
C-TAM-TPB	Combined TAM and TPB
DTPB	Decomposed Theory of Planned Behavior
FC	Facilitating Condition
HTMT	Heterotrait-Monotrait
IDT	Innovation Diffusion Theory
IT/IS	Information Technology / Information Systems
IU	Intention to Use
MM	The Motivational Model
MPCU	Model of PC Utilization
PBC	Perceived Behavioral Control
PC	Personal Computer
PEOU	Perceived Ease of Use
PLS	Partial Least Square

PLS-SEM	Partial least squares structural equation modelling
PR	Performance Risk
PS	Perceived Stigmatization
PU	Perceived Usefulness
SCT	Social Cognitive Theory
SDT	Self-Determination Theory
SE	Self-Efficacy
SI	Social Influence
STAM	Senior Citizens Technology Acceptance Model
SWTAM	Smart Wearable Technology Acceptance Model
TAM	Technology Acceptance Model
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor

List of Appendices

Publications

Chai Wei Yang, Angela Siew-Hoong Lee. "Using Smart Wearable Technology Acceptance Model for Health Monitoring Technology", 2022 7th International Conference on Cloud Computing and Big Data Analytics (ICCCBDA), 2022

1. CHAPTER 1: Introduction

The demand for healthcare coverage and support via smart wearable technology in health monitoring has significantly increased to address issues with the cognitive psychosocial functioning, capabilities, and mobility of the ageing population [1], [2]. Elderly people can now obtain immediate feedback on respiratory rate, mainly blood pressure and heart rate, receive instant healthcare, and send their physical condition data through wireless sensor networks to a medical center with the help of a broad range for smart wearable technology. According to McCann's [3], healthcare technologies can be used to provide continual care for elderly people. Wearable technology can be utilized at home, which can reduce the expense of physical checkups as well as the risk of being admitted to the hospital. Therefore, widespread use of intelligent wearable technologies for the elderly is essential to streamline healthcare delivery and reduce societal hardship. Adullah's study [4] demonstrated a patient monitoring system that monitors and alerts elderly patients' vital signs, allowing the physical signals to be sent to a distant clinic so that medical staff can diagnose and react as soon as feasible. Communication among elderly, caregivers and medical professionals have been enabled via telecare and e-health services, which allows them to obtain home healthcare while also saving the costs on trip expenses [5]–[7].

With the support of sensors, actuators, and smart textiles, a wearable smart technology for health evaluation can be developed. Electronic surveillance systems and wireless sensor networks are examples of technology that can help users make decisions. Applications that track location, body movement, vital signs, and fall prevention have been developed in smart wearable technologies [8]–[11]. However, the majority of developing countries' populations lack access to high-quality healthcare because of a variety of problems, including subpar clinics or hospitals, a lack of medical professionals, high costs for health screenings, etc. [12].

Smart wearable sensors that can track vital signs are now possible thanks to new wireless technologies. With the novel uses of wireless technology, the quality of care for the ageing population may be increased and the cost of care for the ageing population can be decreased [13]. According to Maglaveras's [14] assessment, there are still open problems with user acceptance and friendliness. The acceptability of smart wearable technology by the elderly in developing nations like Malaysia has not yet been adequately studied. Therefore, it is crucial to study how are the factors affecting the elderly in accepting the technology in countries like Malaysia.

There are a few factors to be studied such as human factors, external factors, and perceived values, as these are the main considerations of the elderly on accepting the smart wearable technology. The research issues and objectives will be addressed in this study by the proposal of a novel integration model. Information systems (IS) theoretical frameworks are reviewed, and the benefits and drawbacks of each theory are contrasted. The IS theory applied in this work incorporates TAM along with external inputs. The collected data will also be examined by using the partial least square (PLS) method for validity and reliability assessment of the questionnaire.

1.1 Problem Definition

For health monitoring applications, a number of research endeavors have created smart wearable technologies, including smart clothing, implanted devices, skin devices, and many other devices [15], [16]. To elaborate further, a perfect example would be tracking activity in real-time using accelerometer sensors with a wearable smart device [17], [18], as well as collecting ECG information, and detecting human falls in real-time with a wireless sensor network [19]. However, prior research has indicated that geriatric acceptability of healthcare devices is at a minimal level despite the advancement for smart wearable technology [20]–[22]. Even though Spagnolli's [23] study already examined user acceptability on three devices, the evaluation of the elderly's acceptance of smart wearables for health monitoring is still needed as the factors that affect the acceptance can range from simple to complex which helps to boost their acceptance. In order for technology to better assist the elderly, it is required for a detailed investigation in the aspect of the elderly's acceptance of smart wearables technologies by exploring the factors such as human factors, external factors, and perceived values of the elderly towards the technology. There have been only a limited number of studies on the acceptance of smart wearable technology among the elderly in Asia region, especially in Malaysia which can be shown in figure 1.1.

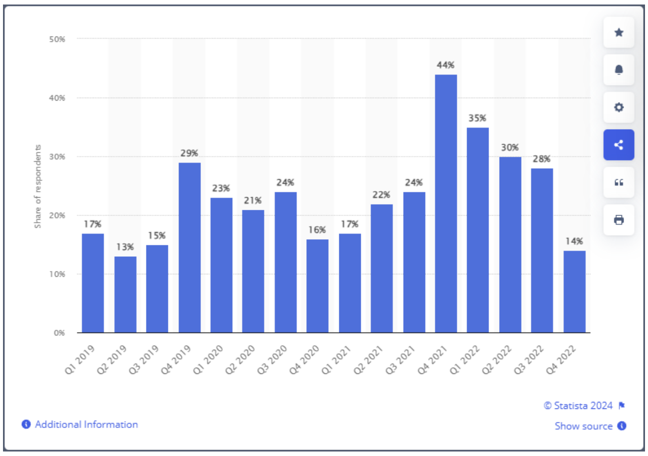


Figure 1.1 Statistics of Smart wearable technology users in Malaysia

Figure 1.1 shows the percentage of total users for smart wearable technology in Malaysia. Based on figure 1.1, the users' percentage has dropped to 14% during quarter 4 of year 2022 according to latest data collected. Figure 1.2 also shows the smart wearable technology users among all the countries in the whole world.

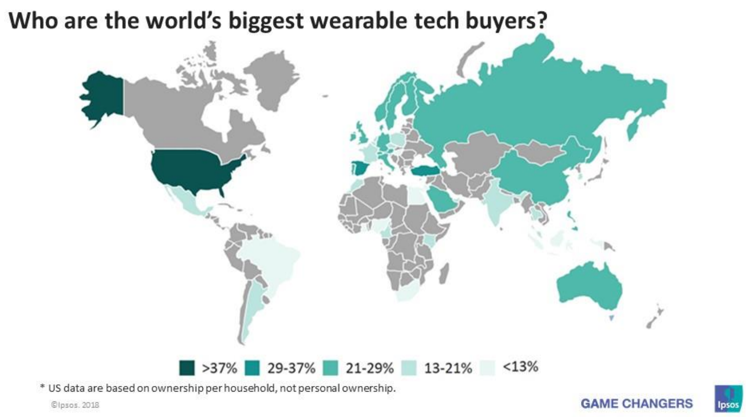


Figure 1.2 Statistics of word's biggest wearable technology buyers

Figure 1.2 demonstrates that Malaysia is the lowest tech buyers in the world with less than 13% of the population. Therefore, a study needs to be conducted in Malaysia in order to address this issue. This study aims to narrow down the gap in the literature by investigating the elements that can affect the elderly to accept smart wearable technologies and better comprehending their intentions for using them. Based on the literature reviews it has shown that many elderly citizen in Malaysia are not accepting the use of new technology moreover on wearing smart wearable. Hence this study is to focus on the constructs which are the factors that influence them on accepting the use of these technologies. The following research questions and objectives will aid to address the issue mentioned in the earlier sections:

1.2 Research Questions

1. What are external factors that could deviate the elderly's intention to use smart wearables technology?
2. What human factors that the elderly might consider before using smart wearables technology?
3. What values do the elderly perceive before using smart wearable technology?

1.3 Research Objective

1. To explore and investigate external factors that might sway the elderly's intention to embrace smart wearables.
2. To discuss the perceived values of the elderly in the usage of smart wearable technology.
3. To introduce an integrated model that combines TAM with variables taken from relevant studies.

2. CHAPTER 2: Literature Review

2.0 Information System Theories

Understanding how individuals adopt and utilize technology is a multifaceted endeavor that draws upon various theoretical frameworks in information systems. From the foundational Expectancy-Value Theory and Theory of Reasoned Action to the more nuanced Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB), each theory offers unique insights into the cognitive, affective, and social factors shaping technology adoption and usage. Additionally, models like TAM2, Decomposed Theory of Planned Behavior (DTPB), Combined TAM and TPB, and the Motivational Model delve deeper into specific dimensions such as perceived usefulness, ease of use, subjective norms, and intrinsic motivation. Innovation Diffusion Theory and the Model of PC Utilization provide contrasting perspectives by focusing on innovation characteristics, system quality, and user satisfaction. Social Cognitive Theory further enriches this landscape by considering self-efficacy, observational learning, and social influences. This introduction sets the stage for a comprehensive exploration of information system theories and their implications for understanding human-technology interactions.

2.0.1 Expectancy-Value Theory

The expectancy value theory was created to comprehend the driving forces behind people's actions. It is believed that behavioral intent is a behavior's immediate precursor. If the elements that sway the intention of an individual are better understood, the likelihood that they will engage in an action can be predicted more precisely. According to Border's [24], people act in particular ways based on the outcomes they expect along with the associated values. Expectancy was defined by Mazis' [25] as the assessment of the possibility that a specific behavior will be associated with or result in either favorable or unfavorable outcomes. The extent of the value and expectation associated with the result can both be used to gauge the tendency to act [25]. Geiger and Cooper (1996) used a simple experiment to show that college students who valued higher marks were more inclined to work harder in class.

2.0.2 Theory of Reasoned Action

The social psychology literature contains references to the theory of reasoned action (TRA). It enhances the Expectancy Value Theory's ability to be both predictive and explanatory. The TRA can be used to describe the factors that influence intentionally planned behaviors [26], [27]. The performance of a certain behavior is predicated on a person's behavioral intention (BI), based on a general model which is TRA [28]. According to Eveland (1986), technology transfer is ultimately a reaction to what an individual believes because what they do is based on their feelings, beliefs, and interests.

Figure 2.1 illustrates how TRA how the TRA presumes that a person's beliefs and assessments influence their attitude (A) on a conduct, which sequentially influences their behavioral intention (BI). Normative motivation and beliefs, which likewise have an impact on BI, can have an impact on subjective norm (SN). The subjective norm can be described as a factor that affects people's decisions about whether or not to accept something. The model defines beliefs an individual's subjective likelihood in engaging the target behavior will have an impact [29]. The individual's attitude (A) toward the targeted behavior and the subjective norm (SN) both have an impact on behavioral

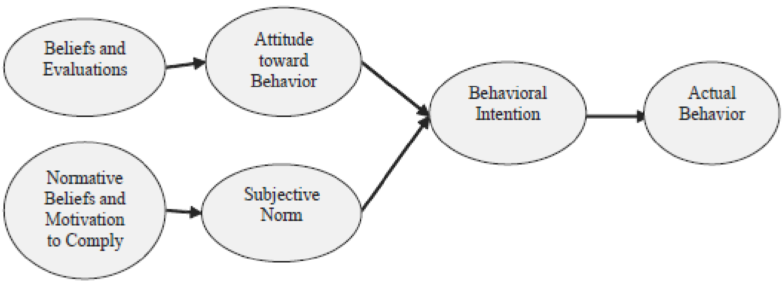


Figure 2.1: Theory of Reasoned Action

intention [29]. An individual's salient beliefs about the consequences of their behavior multiplied by their assessment of those consequences, is the constitution of their attitude toward behavior. The subjective norm (SN), which are perceived expectations of an individual or group in particular, and the motivation of users to accept these expectations, can be determined by the user's normative beliefs.

2.0.3 Technology Acceptance Model (TAM)

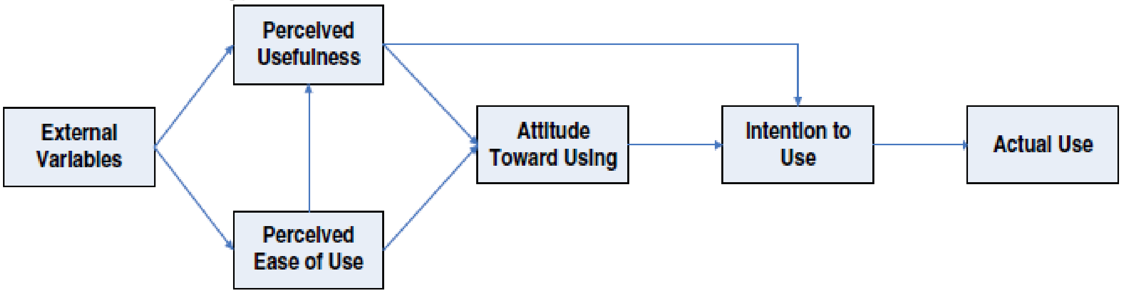


Figure 2.2: Technology Acceptance Model

A very well-known theory for examining the variables and perceptions that affect people's attitudes toward new technology is the Technology Acceptance Model (TAM). In order to model information system user acceptance, Davis developed TAM in 1986. The model’s main objective is to increase IT acceptance by encouraging people to use it. Acceptance promotion will only be successful if the factors that drive it are understood, which can be accomplished by investigating consumers' perceptions of technology use [29], [30]. TAM is a more advanced version of the Theory of Reasoned Action (TRA), a human behavior prediction model [31].

TAM is involved in the factors identification process in which may affect whether a new technology is accepted, such as user behavioral intentions. The model states that when a new technology is presented to the users, there are a wide range of variables that will affect their choice on why and how to use it. Perceived ease of use (PEOU) and perceived usefulness (PU) are 2 of the most crucial characteristics in interpreting those factors that affect the approval of the users towards a new introduced technology, according to Davis' [28]. TAM states that the attitude of a person in using a system affects their behavioral intention. Figure 2.2 illustrates that PU has a direct impact on the behavioral intention.

TAM as a framework has been the subject of extensive research, with TAM2 and TAM3 being the new models that have emerged as a result. TAM3 is fixated on interventions that may have an impact on the acceptance and approval of new information systems in healthcare organizations, as opposed to TAM2, which focuses on factors associated with PU and moderating variables. These studies utilized TAM to look into the choices made by physicians in regard to the patient's acceptance of telemedicine technology. The data of 421 respondents from 1728 distributed questionnaires was analyzed with selected physicians from Hong Kong's public tertiary hospitals. The finding was that PU is a crucial predictor and PEOU is not a significant predictor of intention and attitude [32]. Another study was carried out to provide a thorough analysis of the works on TAM in the context of healthcare IT, with the goal of determining the suitability of TAM as a theory for use and acceptance of health IT and to recommend methods to improve its efficiency through modification. According to this study, TAM accurately predicted a significant percentage of the acceptance or use of health IT, but the prediction still can be better by improving the theory. The study suggested that TAM is an effective theory for describing how healthcare providers react to health IT. It also showed a strong correlation between actual live usage, PU of health IT, and intention to use. As a result, the promotion of user acceptance towards health IT is heavily reliant on their perceived usefulness towards the technology [30].

2.0.4 TAM2

Venkatesh’s [33] proposed and tested a TAM extension that explained users' goals and perceived utility with the influence in society and cognitive instrumental processes. Experiments conducted ten years after TAM's demonstrated that the model could account for 40% of variations in intentions and behaviors. As shown in Figure 2.3, TAM2 was

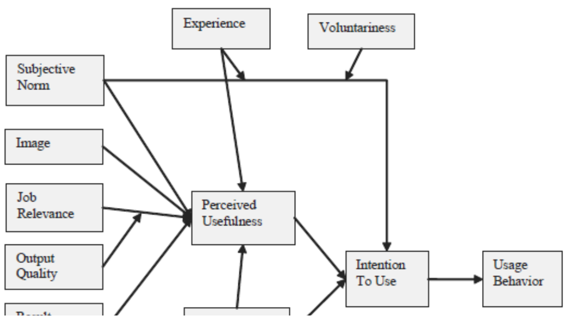


Figure 2.3: TAM2 – extended version of the Technology Acceptance Model (TAM)

created for the model’s explanatory power to be increased with the seven new additional variables in the model. The PU is directly influenced by five out of the seven additional variables. TAM2 considers these 3 under social effects: voluntariness, subjective norm, and image, while these 4 under cognitive instrumental: job relevance, the quality of output, demonstrability of results, and PEOU. 60% of the variation in the factors influencing users' intentions is explained by the expanded model. Despite being less cost effective, the extended model seemed to be more effective than the original TAM.

2.0.5 Theory of Planned Behavior (TPB)

TPB [34] is an extended version of TRA [26] as shown in figure 2.4. TPB addresses situations in which behavior is not completely under the user’s control. An additional variable, perceived behavioral control (PBC), was introduced in the TPB. According to figure 2.4, the 3 constructs: attitude, subjective norm, and perceived behavioral control, are the weighted function to identify behavioral intention. The weighted function of PBC and intention is the actual use, which is behavior (B). The expectancy-value model can be used to determine the relationships between beliefs.

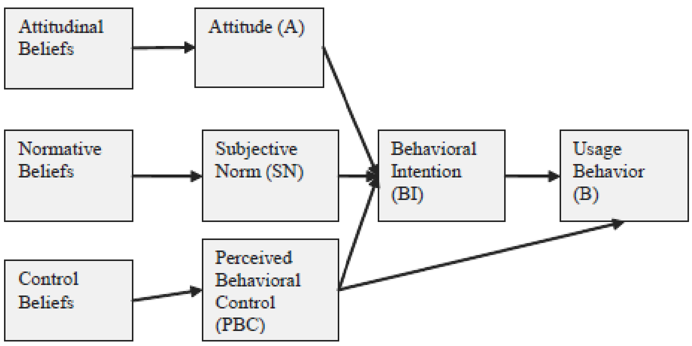


Figure 2.4: Theory of Planned Behavior

2.0.6 Decomposed Theory of Planned Behavior (DTPB)

Figure 2.5 shows the DTPB theory extends the TPB theory by interpreting attitude constructs which derived from these 3 variables: PEOU, PU, and compatibility. The influence of peers and superiors is one of the two constructs that made up the subjective norm. While these 3 variables can each have an impact on perceived behavioral control: facilitating conditions on technology and resource, as well as self-efficacy.

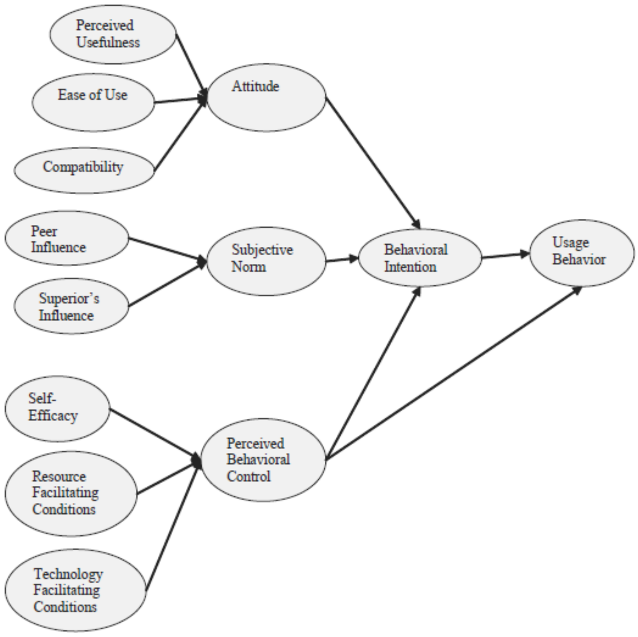


Figure 2.5: Decomposed Theory of Planned Behaviour

2.0.7 Combined TAM and TPB (C-TAM-TPB)

To enhance the application of TPB in technology acceptance, Taylor and Todd made a combination of TAM and TPB, which were created from the information technology sector and social psychology sector respectively in 1995. A hybrid model is created with the combination of TPB predictors with TAM's perceived usefulness [35]. The TAM and TPB theories' core belief is that behavior is affected by one's desire to carry it out. One's attitude toward behavior can reveal one's intent. TAM constructs do not fully explain the particular influences of usage context and technological factors on user acceptance [36]. According to Davis (1989), future studies on the acceptance of technology must explain how other factors influence its usability, usefulness, and acceptance.

Taylor and Todd proposed that PEOU has a positive impact on PU, while both PEOU and PU positively affect attitudes of the users. Therefore, attitudes, perceived behavior control, and subjective norms all have a favorable impact on behaviors of the users.

2.0.8 Model of PC Utilization (MPCU)

Triandis' [37] created a framework that helps in defining how the behavior occurred and what variables influenced the usage of a personal computer (PC) based on the individual's behavior. Based on his explanation of the framework, the individual interprets behavior has objective implications. The individual felt reinforced as a result of these interpretations. The perceived assumptions that the behavior would have certain consequences as well as the perceived value of these consequences were both altered by this reinforcement, which had an impact on the behavior's perceived consequences in two different ways. Other determinants, such as facilitating conditions, relevant arousals, social factors, and habit, were influencing the behavior's intention.

Later, Thompson's [38] adopted and modified Triandis' model for information systems and applied it for PC usage prediction. Due to its features, the model could be used to predict people's willingness to use information systems. They discovered that an individual's feelings about using computers, habits, social norms, expected aftereffects, and conditions enabled can all influence PC usage. They suggested that social factors directly affect behavior, which include effect, facilitating conditions, and perceived consequences. The model excludes usage intent because the research focuses on actual PC usage rather than predictive usage. The model includes complexity and job fit to describe the perceived consequences component. This model made the assumption that users, such as managers or professionals who regularly use computers for work purposes, have the necessary computer-related experience. They suggested that PC use is influenced by experience, in the aspect of moderately, directly and indirectly.

2.0.9 Innovation Diffusion Theory (IDT)

According to Tornatzky’s [39], Rogers developed IDT in 1962 happens to be one of the oldest theories in social science to research all types of innovation. This theory arose from a few diffusion studies conducted in the 1950s that focused on differences in innovativeness among individuals. The 4 main variables that affect behavior, according to Rogers (2003), are channels, societal factors, time, communication, and innovation. The following are his definitions of terms related to innovation, communication, and diffusion:

- Innovation: A person's perception of an idea, object, or practice.
- Communication: The process of gathering information and disseminating it to achieve mutual understanding.
- Diffusion: Members of a social system learn about the process of innovation over time through a variety of channels.

Rogers also stated that there are 5 qualities in innovation that influence people's behaviors, as well as explaining the innovation acceptance rate, including compatibility, complexity, relative advantage, observability, and trialability [40].

Fichman (1992) discussed how IDT can be used to do research on technology acceptance, implementation, and evaluation. Both qualitative and quantitative studies on technology diffusion can be evaluated with IDT. The quality of services aids in assessing the system's level of qualitative advantage accuracy [41]. Moore and Benbasat (1991) completed the IDT extension work in Information Technology. They improved a set of constructs for the study of individual technology acceptance, and also modified IDT's five attributes of innovation [42]. This work contributes to the diffusion of technology within organizations as well as the initial acceptance of IT for individuals within an organization. Voluntary use and images were added to Rogers' model's constructs. As an outcome, variables such as compatibility, complexity (ease of use), and relative advantage (perceived usefulness) appeared to have the most impact in determining the decisions of usage, whereas image, demonstrability result, trialability, and visibility only had little influence on individual usage decisions.

2.0.10 The Motivational Model (MM)

Countless theories have emerged in the field of motivation research since the 1940s, including the Self-Determination Theory (SDT) by Deci and Ryan's (1985). According to SDT, one of the human qualities which is self-determination is associated with making choices, and having choices, the experience of choice [43]. As mentioned by Deci, Pelletier, Ryan, and Vallerand (1991), when the behavior is self-determined, the process of regulation becomes a choice. However, it can be defiance or compliance in some cases when the behavior is constrained.

Several studies have examined and adapted the SDT theory to contribute to the information technology field. Bagozzi's [44] motivational theory was test to understand the usage and acceptance of a new technology [45]. Intrinsic and extrinsic motivation for using technology in the workplace were put to the test by Davis [46], who found that they were significant factors in a person's intention to use technology. According to their definitions, perceived enjoyment from using technology falls under the category of intrinsic motivation, whereas perceived utility from using technology falls under extrinsic motivation. A connection between enjoyment and utility was discovered in their study. It follows that the enjoyability of an information system tends to increase the acceptance of useful systems while having less of an impact on the acceptance of useless systems when people perceive information systems to be more useful [46].

2.0.11 Social Cognitive Theory (SCT)

In 1941, Social Learning Theory (SLT) was developed by Miller and Dollard with the goal of incorporating the model into the principles of learning. There were a lot of researchers that have worked on developing the SLT over the years. The one who made the most contributions was Bandura. From his ongoing research that began in the 1960s, Bandura created SCT in 1986 by expanding SLT to create one of the most effective theories in studying human behavior [47]. Social influence and its effects on both internal and external social reinforcement are the main features of SCT. SCT also takes into account the people's prior experiences. Regardless of whether the person engages in a particular behavior or not, these prior experiences have an impact on expectations, reinforcements, as well as the motivations behind the behavior. SCT presumes that prior experiences influence how people anticipate outcomes when particular behaviors are carried out.

The SCT was modified by Compeau’s [48] research with his contribution. The improved version suggested making SCT more pertinent to research on the environment in which computers are used. They added information technology acceptance and use to the model for gauging self-efficacy and its influence on behavior. The usage factor is a dependent variable in the model that allows for individual prediction. They suggested that the three distinct, but interconnected dimensions of self-efficacy are strength, magnitude, and generalizability. They claimed self-efficacy, emotional reactions to computers, and outcome expectations as three major constructs of computer usage behavior [48], [49]. Personal outcome expectations, performance outcome expectations, and affective responses to computers were defined as outcome expectations, respectively [50].

2.1 The advantages and disadvantages of reviewed theories

IS Theory	Advantages	Disadvantages	References
TRA	1. One of the theories which is basic and able to interpretate human behavior. 2. Can virtually explain any behavior.	1. Too broad and precise. 2. Does not make reference to other constructs that influence behavior intention, such as mood, fear, threat, or prior experience.	[26] [27] [51]
TPB	1. Used to grasp how people use and accept a variety of technologies.	1. Indicates that the actions may have been planned. 2. Does not make reference to other factors that influence behavior intention.	[27] [52] [34] [53]
DTPB	1. Expanded with some factors included from IDT model. 2. The model is more applicable to management level in terms of influencing usage and acceptance with the expanded version.	1. Very similar to TPB. 2. Disassembles the TPB constructs while maintaining the idea that the behaviors are preplanned.	[27] [52] [53] [54] [55] [56]
TAM	1. Effective technology application model. 2. Replaced the TRA's attitude toward behavior with PEOU and PU. 3. Less all-encompassing than TPB and TRA. 4. Offers feedback-based PEOU and PU.	1. The structure does not include TRA's subjective norms. 2. Does not offer feedback on constructs such as integration, information completeness, flexibility, and information currency that might improve acceptance. 3. Does not explain how expectations affect behavior.	[57] [28] [53] [54] [58] [33]

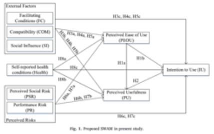
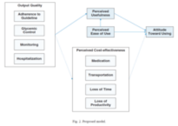
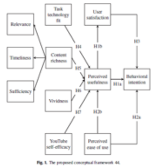
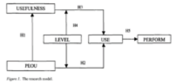
TAM2	1. The descriptions of cognitive instrumental processes and social influence can be used for the interpretation of PEOU and PU. 2. Has an additional construct of subjective norm. 3. Describes how technology is evolving.	1. Does not specify how expectancy influences behavior. 2. Incapable of user behavior prediction within a culture.	[28] [33] [59]
C-TAM-TPB	1. Combination of the TPB and TAM models from social psychology and information technology respectively. 2. Better application compared to TPB in technology embracement.	1. The specific usage-context influences that might alter user acceptance are not entirely captured by TAM's constructs. 2. Does not consider the behavior planning factor. 3. Ignores any usage-related threat or apprehension.	[27] [28] [53] [60]
MPCU	1. Appropriate for individual acceptance and utilize prediction on information technology. 2. Effective in comprehending and describing computer usage behavior and acceptance with the voluntariness factor.	1. The use of computers and technology is a complexity factor. 2. Affects the perceived short-term consequences indirectly.	[37] [28] [38]
IDT	1. Able to research all forms of innovation. 2. Justifies the choice to innovate. 3. Makes use of innovation-related variables to forecast acceptance rates.	1. Too broad in scope. 2. Does not explain how factors such as attitude or innovation influence decisions. 3. Does not take into account the resources or social support available to a person when deciding whether to adopt a new behavior.	[39] [40] [61] [60]

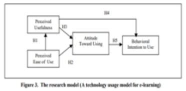
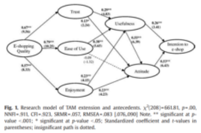
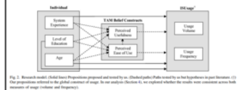
MM	1. Has numerous applications in the fields of learning, healthcare, and motivational studies. 2. Used to understand how new technology is adopted and used.	1. Utilizing this model is not effective for technology usage and acceptance. 2. Requires to adopt many factors to be more suitable for technology usage study.	[43] [46] [62] [63]
SCT	1. One of the most theories that is convincing in studying the behavior of human, especially when looking at how people learn.	1. Particularly in the study of the connections between the environment, behavior, and individual, the model is poorly organized. 2. Instead of focusing on acceptance or motivation, it emphasizes the learning process. 3. The model is not concern about previous experiences and expectations.	[64] [48] [65] [66] [55] [63]

2.2 Smart Wearable Technologies

In earlier studies, wearable technologies were not clearly defined. However, a number of related terms, including wearable electronics, wearable computers, and wearable devices, had very similar definitions. The definitions of the terms have all come to the conclusion that they all have the same meaning and can be used interchangeably except for wearable computers, despite the fact that several terminologies have been defined. Wearable computers are a subset of wearable technology that can perform and enable complex computations [67], according to Dunne's [68], even though there is some debate regarding the distinction between wearable technology and wearable computers. A framework computing device that is capable of data collection and processing is one of the most comprehensive for the wearable technology's definition. This item is either an attachment or wearable body accessory. The gadget, which would enable meaningful interaction with customers, could be standalone or attached to a smartphone. According to Kurwa's [69], wearable technology can be integrated into the body (such as a sensor attached to the heart or embedded in the skin that monitors cardiac irregularities), worn on the body (such as a headband or wristwatch), or attached to the body (such as a smart patch).

2.2.1 Related studies review

Author and Year	Junde Li*, Qi Ma, Alan HS. Chan, S.S. Man (2019)	R. Fensli, P. E. Pedersen, T. Gundersen, O. Hejlesen (2008)	Abd Rahman Ahlan, Barroon Isma'eel Ahmad* (2014)	Doo Young Lee, Mark R. Lehto (2012)	Subhasish Dasgupta, Mary Granger and Nina Macgarry (2002)
Title of the paper	Health monitoring through wearable technologies for older adults: Smart wearables acceptance model	Sensor Acceptance Model – Measuring Patient Acceptance of Wearable Sensors	User Acceptance of Health Information Technology (HIT) in Developing Countries: A Conceptual Model	User acceptance of YouTube for procedural learning: An extension of the Technology Acceptance Model	User acceptance of e-collaboration technology: An extension of the technology acceptance model
Construct					
Unique construct	Self-reported health conditions	Pretrial Expectations, Patient Characteristics, Physical Component, Mental Component Summary, Sensor Acceptance Index	Output Quality, Perceived Cost-effectiveness	User satisfaction, Task-Technology Fit, Content richness, Vividness, YouTube self-efficacy	Level, Individual Performance
Based model	TAM	TAM	TAM	TAM	TAM
Theories	TAM, UTAUT	TAM, UTAUT	TAM	TAM	TAM
Target Construct/Variables	Perceived ease of use, perceived usefulness, and intention to use.	Sensor Acceptance Index	Perceived Usefulness, Perceived Ease of Use, Attitude Towards Using	Perceived Usefulness, User Satisfaction, Behavioral Intention	Perceived Usefulness, Perceived Ease of Use, Individual Performance

Author and Year	Ronnie Cheung, Doug Vogel (2013)	Maslin Masrom (2007)	Vassilios P. Aggelidis, Prodromos D. Chatzoglou (2009)	Sejin Ha, Leslie Stoel (2008)	Andrew Burton-Jones, Geoffrey S. Hubona (2006)
Title of the paper	Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for e-learning	Technology Acceptance Model and E-learning	Using a modified technology acceptance model in hospitals	Consumer e-shopping acceptance: Antecedents in a technology acceptance model	The mediation of external variables in the technology acceptance model
Construct					
Unique construct	-	-	Computer Anxiety, Computer Self-efficacy	-	Computer Anxiety, Computer Self-efficacy
Based model	TAM	TAM	UTAUT	TAM	TAM
Theories	TAM	TRA, TAM	TAM, TRA	TRA, TAM	TAM, TRA
Target Construct / Variables	Perceived Usefulness, Attitude, Behavioral Intention, System Usage	Perceived Usefulness, Attitude Towards Using, Behavioral Intention to Use	Perceived Usefulness, Ease of Use, Attitude Towards Behavior, Self-efficacy, Anxiety	Trust, Ease of Use, Enjoyment, Usefulness, Attitude, Intention to e-shop	Perceived Usefulness, Perceived Ease of Use, Usage Volume, Usage Frequency

2.3 Research model and Constructs

Venkatesh [63]'s unified theory of acceptance and use of technology (UTAUT), and TAM by Davis [29], have extensively been used to research and comprehend acceptance behaviors for both people and organizations. While UTAUT can combine several earlier models and theories and identify 4 determinants: facilitating conditions, social influence, effort expectancy, and performance expectancy, TAM can also confirm the determinants of PEOU and PU. It was discovered that UTAUT has a higher percentage of intentions explained than the previous ones in the context of the organization. The TAM for seniors citizens was developed in Chen's [70] to create the technology acceptance model for seniors citizens (STAM) for the investigation of the four domains for gerontechnology acceptance, which include communication, housing, education and recreation technologies, and health. However, their research did not include smart wearable technologies in the measurement items of the health technology domain, resulting in a lack of tailored factors in the study area of smart wearable acceptance. Factors such as attitude toward using STAM were discovered to have no major impact on usage behavior, so they were excluded from this study. According to the results of the current study, factors such as health status, social influence, and compatibility can help predict whether elderly people will accept smart wearable technology. The following sections discuss the potential variables that impact the smart wearable technology's acceptance.

2.3.1 Perceived ease of use, Perceived usefulness, and Intention to use

PU is examined in various ways by numerous psychometric models and has been demonstrated to be a significant predictor of behavioral intention [29], [71], claimed by Aggelidis et al. [72]. It also has a strong correlation with various usage dimensions. PEOU is the second most significant factor in determining user behavior after PU [29]. However, some researchers discovered that only PU has an effect on intention in using a technology but PEOU does not [63].

In the healthcare industry, perceived usefulness is presumed to be a factor in determining physician behavior and may have an indirect or direct impact on behavior intention. The ease of use and attitude or behavioral intention, however, don't seem to be significantly related [73]. Other articles that support this claim include those by Chismar and Wiley-Patton [74], Hu et al. [32], and Jayasuriya [75]. Despite these results, Aggelidis et al. [72] came to the conclusion that effort expectancy should be incorporated into the research model in order to reduce variance from UTAUT and because additional empirical research is required to confirm the importance of effort expectancy on acceptance decisions.

In earlier technology acceptance models, PEOU and PU were frequently employed in predicting the behaviors of technology acceptance and were proved to have a significant impact on the behavior of the users' intention [76]–[79]. Pertaining to the present study, the self-efficacy of users toward wearable monitoring technologies can be reflected by PEOU, whereas the values and benefits of such technology's usage can be evaluated by PU. Besides that, older health information technology's intrinsic motivation can be directly reflected through intention to use (IU) [70], [80], [81].

2.3.2 Facilitating Conditions

Four different constructs, such as facilitating conditions (MPCU [38]), compatibility (IDT [61]), perceived behavioral control (TPB/DTPB, C-TAM-TPB [34]), facilitating conditions (UTAUT [63]), are represented by the concept of facilitating conditions. Each of these components is outlined to organizational and/or technological constructs that aim to lower the usage barriers.

The facilitating conditions, according to Taylor and Todd [35], were made up of two parts: resource and technological facilitating conditions. Examination of those two facilitating conditions revealed beneficial correlations with successfully implementing computerized systems in studies such as Taylor and Todd's [54]. However, the facilitating conditions of the organizational aspect were found to have little effect on the prediction of behavioral intentions according to an empirical study of UTAUT. The actual use of technology and organizational facilitating conditions, on the other hand, were discovered to have a statistically significant relationship [63]. The literature on health informatics [82], information systems [38], [63], and some telemedicine studies [83] all contain references to research on organizational facilitating conditions.

2.3.3 Compatibility

Some studies have combined IDT with the view of TAM to address the compatibility construct for explaining user acceptance, as such integration may provide a stronger model over a stand-alone model [79], [84]–[88].

It was discovered that compatibility directly affected PU and usage intention [84]–[86]. Wu et al. [88] demonstrated that professionals in healthcare industry would perceive mobile healthcare systems (MHS) as useful to them, have a preference on a more user-friendly interface, and increase their intention to use MHS if the MHS were compatible with the practices of their healthcare. Additionally, it was found that older online users were more likely to value benefits such as the usefulness of video user-created content (UCC) when they believed it to be complementary to their current standard of living and usage [79]. They would also favor a video UCC that allows them to continue with their current behaviors without interference. It has also been demonstrated that if ageing women perceived Infohealth (an application for mobile phone) to be compatible with their current habit of usage, their intention to use Infohealth would increase if the application is simple and easy to use [87].

2.3.4 Social Influence

Social influence has an impact on decision-making and human behavior significantly [34], [54]. The effects of social influence on the decision to accept technology were investigated in a number of studies on technology acceptance, but the findings were conflicting. Davis's [29] and Mathieson's [89] revealed a tenuous relationship between subjective norms and other variables. On the contrary, Moore's [61], Taylor's [35] and Thompson's [38] identified a significant relationship. Taylor's [54] discovered that subjective norms are better in predicting the user intention in inexperienced subjects. Moreover, the discovery in Venkatesh's [33] was that subject norms had a significant impact on intention under imperative circumstances, and that it depleted over time.

However, as shown in studies of technology acceptance, the results of research in the health sector do not support the idea that social influence directly affects behavior intention. To be more precise, social influence appears to be significant in physicians' decisions to use telemedicine [73], [83] and Internet-based health application [74].

2.3.5 Perceived Stigmatization and Performance Risk

The use of smart wearable technology by the elderly carries a number of potential risks, including perceived stigmatization (PS) and performance risk (PR) [10], [11]. PS stands for the degree to which people's perceive social risk and shame when they monitor their health with smart wearable technology [90]. PS could be a significant obstacle for some of the users who want to hide their devices to avoid being seen for wearing it [91].

Since older adults do not generally accept smart wearable health monitoring systems, such systems may present unforeseen risks. The degree to which users are persuaded that the technology may pose unanticipated risks, such as privacy violations, functionality risks, and safety risks, is referred to as PR [92]. While using smart wearable systems, PR particularly involves electric shock, invasion, or radiation. With electronic circuits built into wearable devices, the system can conduct minimally invasive diagnostic tests, such as monitoring the glucose level [93]. However, these electronic circuits could pose a safety risk when worn by elderly people.

2.3.6 Anxiety and Self-efficacy

Computer anxiety (CA) and self-efficacy (SE) are both affective reactions to using IT, which have been extensively researched. Computer anxiety has been hypothesized and proven to play a significant role in shaping users' intentions and behavior as well as cognitive reactions. On the other hand, it has been discovered that people's expectations for the results of using computers, as well as their ultimate decision to use them, are significantly influenced by their level of computer self-efficacy.

In accordance with Bandura's self-efficacy theory, people who attempt to perform behaviors for which they lack competence experience anxiety, and their beliefs in their own abilities are boosted by a decrease in anxiety [94]. As opposed to those with lower self-efficacy, those with higher self-efficacy are more likely to experience a positive effect. A number of IS studies have empirically supported this two-way relationship [95], [96].

Computer anxiety has been shown to play a significant role in influencing computer self-efficacy [96], as well as in determining users' actual and intended behavior [49], [95]. The affective factors such as anxiety and affect, as well as other cognitive concepts including PU [49] and PEOU [33]. Studies have also shown how computer self-efficacy affects how useful and simple something is perceived to be [95].

2.4 Summary of IS theories, constructs and proposed model

Information system theories, encompassing Expectancy-Value Theory, Theory of Reasoned Action, Technology Acceptance Model (TAM), TAM2, Theory of Planned Behavior (TPB), Decomposed Theory of Planned Behavior (DTPB), Combined TAM and TPB, Model of PC Utilization, Innovation Diffusion Theory, The Motivational Model, and Social Cognitive Theory, collectively delve into the complexities of technology adoption and usage. While TAM and TAM2 focus on perceived usefulness and ease of use, TPB and DTPB delve deeper into attitudes, subjective norms, and perceived behavioral control. The Combined TAM and TPB model integrate these aspects, highlighting the interplay between utility, ease of use, attitudes, norms, and control. On the other hand, Innovation Diffusion Theory emphasizes the characteristics of innovation itself and its diffusion through social systems, contrasting with models like the Model of PC Utilization that stress system and information quality. The Motivational Model and Social Cognitive Theory bring attention to intrinsic motivations, enjoyment, self-efficacy, and observational learning, adding a psychological dimension to technology adoption theories. These comparisons underscore the multidimensional nature of understanding technology adoption, incorporating cognitive, affective, social, and environmental factors to provide a comprehensive framework for analysis.

After studying and comparing the IS theories, we have come to a decision on using TAM as our base model for the study of the user acceptance in smart wearable technologies among elderly people. The reason being is TAM studies are more focused on the behavioral of human beings while other theories study more on the psychology of human being. This study demonstrates the need to study the behavior of the elderly user in accepting these smart wearable technologies.

The related article constructs have also been studied in order to propose a new integrated model to address the research questions and objectives. Li's [97] will be used as a guide because it addresses key factors that influence users' intentions to use smart wearable technologies. Only external factors such as facilitating conditions, social influence, and compatibility, as well as perceived risks from the model, will be considered in our proposed model because these two factors have been studied as factors in using smart wearable technologies in previous studies. As anxiety and self-efficacy were mentioned multiple times in previous studies, self-reported health condition will be replaced with individual context. The difference between Li’s [98] model and our proposed model is we will remove self-reported condition and replace with individual context. The main reason is to look into the individual constructs that may have influenced elderly people's acceptance of health monitoring via smart wearable technologies.

Anxiety is a study of people's anxiety about using smart wearable technologies and the constructs can be found in Fensli’s and Aggelidis article [72], [99]. In these studies, they investigated the computer anxiety that people experience when attempting to use the technologies proposed in their studies and discovered that computer anxiety is an important factor in intention to use, as discussed in their analysis results.

The study of self-efficacy is the individual's belief in his or her ability to perform specific performance attainments. In this case, we will look into what aspects of self-efficacy may influence elderly people to monitor their health by using smart wearable.

2.5 CONCEPTUAL FRAMEWORK AND HYPOTHESES

TAM is used as the main conceptual framework then integrated into the proposed model for this study to explain the acceptance of the elderly on smart wearable. With the external factors linking to these 3 major constructs: PEOU, PU, and actual usage (AU), the TAM model is able to predict the intention to use (IU). Apart from AU, these 3 constructs including PEOU, PU, and IU will be incorporated in the proposed model. We excluded AU because we will not be evaluating the technology with our subjects using the actual smart wearable technologies.

Individual context is included in our proposed model to help comprehend the elderly's willingness in using smart wearable technology because there are few studies in the healthcare industry included this component in their proposed model. This section explains the constructions that will be included in the proposed model, as well as the hypotheses for each construct, in order to better understand the constructs that may influence the intention of elderly people to use smart wearable technology.

Figure 2.6 depicts the model we suggested in this study to describe how old people embrace smart wearables technology, by incorporating individual context into TAM along with some other external variables.

2.6 External Factors

2.6.1 Facilitating Conditions

According to Venkatesh's [63], facilitating conditions (FC) refers to the degree to which an individual is encouraged to use information technologies by the availability of technical infrastructure and a favorable environment. Ma's [100] claims that lack of access to information technology is a factor that influences older folks' acceptance of smartphones. Furthermore, Pan's [80] came to the conclusion that the availability and cost of technological help for older persons should be included in the FC.

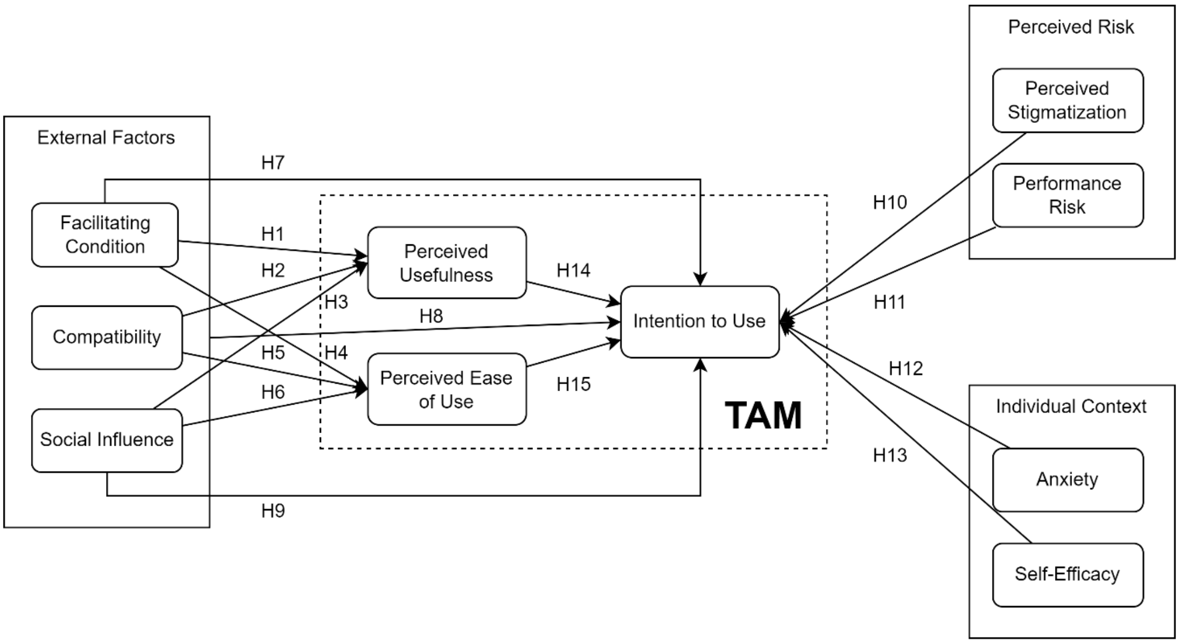


Figure 2.6: Smart Wearables Technology Acceptance Model (SWTAM)

The FC may appear to be more important for IU prediction given that smart wearable devices rely on wireless networks from network operators and the community to broadcast health monitoring data widely. As a result, the following are the FC-related hypotheses in the Smart Wearables Technology Acceptance Model:

H1. Facilitating conditions has positive impacts on perceived usefulness explicitly.

H4. Facilitating conditions has positive impacts on perceived ease of use explicitly.

H7. Facilitating conditions has positive impacts on the intention to use explicitly.

2.6.2 Compatibility

Compatibility (COM) refers to how well is the integration between a technology and the other current devices' technical functionality (e.g. smartphones, tablets, etc.), as well as the demands and everyday habits of the users [76], [101]. Compatibility has been shown to have a substantial impact on the desire to use Web 2.0 services and mobile learning [102], [103].

The degree to which the monitored data may be transmitted to remote devices for smart wearable technologies is measured by technical compatibility with already-existing devices such as PCs, wireless sensor networks, and cellphones. Additionally, it is believed that a technology's compatibility with the users' lifestyles has a significant influence on acceptance behavior. The following are the compatibility hypotheses as a result:

H2. Compatibility has positive impacts on perceived usefulness explicitly.
H5. Compatibility has positive impacts on perceived ease of use explicitly.
H8. Compatibility has positive impacts on the intention to use explicitly.

2.6.3 Social Influence

Social influence (SI) is the extent to which significant peers or family members support a participant's acceptance of a technology [38], [63], [81]. When important people, such as friends and family members, have an impact on an individual's behavior, opinions, and feelings, this is known as social influence. Social impact was found to be a powerful antecedent for Internet usage intention as well as perceived utility of users for health information technology in prior studies [70], [80], [81]. Social influence examines the effects of key peers and family members, as well as commercial marketing, on wearable health monitoring devices. As a result, these are the following hypotheses about social influence:

H3. Social influence has positive impacts on perceived usefulness explicitly.
H6. Social influence has positive impacts on perceived ease of use explicitly.
H9. Social influence has positive impacts on intention to use explicitly.

2.7 Human Factors

2.7.1a Perceived stigmatization

PS (perceived stigmatization) which begins with societal beliefs, is known as the fear of imposed stigma or discrimination [104]. Patients who are stigmatized will refuse to seek services, social engagement, or even employment chances [105], [106]. The following is the hypothesis about perceived stigmatization:

H10. Perceived stigmatization has negative impacts on intention to use explicitly.

2.7.1b Performance risk

Perceived performance risk refers to the risk associated with a product or service's ability to deliver benefits to the users [107]. The concern of loss that may occur when a supplier, brand, or product does not perform as planned is known as performance risk (PR) [108]. As a result, perceived stigmatization and performance risk are thought to be possible drivers of older persons' intention to use. The following is the hypothesis about performance risk:

H11. Performance risk has negative impacts on intention to use explicitly.

2.7.2 Anxiety and Self-efficacy

Computer anxiety (CA) is the term used to describe people's anxiety or even fear when faced with the prospect of using a computer [49]. While the definition of computer self-efficacy (CSE) is a person's assessment of their ability to use computers to complete a task [49]. Given that health institution workers differ from other users in terms of their perspectives of technology use, the following two-way relationship is tested in this study, as illustrated in figure 2.6:

H12. Computer anxiety has negative impacts on intention to use explicitly.
H13. Self-efficacy has positive impacts on intention to use explicitly.

2.8 Values perceived by the users

2.8.1 Perceived usefulness and perceived ease of use

PU is the extent to which a person thinks that using a particular application system would help him or her enhance their performance while working within the structure of an organization [29]. PEOU is the idea that using computers will enable one to complete their tasks with the least amount of effort possible [29]. A person's willingness to use smart wearable technology is also evaluated by their intention to use. These findings lead to the development of the following hypotheses regarding PU, PEOU, and IU:

H14. Perceived usefulness has positive impacts on intention to use explicitly.

H15. Perceived ease of use has positive impacts on intention to use explicitly.

3. CHAPTER 3: RESEARCH METHODOLOGY

In order to examine the proposed conceptual model and its hypothesis, this chapter discusses the methodological approach used to gather data and analyze the data. The subsections below highlight specific information about research design, population and sampling, instrument development, data collection, and the data analysis method.

3.1 Research Design

Research design can be considered as the framework of the whole study [109]. It serves as a foundation that holds all of the constructs in a research project together. Hence, it is crucial to determine the delivery of the study and achieve balance in the whole research duration and its budget. This study uses a quantitative approach and a cross-sectional design survey.

3.1.1 Quantitative Approach

In quantitative research, the data are quantified by using statistics or numbers, allowing us to numerically describe phenomena. Quantitative methods also support the use of hypothesis testing to ascertain the relationships between two or more variables [110]. The justification behind the selection is as shown from the following factors:

- The base model used in this study is TAM, which is a model with the nature of quantitative.
- Quantitative approach is the main tool for establishing empirical relationships by figuring out what influences an outcome. This study aims to pinpoint the constructs that affect older people's acceptance of smart wearable technology.
- Quantitative approach is used to study and identify difference or filling in the knowledge gaps by formulating some hypotheses that will address the issues [110].

3.1.2 Cross-sectional design survey

Most of the previous related studies are either a cross-sectional study or longitudinal study. Both methods are observational approaches where the participants will be observed in their natural environment. When participating in a longitudinal study, participants are observed at various points in time, allowing patterns in the results to be tracked over time. A cross-sectional study, on the other side, is a better choice for determining the prevalence of a behavior or disease in a population. Cross-sectional design is often a better preference for researchers as it is comparatively faster and lesser cost to conduct, and the formulation of hypothesis is straightforward also [111].

3.2 Population and Sample

3.2.1 Target Population

The target population of this study is the older adults residing in Malaysia, aging from 60 years and above. According to department of statistics Malaysia, there is about 6% of older adults with age greater than 65 in year 2020 [112]. The respondents are required to be a smart wearable technology user, or at least have the basic knowledge on what is a smart wearable technology. Respondents that have not heard of smart wearable technology or do not have the basic knowledge of smart wearable technology will be excluded from the study.

3.2.2 Sample Size

Determining a suitable sampling size determination is essential for realistic conclusions to be drawn from research findings. Despite the presence of a few commonly used guidelines for calculating sample sizes, it is still unclear which one should be taken into account in the researchers' studies. However, Memon's [113] study has discussed the factors that influence the decisions on the sample size, reviewed the calculation of sample size's existing rules of thumb, and lastly presented the recommendations for performing power analysis using the G*Power program.

One of the constructs affecting the choice of analytical programs is the sample size. Partial least squares structural equation modelling (PLS-SEM) programs, such as SmartPLS, can be used to run analyses with small sample sizes when models contain many constructs and a large number of items, but this does not necessarily mean that PLS-SEM can produce accurate results when the sample size of the data is too small [114].

The sample size can be determined in a number of ways, according to previous studies. These criteria can be categorized into a few different groups, including population-sample tables, item-simple ratios, and general guidelines for calculating sample sizes. Recent research suggests that power analysis should be used to determine sample size [114]–[116]. By considering the portion of a model with the greatest number of predictors, power analysis establishes the minimal sample size necessary. For the purpose of calculating the minimum sample size, information on effect size, power, and significant level is needed. One of the most popular statistical programs for conducting power analysis for business and social science research is G*Power [117], [118], [119].

The procedure of sample size calculation and power analysis is often too complicated. Some tools require a great understanding of statistics and/or software programming for sample size computation and some commercial applications are too costly to use. Hence, we chose G*Power software that is user-friendly and is free to use.

The result in figure 3.1 suggested that the optimum sample size needed for this study is 146, based on the number of predictors and relevant parameters.

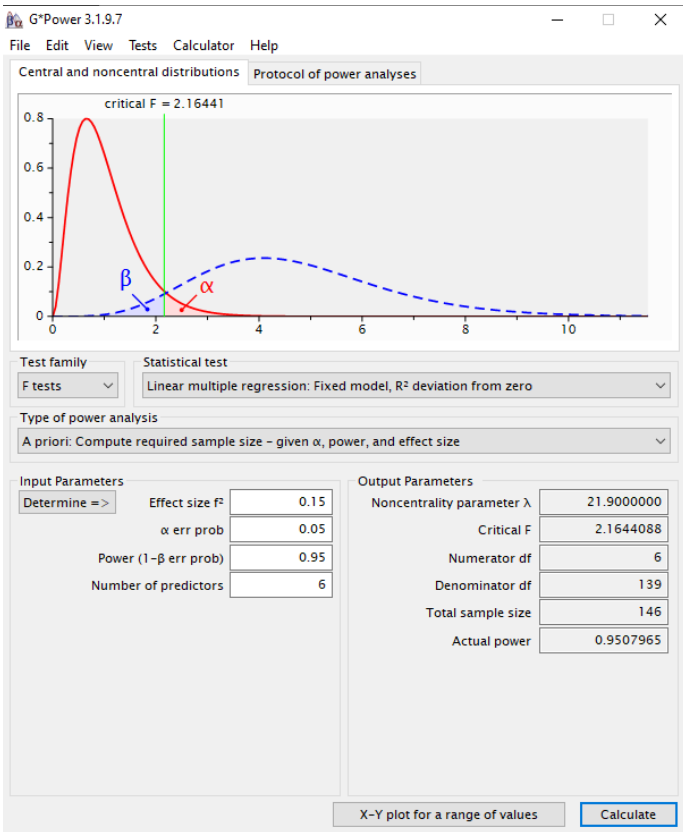


*Figure 3.1: G*Power program*

3.3 Data collection

3.3.1 Sampling Method

Any research study's best approach to tackling a problem is to gather data from the entire population. To study the entire population, however, is not always feasible in practice [120]. As a result, a sample that is sizable enough can be representative of the entire population. Simple random sampling will be used as the sampling technique for this study. All members of the population have an equal chance of being chosen using this method. Through social media sites like Facebook, WhatsApp, and WeChat, the questionnaire is made available to the intended respondents.

3.3.2 Instrument development

The necessary information to test the hypotheses will be gathered through an online survey questionnaire. Items in the questionnaire were acquired from previous related studies based on the constructs that are relevant to our study. The items in the questionnaire were then modified accordingly to fit the context of smart wearable technology for elderly. The items for each construct will be classified into the proposed model accordingly, those items include FC, COM, SI, PS, PR, CA, and CSE. The questionnaire consists of 30 total items, with responses on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Given that the majority of related studies used a seven-point Likert scale, we chose to study the results from a different perspective and look into how modelling and results varied. One of the other reasons is Likert Scale with middle point allows respondents' true neutral/indifferent opinion to be expressed as they are not forced to agree or disagree [121]. In addition, the Likert scale point with 3-point range is too small to produce accurate result, while 10-point Likert scale point does not have a middle point. Hence, 5-point Likert Scale will be the better option for this study.

Before the survey was administered, the questionnaire undertook a pre-test and pilot test. Pretesting is essential for identifying questionnaire issues. Misunderstanding of specific terms or concepts in the question's content, as well as uncertainty regarding the question's overall meaning, are among the issues with the question [122]. Missing data due to difficulties skipping or navigating from question to question can frustrate interviewers and respondents respectively. If unaddressed, the concerns about questionnaire formatting, which are particularly relevant to self-administered questionnaires, could result in the loss of crucial information. Pre-test was caried out by inviting 20 participants that fit the criteria to participate. A questionnaire was given for them to answer followed by another questionnaire to collect their feedback on the structure, understandability, and grammar of the questionnaire. According to the participants, some terms used in the questionnaire were jargon and some questions were too vague to be understandable. The issues were addressed and resolved by rectifying those terms and questions then sent to the participants again for review. Table 3.1 shows the final rating on the summary of the questionnaire from different aspects.

Table 3.1: Pre-test results

Questionnaire Aspect	**Rating Scale**				
	1	2	3	4	5
Design/Outlook	0	0	0	5	15
Structure	0	0	3	10	7
Grammar	0	0	0	2	18
Understandability	0	0	0	8	12

After two rounds of pre-tests, the reliability and the validity of the items with the same participants was conducted with pilot test. Pilot-test is a 'dress rehearsal' on the questionnaire [123], where the questions are placed together as it is expected that those same set of questions will appear on the final questionnaire and the dynamics of the survey are investigated as a whole. During the pilot test, the final questionnaire will be run on trial to test the entire methodology, from sampling methods to data collection, and lastly analysis in the actual field conditions with intention for the success of the study to be increased. Since this study is conducted via online survey, it is even more crucial for pilot test to be conducted beforehand as the researcher will not be there for any clarification on the ambiguities of the questionnaire to the survey respondents [124]. Unlike pre-testing, pilot test was done systematically on the subset of the target sample to assure that the entire survey works smoothly, as well as the coding and analysis can be done correctly.

The results of the pilot test were imported into SAS Enterprise Guide after data collection in order to assess the constructs' dependability in terms of internal consistency and the ability to replicate the same outcomes in similar circumstances [125]. Researchers have been using Cronbach's alpha coefficient (CA) to measure the internal. Higher value indicates higher internal consistency of the questionnaire in general. The CA value of 0.7 indicates an acceptable level of reliability, while the CA value of 0.8 indicates good reliability, based on a few suggested CA cut-off values [126], [127]. On the other hand, Hair's [128] stated that exploratory research is also acceptable with CA values between 0.6 and 0.7. The reliability test of the data from the pilot test is shown in Table 3.2. The CA score of all the constructs is in the range from 0.836 to 0.959 which indicates that the constructs have a good reliability for the questionnaire.

Table 3.2: Reliability test result

Construct	**Items**	**CA**
Facilitating Condition	3	0.878
Compatibility	3	0.903
Social Influence	3	0.836
Perceived Stigmatization	3	0.923
Performance Risk	3	0.89
Anxiety	3	0.893
Self-Efficacy	3	0.928
Perceived Usefulness	3	0.954
Perceived Ease of Use	3	0.893
Intention to Use	3	0.959

Table 3.3: Summary of construct with measurement items

Constructs	Items	Items	Sources
Facilitating Conditions (FC)	F1	Getting help from a person or group is important when I use wearable technologies.	[63], [79]
	F2	I have the necessary knowledge to use it.	
	F3	My financial status can support my acceptance.	
Compatibility (COM)	COM1	Wearable technologies are compatible with my existing electronics (smartphone and others).	[129]
	COM2	Using wearable technologies fits into all aspects of my work.	
	COM3	Using it would not affect my daily life (because of its weight, volume, and others).	
Social Influence (SI)	SI1	People who affect my behavior think that I should use wearable technologies.	[98], [72]
	SI2	My family members and friends support my decision to use it.	
	SI3	If the product has become a trend among people around me, I would consider using it.	
Perceived Stigmatization (PS)	PS1	People will look at me strangely if they see me using it.	[98]
	PS2	I am embarrassed to wear health monitoring devices.	
	PS3	People around me would laugh at my wearable technology acceptance.	
Performance Risk (PR)	PR1	I'm concerned about whether it will provide the expected benefits (functionalities and others).	[130], [76]
	PR2	Smart wearable technologies may not work satisfactorily (measuring accuracy and quality concerns, and others).	
	PR3	Such technologies may lead to privacy violation.	
Anxiety (CE)	CE1	Wearing this equipment is frightening.	[91]
	CE2	I don't want it to be seen by other people.	
	CE3	I am afraid that the equipment may suddenly stop functioning.	
Self-efficacy (SE)	SE1	I feel confident wearing smart wearable technologies even if it can be seen by other people.	[131]
	SE2	I feel confident using smart wearable technologies.	
	SE3	I feel confident getting information from wearing smart wearable technologies.	
Perceived Usefulness (PU)	PU1	Using the technology will make one's life more effective.	[132], [98]
	PU2	My life will become more convenient when I use such technologies.	
	PU3	It is very useful to use wearable technologies in life.	
Perceived Ease of Use (PEOU)	PEOU1	I think wearable technologies are easy to use.	[132], [98]
	PEOU2	My interaction with smart wearable technologies is clear.	
	PEOU3	I can easily learn how to operate such technologies.	
Intention to Use (IU)	IU1	Using smart wearable technology (it) is worthwhile.	[98]
	IU2	Using a smart wearable technology is a good idea.	
	IU3	I intend to use wearable technologies in the future.	

The detailed items of each construct and their sources are listed in Table 3.3. Refer instrument in Appendix 1.

3.4 Data Analysis

3.5.1 Partial Least Squares Structural Equation Modelling

The suggested research model will be evaluated for validity and reliability using the method of partial least squares structural equation modelling (PLS-SEM). PLS-SEM has grown in popularity for the estimation of path models with latent variables and their relationships. The identification of competitive advantage for significant target constructs such as the loyalty and satisfaction of the customers, as well as user behavior, and behavioral intentions is one of the common goals of PLS-SEM analyses [119]. PLS-SEM differs from Covariance-Based Structural Equation Modelling (CB-SEM) as the latent variable case values (construct scores) are explicitly calculated by the algorithm. While CB-SEM uses the covariance matrix for model parameters estimation by only taking common variance into account. On the other hand, PLS-SEM is variance-based by taking total variance into consideration and using it for parameters estimation [133], [134]. There has been a great amount of debate on when to use PLS-SEM [135]–[138].

According to Anderson and Gerbing (1988), SEM offers researchers a more thorough method for evaluating and changing theoretical models. Up until a recent study, CB-SEM was by far the most popular SEM technique [139], whereas the usage of PLS-SEM has increased significantly in the recent years [119]. Studies have been conducted in the fields of marketing, accounting, information systems, family businesses, and tourism, all of which have articles published with the use of PLS-SEM [140]–[146]. Although there were a few academics criticized the PLS-SEM method, the majority of the critiques remain unsupported. [137].

Hair Jr.'s [147] conclusions outlined the similarities and contrasts in the presumptions, implementation, and potential varieties of assessments between PLS-SEM and CB-SEM. One of the main differences is that CB-SEM makes the assumption that the data are normally distributed, which is very unlikely to occur in social science research.

On the contrary, PLS-SEM is non-parametric and operates well even when the data given are not normally distributed, as well as having only a few restrictions on the use of binary and ordinal scales with proper coding. Other CB-SEM methods (aside from the maximum likelihood algorithm) can be used for analysis with data that are not normally distributed, but they require a large sample size of date. On the other hand, the PLS-SEM method made it possible to keep track of a lot more indicator items, which can help with the advancement of structural theories. If the study's objective is to make predictions, then PLS-SEM is the more preferable method compared to CB-SEM as its variance explained in the dependent variables is noticeably higher when compared directly with CB-SEM, according to their final comparison of R2 output for the two methods. As a result, when comparing with CB-SEM in the theory development stage, the PLS-SEM method is much more applicable.

4. CHAPTER 4: Result

4.1 Introduction

The analysis from the collected data is presented in this chapter. The data obtained from the Google Form was exported into an Excel format (xlsx). Each item in the questionnaire was then recoded in Microsoft Excel. Both preliminary demographic analysis and descriptive analysis for each construct's item is done in Microsoft Excel and SAS Enterprise Guide.

4.2 Demographic Analysis

Gender and age group

Characteristics	Frequency	Percentage (%)
Gender		
Female	181	60.33%
Male	119	39.67%
Age		
60 to 64	61	20.33%
65 to 69	86	28.67%
70 to 74	74	24.67%
75 to 79	58	19.33%
80 and above	21	7.00%

Table 4.1: Gender and age group of respondents

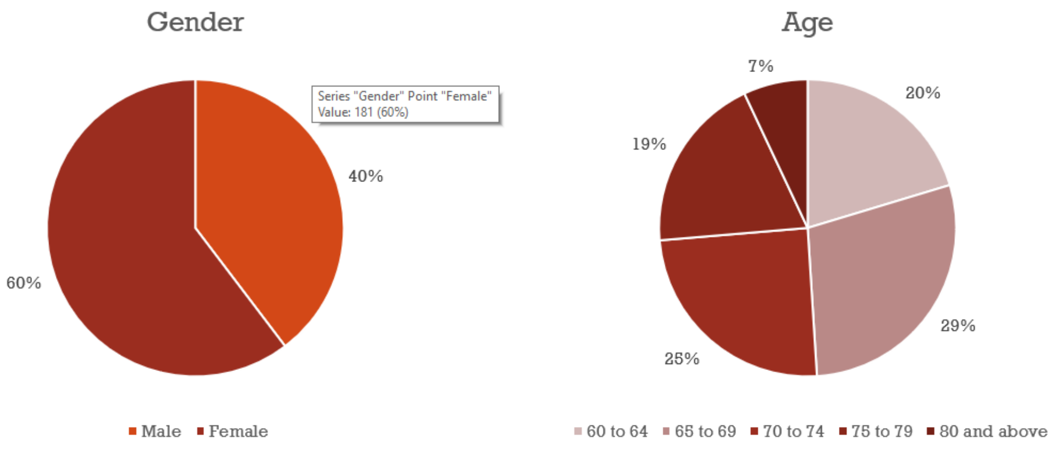


Figure 4.1: Gender and age group of respondents

Table 4.1 presents that female is the majority of the respondents, with about 60.33% of the whole group, while only 39.67% of the respondents are male. Based on world's data, it has been found that female lives longer life than male with the life expectancy of 73.8 years vs 68.4 years, which explains one of the reasons of the majority for our respondents are female. As for age group, we have split a range of 5 ages for each group. The highest percentage of age group is between 65 to 69 with 28.67%, followed by age group of 70 to 74 with 24.67%. The slightly smaller group are the age group of 60 to 64 and 75 to 79, which have the percentage of 20.33% and 19.33%. The age group of 80 and above is the minority respondents with only 7% of the total respondents.

Education background

Education Level	Frequency	Percentage (%)
Bachelor's Degree Level or higher	85	28.33%
Diploma Level	162	54.00%
High School Level or lower	53	17.67%

Table 4.2: Education level of respondents

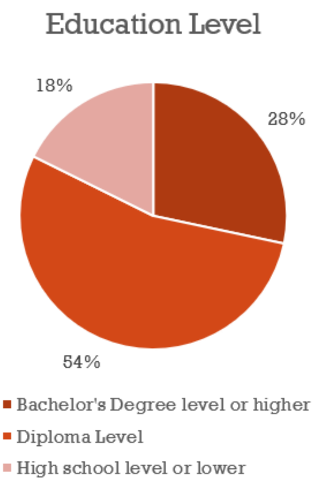


Figure 4.3: Education level of respondents

Education background is measured with 3 different levels, high school level, diploma level, and bachelor’s degree level. Based on table 4.2, there are a total of 162 with 54% of the respondents have an education background of diploma level. While a total of 85 of the respondents’ education level are higher than diploma level with 28.33%. The remaining 17.67% with 53 respondents are high school level or lower.

Living arrangement

Characteristics	Frequency	Percentage (%)
Are you currently living alone?		
No	251	83.67%
Yes	49	16.33%

Table 4.4: Living arrangement of respondents

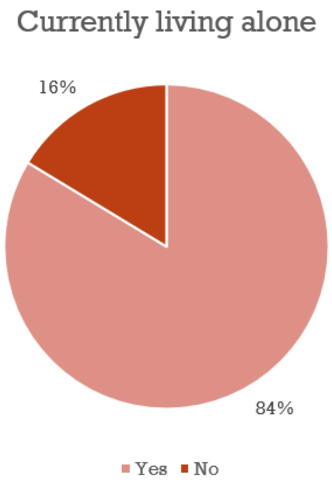


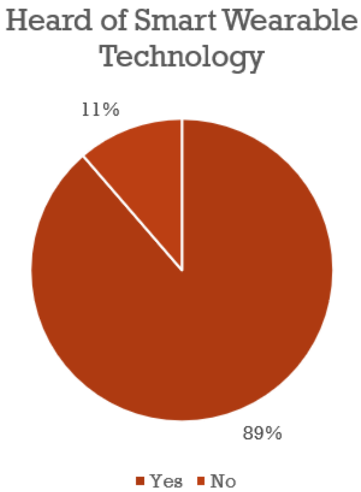
Figure 4.5: Living arrangement of respondents

Based on Table 4.3, 83.67% of the majority respondents are not living alone. Which means they might be living with family, living with spouse only, or living in a nursing home, etc. Only 49 of the respondents with 16.33% are currently living alone.

Smart wearable technology awareness

Characteristics	Frequency	Percentage (%)
Have you heard of Smart Wearable Technology (E.g., Smartwatch, Fitness Tracker, Fall detection sensors, etc.)?		
No	34	11.33%
Yes	266	88.67%
Are you a user of Smart Wearable Technology (E.g., Smartwatch, Fitness Tracker, Fall detection sensors, etc.)?		
No	146	48.67%
Yes	154	51.33%

Table 4.6: Smart wearable technology awareness of respondents



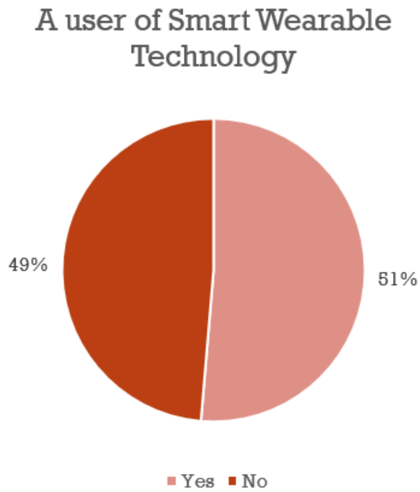


Figure 4.7: Smart wearable technology awareness of respondents

Table 4.4 shows that 266 with 88.67% of the respondents are aware of the existence of smart wearable technology. While only 34 with 11.33% of the respondents do not know what smart wearable technology will be excluded from the study. As for people who have heard of smart wearable technology, the percentage of the respondents are divided into almost half of the total sample size, which is 48.67% for non-smart wearable technology user, and 51.33% for smart wearable technology user.

4.3 Descriptive statistics of the construct

By presenting the summary statistics for each construct, this section presents the descriptive statistics for each construct in the model. When conducting a questionnaire survey, a straightforward approach can be employed by using descriptive statistics that include mean and standard deviation [148]. A 2:1 ratio between the maximum standard deviation and the minimum standard deviation should be used as a general rule to apply on the items when focusing on validity, reliability, and assessment. If the item did not comply with the rule, it must be standardized to prevent significant differences within a scale. This approach can be used in any study that involves a questionnaire. Table 4.5 presents the approximately equal means and standard deviation difference is within the ratio of 2:1 as recommended. Hence, all items can be kept for further analysis based on the rule of thumb.

Table 4.8: Summary statistics of each construct

Constructs	Items	Items	Minimum	Maximum	Mean	Std. Deviation
Facilitating Conditions (FC)	F1	Getting help from a person or group is important when I use wearable technologies.	1	5	3.82	1.292
	F2	I have the necessary knowledge to use it.	1	5	3.86	1.173
	F3	My financial status can support my acceptance.	1	5	3.82	1.258
Compatibility (COM)	COM1	Wearable technologies are compatible with my existing electronics (smartphone and others).	1	5	3.52	1.268
	COM2	Using wearable technologies fits into all aspects of my work.	1	5	3.42	1.352
	COM3	Using it would not affect my daily life (because of its weight, volume, and others).	1	5	3.40	1.369
Social Influence (SI)	SI1	People who affect my behavior think that I should use wearable technologies.	1	5	3.82	0.983
	SI2	My family members and friends support my decision to use it.	1	5	3.86	0.988
	SI3	If the product has become a trend among people around me, I would consider using it.	1	5	3.78	1.055
Perceived Stigmatization (PS)	PS1	People will look at me strangely if they see me using it.	1	5	2.84	1.225
	PS2	I am embarrassed to wear health monitoring devices.	1	5	2.79	1.269
	PS3	People around me would laugh at my wearable technology acceptance.	1	5	3.08	1.288
Performance Risk (PR)	PR1	I’m concern about whether will it provide the expected benefits (functionalities and others).	1	5	3.77	1.152
	PR2	Smart wearable technologies may not work satisfactorily (measuring accuracy and quality concerns, and others).	1	5	3.77	1.190
	PR3	Such technologies may lead to privacy violation.	1	5	3.73	1.141
Anxiety (CE)	CE1	Wearing this equipment is frightening.	1	5	2.99	1.339
	CE2	I don’t want it to be seen by other people.	1	5	3.15	1.361
	CE3	I am afraid that the equipment may suddenly stop functioning.	1	5	3.15	1.279
Self-efficacy (SE)	SE1	I feel confident wearing smart wearable technologies even if it can be seen by other people.	1	5	3.36	1.184
	SE2	I feel confident using smart wearable technologies.	1	5	3.40	1.188

	SE3	I feel confident getting information from wearing smart wearable technologies.	1	5	3.57	1.182
Perceived Usefulness (PU)	PU1	Using the technology will make one's life more effective.	1	5	3.87	1.028
	PU2	My life will become more convenient when I use such technologies.	1	5	3.75	1.111
	PU3	It is very useful to use wearable technologies in life.	1	5	3.84	1.070
Perceived Ease of Use (PEOU)	PEOU 1	I think wearable technologies are easy to use.	1	5	3.14	1.303
	PEOU 2	My interaction with smart wearable technologies is clear.	1	5	3.10	1.303
	PEOU 3	I can easily learn how to operate such technologies.	1	5	3.08	1.322
Intention to Use (IU)	IU1	Using smart wearable technology (it) is worthwhile.	1	5	3.66	1.102
	IU2	Using a smart wearable technology is a good idea.	1	5	3.76	1.116
	IU3	I intend to use wearable technologies in the future.	1	5	3.71	1.105

4.4 Assumption Testing

The assumptions supporting the statistical foundations for multivariate analysis must then be put to the test. The explanation for the reason it is necessary to test the assumptions is divided into two main categories. First, there is a risk of bias and distortion due to the complexity of the relationships resulting from a large number of variables. Second, the indicators of assumptions violations might be covered in the complexity of the analysis and results that can be found in univariate analysis, which is a more straightforward approach [149].

4.4.1 Normality

In the study field of statistic, the assumption of the observations to be normal tend to be conventional. This assumption reinforces the entire statistical framework, and the inference will fail if it is compromised. Therefore, it is crucial to check or test this assumption before performing any statistical analysis on the data [150].

There are various statistical methods used for normality assumption on data analysis including regression, correlation, variance analysis, and *t*-tests. When the size of the sample has 100 or more observations, the central limit theorem stated that normality violation is not a major problem [151], [152]. The assumption of normality must be upheld regardless of the sample size in order to draw valid conclusions. However, the mean value of the data will be displayed if a continuous data set has a normal distribution. The significance level (P value) will then be determined by comparing the mean value between or among the groups. The mean value won't be a good indicator of the data's representativeness if the given data is not distributed normally. When the representative value of a dataset is selected wrongly, further calculation of significance level using this representative value will provide wrong interpretation and conclusions [153].

The assumption of each item's normal distribution in addition to all linear combinations of items incorporates the first presumption of multivariate analysis, which is normality [154]. The data in this study are checked for normality using Mardia's multivariate kurtosis. There were few studies suggested that the software available online in statistical analysis website are used to measure the multivariate skewness and kurtosis, which can be found with the keyword “webpower multivariate kurtosis” in Google [119], [155].

The multivariate skewness and kurtosis were evaluated following the suggestion of Hair et al. [139] and Cain et al. [156]. As shown by the results in figure 4.1, presenting Mardia's multivariate skewness and kurtosis, with ($\beta = 17.856$, p 0.01) and ($\beta = 144.777$, p 0.01) respectively, which indicates non-multivariate normal. According to Kline, a multivariate skewness should be ± 3 and multivariate kurtosis should be ± 20 [157]. As a result, a procedure of 5000-sample re-sample bootstrapping was used later in the structural modelling process with the report of path coefficients, followed by the standard errors, t-values, and p-values for the structural model, as suggested by Hair et al. (2019) [158].

```
Sample size:  266
Number of variables:  10

Univariate skewness and kurtosis
                          Skewness SE_skew Z_skew Kurtosis SE_kurt Z_kurt
Anxiety                     -0.046   0.149 -0.309   -0.990   0.298 -3.328
Compatility                 -0.646   0.149 -4.328   -0.543   0.298 -1.823
Facilitating.Condition      -0.994   0.149 -6.656    0.279   0.298  0.936
Intention.to.use            -0.784   0.149 -5.249   -0.031   0.298 -0.105
Perceived.Ease.of.Use       -0.137   0.149 -0.921   -0.932   0.298 -3.130
Perceived.Stigmatization     0.117   0.149  0.783   -0.998   0.298 -3.353
Perceived.Usefulness        -0.994   0.149 -6.658    0.532   0.298  1.788
Performance.Risk            -0.815   0.149 -5.454   -0.028   0.298 -0.094
Self.Efficacy               -0.698   0.149 -4.672   -0.271   0.298 -0.910
Social.Influence            -1.061   0.149 -7.104    1.531   0.298  5.144

Mardia's multivariate skewness and kurtosis
                b         z p-value
Skewness  17.8567 791.6468       0
Kurtosis 144.7774  13.0425       0
```

Figure 4.1: Mardia’s multivariate skewness and kurtosis

4.4.2 Common Method Variance

Although some procedural measures have been taken before the distribution of questions, given that the data used in this study was gathered from a single source which may lead to common method variance (CMV). A systematic error variance is known to be CMV which is shared by variables that are measured using the same techniques or sources [159]. If the data is obtained through a self-administered questionnaire, testing on the risks of CMV is crucially important, especially when the criterion and predictor variables are gathered from the same participant [160]. CMV may have a bad influence on the validity of the constructs and a systematic bias will exist in the study [161].

Statistical remedy in this study have been opted after data collection for reducing the CMV for this study. To determine which constructs exhibit variance inflation factor (VIF) values that are equal to or higher than threshold values, a full collinearity test was conducted [162]. Collinearity can be defined as a predictor-predictor phenomenon in multiple regression models. According to this conventional viewpoint, collinearity occurs when the same underlying construct are being assessed by two or more predictors. The lateral collinearity is defined by a predictor-criterion phenomenon when the same underlying construct as a variable is measured by a predictor variable to which is pointed in a model. In the relationship between the predictor and the criterion, the latter is the relevant criterion variable. The full collinearity test is one of the methods for determining the lateral collinearity. This can be accomplished by creating a block that contains all of the model's latent variables where the predictors are pointing at a single criterion (i.e., a dummy variable). Since it enables the identification of collinearity across all the constructs in the model, despite where they are positioned in the model, this constitutes a more cautious and thorough test of collinearity.

The frequently advised values are 3.3, 5, and 10 [162]. The presence of collinearity among the variables would be implied if the VIF is greater or equal to the threshold values (a.k.a. multicollinearity). A full collinearity test using the VIF has been proven to be successful in identifying CMV [163]. All constructs will be regressed using this method against a common variable; if a construct's VIF is greater than 3.3, this is a sign of pathological collinearity and also suggests that the model may be corrupted by the CMV. The VIF of the constructs used in this study is shown in Table 4.6. Despite the fact that two constructs have VIF values higher than 3.3, the values are still below the second cutoff point of 5. Therefore, a conclusion can be drawn that CMV is not a major issue for the data gathered in this study.

Constructs	**VIF**
Anxiety	2.545
Compatibility	2.564
Facilitating Condition	1.847
Intention to use	2.895
Perceived Ease of Use	2.046
Perceived Stigmatization	2.674
Perceived Usefulness	3.940
Performance Risk	1.317
Self-Efficacy	3.459
Social Influence	1.720

Table 4.9: Full Collinearity Testing

4.5 Measurement Model Assessment

The model was put to the test using a two-step procedure, as Anderson and Gerbing (1988) recommended [164]. The validity and reliability of the components used in the measurement model were evaluated in the first step as recommended by Hair et al. (2019) and Ramayah et al. [114], [158]. The structural model was then run to put the developed model's hypothesis to the test. A bootstrapping method was used to evaluate the significance of the path coefficients and loadings. Since all of the research model's constructs in this study are multi-item constructs, they are conceptualized as reflective rather than formative. The reflective construct seeks to identify measurements with strong internal consistency, inter-correlation, and one-dimensionality. The procedures for accessing the measurement model are covered in the subsequent subsections.

4.5.1. Internal Consistency Reliability

The evaluation of internal consistency and reliability is the first assessment that is constructed by running two tests with Cronbach's Alpha and the Composite Reliability Index. Table 4.7 demonstrates that the Cronbach's Alpha values for each construct in this study is in the range of 0.878 to 0.959, meeting the threshold value of 0.7 [149].

The use of Cronbach's Alpha as a tool to assess the consistency of the constructs has been the subject of discussions. It has been claimed that Cronbach's Alpha value underestimates the true reliability [134], [165]. As a result of its shortcomings, the Composite Reliability Index has been proposed as a substitute reliability test [166]. When comparing with Cronbach's Alpha, composite reliability has been viewed as a more accurate measurement of reliability [167]. Recommendations state that the composite reliability should be higher than 0.7 to imply adequate internal consistency [168], [169]. Table 4.7 presents the composite reliability of all the constructs for the data in each group. The values for each group exceeded the recommended threshold value of 0.7, ranging between 0.841 and 0.975, which suggests that the constructs' reliability is acceptable for the measurement model.

4.5.2 Indicator Reliability (Outer Loadings)

The indicator reliability is then assessed following the validation of the reliability for each internal consistency reliability. All items have satisfactory indicator reliability, as shown in table 4.7, with a range of 0.646 to 0.97. Since all of the values complied Byrne (2016)'s suggested threshold value of 0.5, none of the items were dropped.

4.5.3 Convergent Validity

Convergent validity refers to how closely individual indicators reflect a construct when compared to items measuring other constructs [170]. To determine convergence validity, the Average Variance Extracted (AVE) is measured with at least 0.5 or above on average in order to justify more than half of the indicators' variance [133], [171]. The PLS Algorithm in SmartPLS 3.0 is used to determine the AVE value as shown in Table 4.7. For each group of data, all of the constructs recorded has an AVE value higher than 0.5. Performance Risk has the lowest AVE value reported with 0.643, followed by SI (0.761), FC (0.808), CA (0.820), PEOU (0.837), COM (0.841), PS (0.885), SE (0.888). The variable with the highest AVE, perceived usefulness, accounts for more than 90% of the variance. These findings show that the measurement model had sufficient convergent validity.

Variable	Item	Loading	CR	AVE
Anxiety (CA)	CA1	0.937	0.932	0.820
	CA2	0.941		
	CA3	0.836		
Compatibility (COM)	COM1	0.902	0.941	0.841
	COM2	0.918		
	COM3	0.931		
Facilitating condition (FC)	FC1	0.849	0.926	0.808
	FC2	0.909		
	FC3	0.936		
Intention to Use (IOU)	IOU1	0.967	0.975	0.930
	IOU2	0.970		
	IOU3	0.956		
Perceived Ease of Use (PEOU)	PEOU1	0.942	0.939	0.837
	PEOU2	0.890		
	PEOU3	0.911		
Performance Risk (PR)	PR1	0.777	0.841	0.643
	PR2	0.646		
	PR3	0.954		
Perceived stigmatization (PS)	PS1	0.961	0.959	0.885
	PS2	0.924		
	PS3	0.937		
Perceived Usefulness (PU)	PU1	0.969	0.973	0.922
	PU2	0.950		
	PU3	0.962		
Self-Efficacy (CSE)	CSE1	0.941	0.960	0.888
	CSE2	0.947		
	CSE3	0.939		
Social Influence (SI)	SI1	0.895	0.905	0.761
	SI2	0.892		
	SI3	0.829		

Table 4.10: Measurement Model

4.5.4 Discriminant Validity

The discriminant validity of the model is then assessed where the extent to which items can be distinguished from other constructs [172]. Additionally, it evaluates how differently the overlapping constructs differ from one another. The Heterotrait-Monotrait (HTMT) correlation ratio is applied in this study for the assessment of discriminant validity. Through a Monte Carlo simulation study, Henseler et al. (2015) demonstrated the method's exceptional performance and discovered that this method has higher specificity and sensitivity rates (97% to 99%), when comparing to other methods such as

Fornell-Lacker and cross-loadings criterion. In this study, two techniques were chosen to evaluate discriminant validity.

If the HTMT value is higher than the $HTMT_{.85}$ value of 0.85 for the first technique, discriminant validity issues can be discovered [157]. Table 4.8 was produced using the PLS algorithm, and it demonstrates that none of the individual constructs have reached the $HTMT_{.85}$ threshold. which shows that the measurement model accepts the construct validity.

Additionally, a bootstrapping was used to determine whether the HTMT values deviate significantly from 1.00, as advised in [114]. The lack of discriminant validity is indicated by HTMT values close to 1 [173]. Comparing the value to a predetermined threshold is necessary when using the HTMT as a criterion. While some authors proposed a value of 0.90 [172], others suggested 0.85 as the threshold value [157]. None of the upper bounds of the HTMT 95% confidence intervals are higher than 0.85 or 0.90, as can be seen in Appendix 2.

The evidence of bootstrap confidence interval results of the HTMT strengthens further to show that this study has established the discriminant validity on top of the conservative HTMT threshold of 0.85 supporting the discriminant validity. Therefore, it can be stated that this study's reliability and validity requirements have been satisfied.

.

Table 4.11: Discriminant Validity

Variable	1	2	3	4	5	6	7	8	9	10
1. Anxiety										
2. Compatibility	0.382									
3. Facilitating condition	0.359	0.511								
4. Intention to Use	0.563	0.494	0.562							
5.Perceived Ease of Use	0.616	0.579	0.424	0.626						
6.Perceived Usefulness	0.746	0.447	0.523	0.653	0.581					
7. Perceived stigmatization	0.509	0.688	0.655	0.789	0.651	0.637				
8. Performance Risk	0.340	0.381	0.126	0.065	0.186	0.249	0.090			
9. Self-Efficacy	0.645	0.738	0.561	0.696	0.689	0.653	0.782	0.171		
10. Social Influence	0.147	0.317	0.591	0.537	0.320	0.425	0.573	0.167	0.429	

4.6 Structural Model Assessment

The analysis is then carried out further with a structural model evaluation after the measurement model has been established. The ability of the model to predict one or more target constructs is determined by using the structural model assessment [119].

4.6.1. Collinearity Issues

The structural model evaluation process begins with the collinearity issue assessment. In order to avoid construct collinearity issues, a latent variable analysis in the structural model must be performed first. The VIF value is calculated in order to address the collinearity issues. According to Hair et al. [169] and Diamantopoulos & Siguaw [174], the threshold value for this assessment is 5 or 3.3, respectively. All inner VIF values for constructs as shown in Table 4.6 in section 4.4.2, fall within the range of 1.317 to 3.94, although is slightly higher than the value of 3.3 suggested by the study [174], it is still below the value of 5 which is supported by a more recent study [169]. As a result, the issue of collinearity in this study is not a major concern.

4.6.2 Path Coefficients

The earlier section 4.4.1 evaluates the multivariate skewness and kurtosis, as suggested by Hair et al. [119] and Cain et al. [156]. The outcomes showed that the data gathered for this study was not multivariate normal, as evidenced by Mardia's multivariate skewness and kurtosis based on $\beta = 17.856$ and $\beta = 144.777$ respectively with $p < 0.01$. As a necessary consequence, we used a 5000-sample re-sample bootstrapping procedure with the advice of Hair et al. [114], the path coefficients, standard errors, t-values, and p-values of the structural model were reported in this study [158]. The bootstrapping procedure is not constrained by the assumptions of statistical normality [175]. This is especially useful when the empirical data is commonly non-normally distributed. The PLS algorithm uses the one-tail option because the outcome of the study's hypothesis testing can be either positive or negative.

In this study, there are 15 hypotheses developed for the constructs. For significance level testing, p-values for all hypotheses are generated via SmartPLS 3.0 bootstrapping function. The critical value for a significance level is 0.05 (one-tailed test) as suggested in [119]. The results of the hypothesis testing Table 4.9 indicates that 9 out of 15 hypotheses were supported whereas 6 were not supported including H6 (p-value = 0.092), H7 (p-value =0.563), H8 (p-value = 0.165), H11 (p-value = 0.116), H12 (p-value = 0.056), and H13 (p-value = 0.128)

In the past decades, p-value has been frequently used as a decision rule to support the results of the model. However, it has been criticized that p-value is not enough to be a decision rule due to these three main reasons [176]. Firstly, the effect size or results' importance is not being measured by the p-value. Second reason is p-value alone is not sufficient enough to be the evidence in supporting the hypotheses or the model. Lastly, scientific conclusions should not be made solely on the threshold of the p-value. In addition, p-values are no longer a good criterion to test the significance of a hypothesis, according to Hahn and Ang's criticism [177], In order to reach more accurate conclusions, they recommended a combination of criteria including p-values, confidence intervals, and effect sizes.

4.6.3 Confidence Intervals

When the indicator weight bootstrap distribution is skewed, Hair et al.'s [119] suggested using suggested using bootstrapping confidence intervals for significance testing. Additionally, Aguirre-Urreta and Ronkko [178] also suggested constructing bootstrap-based confidence intervals using the percentile method. The hypothesis is not statistically significant if there is a zero in between the bias correct interval lower limit (BCI LL) and bias correct interval upper limit (BCI UL) of a confidence interval for an indicator weight. According to the results in Table 4.9, 9 out of 15 hypotheses were supported whereas 6 hypotheses were rejected as their BCI LL and BCI UL include a zero in it. These 6 hypotheses are H6 (BCI LL = -0.021, BCI UL = 0.192), H7 (BCI LL = -0.08, BCI UL = 0.126), H8 (BCI LL = -0.26, BCI UL = 0.032), H11 (BCI LL = -0.055, BCI UL = 0.151), H12 (BCI LL = -0.182, BCI UL = -0.001), and H13 (-0.025, BCI UL = 0.200).

4.6.4 Assessment of Effect Size (f^2)

Last but not least, effect size is employed to evaluate the construct's significance which is the most commonly used Cohen's f^2 coefficient effect size in PLS-SEM [179]. The f^2 calculates a predictor construct's relative influence on endogenous constructs. Both statistical significance (p-value) and substantive significance (effect-size) should be reported, as suggested by Sullivan and Feinn [180]. According to Cohen's rule of thumb [179], the effect size is calculated with the values of 0.35, 0.15, and 0.02 denoting large, medium, and small effects respectively.

According to H1 ($f^2 = 0.109$) and H3 ($f^2 = 0.112$), the FC and SI have a minimal effect on PU. COM has a significant effect on PU based on H2 ($f^2 = 0.406$) and a moderate effect on PEOU based on H5 ($f^2 = 0.235$). PS has a minimal effect on IU based on H7 ($f^2 = 0.034$). While the effect of PU on IU is moderate with H11 ($f^2 = 0.264$). Despite the fact that the hypothesis is supported, the FC is found to be having insignificant effects PEOU because the effect size is below 0.05 with $f^2 = 0.019$. PEOU is also reported to be not insignificant on IU with ($f^2 = 0.016$) even though the hypothesis is supported.

Based on the effect size, only 7 proposed hypotheses appeared to be important in this study. Those 6 proposed hypotheses include H1 (FC -> PU), H2 (COM -> PU), H3 (SI -> PU), H5 (COM -> PEOU), H9 (SI -> IU), H10 (PS -> IU) and H14 (PU -> IU).

Table 4.12: Hypothesis Testing

Hypothesis	Relationship	Std. Beta	Std. Dev	T-value	P-value	BCI LL	BCI UL	f^2	Effect size	Result
H1	Facilitating Condition -> Perceived Usefulness	0.267	0.062	4.292	$p < .001$	0.165	0.365	0.109	Small	Supported
H2	Compatibility -> Perceived Usefulness	0.460	0.057	8.113	$p < .001$	0.351	0.545	0.406	Large	Supported
H3	Social Influence -> Perceived Usefulness	0.249	0.053	4.688	$p < .001$	0.150	0.323	0.112	Small	Supported
H4	Facilitating Condition -> Perceived Ease of Use	0.144	0.079	1.810	0.035	0.006	0.265	0.019	No	Supported
H5	Compatibility -> Perceived Ease of Use	0.452	0.063	7.118	$p < .001$	0.344	0.561	0.235	Medium	Supported
H6	Social Influence -> Perceived Ease of Use	0.081	0.061	1.330	0.092	-0.021	0.192	0.007	No	Not supported
H7	Facilitating Condition -> Intention to Use	0.031	0.053	0.579	0.563	-0.08	0.126	0.001	No	Not supported
H8	Compatibility -> Intention to Use	-0.102	0.074	1.39	0.165	-0.26	0.032	0.012	No	Not supported
H9	Social Influence -> Intention to Use	0.121	0.046	2.657	0.008	0.038	0.217	0.025	Small	Supported
H10	Perceived Stigmatization -> Intention to use	-0.172	0.071	2.419	0.008	-0.304	-0.071	0.034	Small	Supported
H11	Performance Risk -> Intention to use	0.068	0.057	1.199	0.116	-0.055	0.151	0.011	Small	Not supported
H12	Anxiety -> Intention to use	-0.092	0.058	1.595	0.056	-0.182	-0.001	0.010	No	Not supported
H13	Self-Efficacy -> Intention to use	0.080	0.070	1.135	0.128	-0.025	0.200	0.006	No	Not supported
H14	Perceived Usefulness -> Intention to use	0.498	0.067	7.461	$p < .001$	0.375	0.598	0.264	Medium	Supported
H15	Perceived Ease of Use -> Intention to use	0.105	0.056	1.879	0.030	0.014	0.192	0.016	No	Supported

4.6.5 Coefficient of Determination (R^2)

The explanatory power of the model is assessed using the coefficient of determination score (R2) [181]. In-sample predictive power is another term for the R^2 [182]. With a value range of 0 to 1, the R^2 calculates the mode's predictive power, with higher values accounting for higher levels of explanatory power [133]. The values 0.75, 0.50, and 0.25 of R^2 are generally considered to be substantial, moderate, and weak respectively based on the rule of thumb [169], [183]. However, since R2 values also depend on the practice and the area of study, this general rule of thumb should only be used as a rough guide. When predicting stock returns, the acceptable R^2 value of 0.10 is considered satisfactory [184]. Additionally, since the R2 depends on the quantity of predictor constructs, a higher R2 value is obtained when there are many predictor constructs. Therefore, the study context should always be taken into consideration when interpreting the R2.

The R^2 is calculated and presented using the SmartPLS algorithm. Due to R^2 value will increase when the number independent variables increase, adjusted R^2 was suggested instead as it relieve this issue by taking number of independent variables and sample into consideration [119]. Table 4.10 presents both the results of R^2 and adjusted R^2 for this study. The results present that the independent variables explain 64.20% of variance in the intention to use indicate a moderate predictive accuracy for the proposed model. Whereas perceived ease of use (R^2 adjusted = 31.90%) and perceived usefulness (R^2 adjusted = 59.10%) also indicate a moderate predictive accuracy for the proposed model. Generally, the model is valid and appropriate to examine the elderly’s intention to use smart wearable technology using these constructs.

Table 4.13: Coefficient of Determination (R2)

Hypothesis	Dependant Variable	R^2	R^2 Adjusted
Facilitating Condition -> Intention to use Compatibility -> Intention to use Social Influence -> Intention to use Perceived Stigmatization -> Intention to use Performance Risk -> Intention to use Anxiety -> Intention to use Self-Efficacy -> Intention to use Perceived Usefulness -> Intention to use Perceived Ease of Use -> Intention to use	Intention to use	0.655	0.642
Facilitating Condition -> Perceived Ease of Use Compatibility -> Perceived Ease of Use Social Influence -> Perceived Ease of Use	Perceived Ease of Use	0.327	0.319
Facilitating Condition -> Perceived Usefulness Compatibility -> Perceived Usefulness Social Influence -> Perceived Usefulness	Perceived Usefulness	0.596	0.591

5. CHAPTER 5: Discussion

This chapter discusses the results and outcomes of the study on the basis of the research questions. The first section will present the overall conclusion for the results in this study. A detailed overview of the study's theoretical, practical, and contributing aspects is followed in the next section. Finally, this study's limitations and suggestions for future research are discussed.

5.1 Recapitulation of the study

This study concentrated on the variables that affect elderly people's intentions to use wearable smart technology. As the studies for the elderly’s acceptance on smart wearable technology are limited, hence, it is still unclear what factors affect older people's acceptance of smart wearable technology. An integrated Smart Wearable Technology Acceptance Model (SW-TAM) has been developed to address this concern and examine those factors. The results and outcomes used to support the objectives of this research are summarized as below:

1. To explore and investigate external factors that might sway the elderly’s intention to embrace smart wearables.
2. To discuss the perceived values of the elderly in the usage of smart wearable technology.
3. To introduce an integrated model that combines TAM with variables taken from relevant studies.

By reviewing previous related studies, a preliminary study was carried out to identify the factors influencing users' acceptance of technology. The final constructs to be included in this study were based on constructs that were most commonly discussed in the past related studies as discussed in Section 2. Some of the constructs were dropped while some were added to explore the factors on a different angle. All items were adapted from the most valid and reliable measurement instruments based on the current literature. After the proposed model's final constructs were confirmed, questions for the survey were modified to fit our study after being obtained from earlier related studies. The respondents without any knowledge of smart wearable technology were removed from the data to avoid outliers and misinterpretation.

The structural model was assessed for the purpose of hypothesis testing after the measurement model's validity and reliability were established. The results of the analysis were also emphasized in the chapter previously. According to our study, the research model significantly explains 63% of the variation in IU, 31.80% of the variation in PEOU, and 59% of the variation in PU. In addition, this study accepted 8 of the 10 hypotheses. The results of this study are covered in the following section.

5.2 Discussion of the Findings

Given the paucity of studies on older people's acceptance of smart wearable technology, the primary goal of this study is to examine the factors that affect older people's intentions to use such technology. The relationship between PEOU and IU, as well as PU and IOU, have been the main determinants of the 12 hypotheses developed for this study. The following section discusses the study's findings as well as the responses to the research questions.

One of the study's main findings is that although the majority of the respondents are aware of smart wearable technology, almost half of them are not a user of smart wearable technology. This indicates that there is low awareness of smart wearable technology in Malaysia comparing to users in other countries. This statement can be supported by a survey done by Ipsos in 2018, where Malaysia is one of world’s smallest tech buyers with less than 13% smart wearable users in the country [185]. Studies on the acceptance of elderly in using the technology to monitor their health mostly have been conducted in modern countries [72], [98], [186], thus leading to the lack of studies in this field for developing countries such as Malaysia. A study on the acceptance of health IT by users in developing nations was conducted, but no statistical analysis was offered; only an extension of the TAM with new model variables was suggested [187]. Therefore, this study will provide new insights to the current literature on the factors influence the elderly's acceptance in using smart wearable technology. Furthermore, due to the fact that almost 50% of the participants are not a smart wearable technology user brings up the need to explore further in this industry.

5.2.1 Research Question 1

What are the external factors that could deviate the elderly's intention to use smart wearables technology?

5.2.1.1 External Factors

H1. *Facilitating conditions have positive impacts on perceived usefulness explicitly.*

H4. *Facilitating conditions have positive impacts on perceived ease of use explicitly.*

H7. *Facilitating conditions have positive impacts on intention to use explicitly.*

The facilitating conditions for the supported hypotheses may aid in boosting PEOU and PU. But due to the effect size f^2 of facilitating condition on PEOU, this construct may not be important although the hypothesis is supported. In Lin et al.'s study, FC was found to be not having direct effect on PU [97]. On the contrary, our study's results indicate otherwise. This may be due to having a larger sample size in our study as they only collected response from 146 of participants in their data. In Aggelidis and Chatzoglou's study [72], facilitating condition is the main factor in affecting the behavioural intention also. It has shown that FC has positive effects on IU. Therefore, with the supported hypotheses and previous studies, it can be concluded that FC have direct positive effects on PEOU and PU. FC however has found to be not significant and direct positive effects on intention to use as the hypothesis was not supported.

H2. *Compatibility has positive impacts on perceived usefulness explicitly.* ***H5.*** *Compatibility has positive impacts on perceived ease of use explicitly.* ***H8.*** *Compatibility has positive impacts on intention to use explicitly.*

PEOU and PU are directly benefited by compatibility. COM has been commonly discussed in the field of user acceptance in technology industry [95], [103], [188]. These studies also concluded that COM has a significant effect on IU. Table 4.9 also indicates that COM has a medium to large effect on the proposed model based on the effect size (f^2). Hence, it can be concluded that COM has direct positive effects on PEOU and PU with supported hypotheses and the findings of the previous studies. On the contrary, COM has no significant and positive effects on IU. Meaning to say the COM of the smart wearable technology may not be one of the concerns that the elderly have in using the technology.

H3. *Social influence has positive impacts on perceived usefulness explicitly.* ***H6.*** *Social influence has positive impacts on perceived ease of use explicitly.* ***H9.*** *Social influence has positive impacts on intention to use explicitly.*

Lastly, SI has direct positive impacts on both PU and IU but has no significant or direct impacts on PEOU. It also indicated that SI has significant and positive effects on PU and IU in previous studies also [72], [97]. It has been previously reported that the opinions of the family members affected the mobile phone usage decisions of the older adults significantly [189]. Therefore, SI can be concluded as having positive direct effects on PU and IU with the supported hypotheses and the findings of the previous studies.

5.2.2 Research Question 2

What human factors that the elderly might consider before using smart wearables technology?

5.2.2.1 Human Factors

H10. *Perceived stigmatization has negative impacts on intention to use explicitly.* ***H11.*** *Performance risk has negative impacts on intention to use explicitly.*

PS can be also known as perceived social risk [97]. In Akturan and Tezcan's study [190], they found that PS has negative direct effects on IU in mobile banking. It was also identified as a significant determinants on IU in online banking in Vietnam [191]. However, there are a few studies that identified perceived social risk as a non-significant factor in explaining behavioral intention [97], [192], [193]. As a result, this factor can be thoroughly investigated in order to determine what perceptions of social risk actually influence behavioral intentions. Regarding this study, it was discovered that PS had significant and negative impacts on the IU with the supported hypothesis and having a small effect size based on the f^2 value. On the contrary, PR has found to be not significant and have no negative effects on IU as the hypothesis was rejected in the previous section. Which suggests that the PR of the wearable smart technology may not be a factor in determining whether to use it.

H12. *Computer anxiety has negative impacts on intention to use explicitly.* ***H13.*** *Self-efficacy has positive impacts on intention to use explicitly.*

CA has no significant negative effects on IU. In Dehghani et al.'s [194] study, CA has found to be having significant effects only on the intention to continue using the smart wearable technology. It has also been found that CA although has been reported having a significant effect on behavioral intention in smart wearable devices, they stated that the effect has neither to be positive or negative effect [195]. Therefore, CA should be further analyzed with more perspectives to understand the insights of computer anxiety influencing the behavioral intention. As for this study, CA is not one of the factors that the elderly considered when intending to use smart wearable technology.

SE also has no significant positive effects on intention to use as the hypothesis is rejected in the previous section. In previous studies, SE has found to be useful in predicting the behavioral intention [72], [188], [196]. However, there have been limited study that include SE as one of their factors on behavioral intention in smart wearable technology. Hence, this item could be an interesting insight for future researchers to be explored on. For this study, self-efficacy is not one of the factors affecting the intention to use.

5.2.3 Research Question 3

What values do the elderly perceive before using smart wearable technology?

5.2.3.1 Perceived Values

H14. *Perceived usefulness has direct positive effect on intention to use.*

H15. *Perceived ease of use has a direct positive effect on intention to use.*

PEOU and PU have been found to have significant positive effects on IU. However, PU has appeared to be more important and greater effect size compared to PEOU based on the f^2 value. In the previous studies, PEOU has also found to be not having a significant effect on IU [70], [100], as the majority of the participants find that smart wearable technology is easy to use. In the field of this industry, PU has also found to be significant on the IU in many researches [72], [97], [188], [194], [197]. Therefore, PU is one of the crucial factors to be studied when researching the behavioral intention on the acceptance of technology.

6. CHAPTER 6: Conclusion

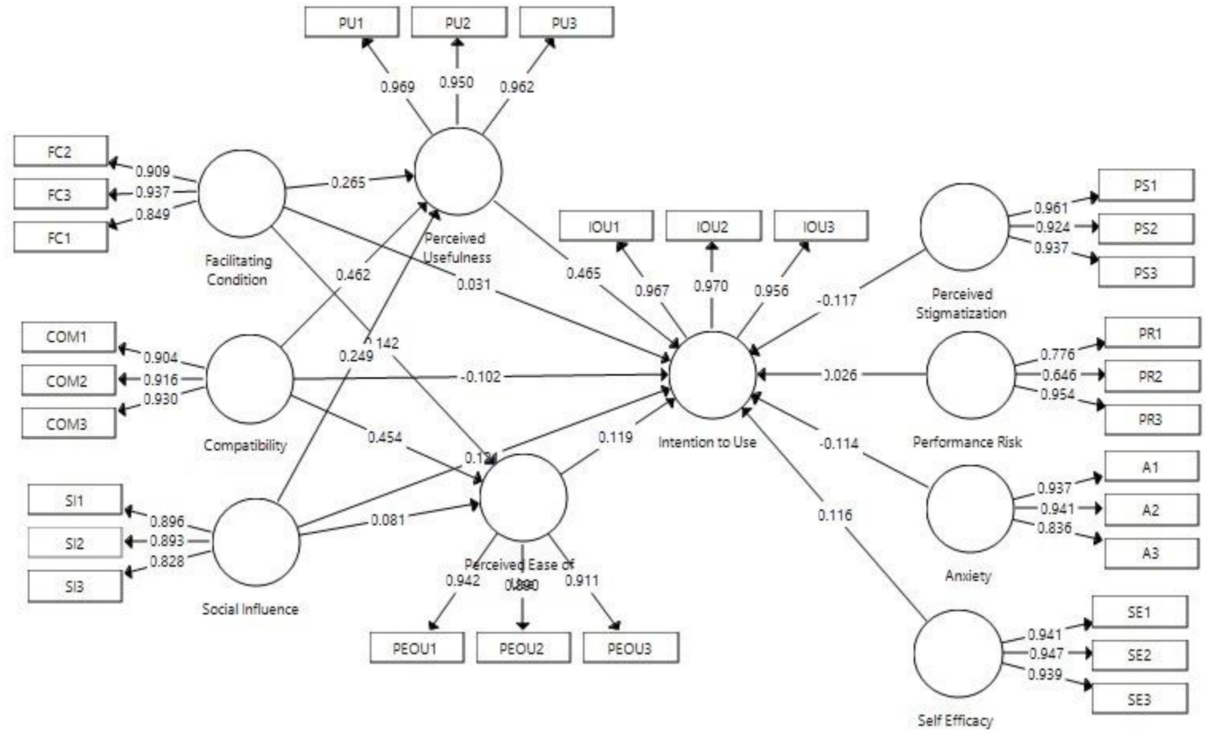


Figure 6.1: Summary of the proposed model

This study was carried out to determine the variables that affect elderly people's intention to use smart wearable technology in Malaysia. Smart wearable technology is a device that could help the elderly or their family members to monitor their health every day without affecting their daily routine remotely. Although there have been studies of the elderly's acceptance of smart wearable technology, the factors that influence their decision in using the technology remain unresolved. As a result, this study has been carried out to investigate the variables that affect their decision from a different perspective by suggesting an integrated model, as shown in Figure 6.1. In our proposed model, we have integrated some additional constructs in the base model of TAM. To answer our research questions and objectives, these constructs are divided into three main categories. The 3 main factors include external factors (i.e., FC, COM, SI), human factors (i.e., PS, PR, CA, SE), and perceived values (i.e., PEOU, PU). There were 9 out of 15 of the supported hypotheses in our findings of this study. Out of the 9 items, COM has been found to be important in explaining the IU of the elderly on smart wearable technology. While FC is not an important item in explaining the IU. To summarize, external factors seem to be more having a significant effect on PU when comparing with PEOU. However, when it comes to explaining the factors that influence behavioral intention, perceived values are the better factors to be explored in influencing the decisions of the elderly.

6.1 Research Implications

6.1.1 Theoretical Implications

In general, this research has made a number of significant theoretical contributions. By describing the factors that affect the acceptance of elderly people using smart wearable technology, this study fills a gap in the literature.

First of all, this study is one of the first few studies to investigate the factors that influence the acceptance of elderly people on smart wearable technology in developing countries. The items in our study were divided into 3 main categories: perceived values, human factors, and external factors. In previous related studies, there were very few that have looked into external and human factors. They only studied some of the external factors which were usually compatibility and social influence. Very few of them combined facilitating condition with compatibility and social influence. Only Li et al. [98] has included these 3 factors as external factors in their study but their study was conducted in a developed country. Therefore, in order to better understand the behavioral intentions of the elderly with regard to smart wearable technology, these three external factors can be further investigated in developing nations like Malaysia.

Second of all, the construct of individual context to be included in this study's technology acceptance model for the suggested model happens to be among the first few studies. As previously stated, the purpose of this study is to examine the variables that affect elderly people's behavior when using smart wearable technology. Although the hypotheses for both items have been rejected from our findings in this study, these items should still be included for further investigation as here are very few prior studies that have looked at these 2 aspects of smart wearable technology acceptance. This study has found that compatibility has a medium to large effect on perceived usefulness and perceived ease of use based on the value of effect size f^2 with the exception of individual context. Based on our literature review study, the previous related studies that include effect size in their analysis and results are close to none. Meaning this might be quite a new analysis for researchers to consider to be included in their analysis as it explains the sensitivity of their dependent variables to changes in the independent variable [198]. As Lin et al. [198] mentioned that p-values criterion is no longer as effective in supporting the hypothesis of the relationships.

Another theoretical contribution is this study presents the influence of PU and PEOU towards the acceptance of the smart wearable technology among the elderly. The finding of this study is consistent with what have been reported in the previous studies [199]–[203] which found that PEOU has lesser impact and is less important in the aspect of measuring the behavioral intention in using smart wearable technology compared to PU. This study also incorporated individual items to better understand what are the factors that the elderly will perceive as useful before considering using the smart wearable technology. It was found that facilitating condition, compatibility, and social influence are significant in determining the usefulness of the smart wearable technology. However, based on the findings of this study, compatibility is the most important in explaining the usefulness of the technology. Thus, it can be argued that the elderly will consider the usefulness of the smart wearable technology more than the ease of use when intending to use the technology.

Last but not least, this study significantly advances our knowledge of how elderly people intend to use smart wearable technology, especially in the context of developing nations such as Malaysia. Despite the fact that there were numerous studies on smart wearable technology, most of them were conducted in developed. Hence leading to the lack of research on smart wearable technology among Malaysian consumers. Since the results from developed countries cannot be applied to developing nations such as Malaysia, it is essential to implement research with a local context focus.

6.1.2 Practical Implications

According to the study's findings, the majority of the tested variables in the Smart Wearable Technology Acceptance Model (SWTAM) have significant impacts on older people’s behavioral perspective to use smart wearable technology. In this light, understanding the factors will provide valuable insights to smart technology marketers, developers, and marketing researchers.

The findings of this study will provide crucial knowledge for smart wearable technology developers. This is very useful for the developers who are looking to increase their technology purchases and their revenues. Smart wearable technology developers and marketers can use the inputs from this study to form strategies to attract more users not only to buy the technology, but to continue using it and getting more advanced devices when they are launched.

Rich contextual information generated by the devices can be captured by smart wearable technology, and hence allowing the information to be used for a personalized experience deliverance [204]. Smart wearable technology's main advantage is its ability to offer a variety of inspection and tracking features, including biofeedback or any other sensory physiological functions that are related to biometry. Smart wearable technology can be a useful tool for expanding access to healthcare, empowering people to monitor their own health, and potentially lowering the cost of medical care. Understanding the determinants of SWTAM can help in better understanding potential consumer behaviors because the majority of target users are those who are health-conscious and capable of managing their own healthcare.

One important consideration for smart wearable technology marketers is the compatibility of the technology. In the case of Malaysian smart wearable technology users, the study has found that compatibility is one of the biggest concerns in perceiving the usefulness of the technology. Furthermore, the elderly are also concerned about the compatibility in perceiving whether the technology is easy to use or not. Based on the findings, smart wearable technology designers should consider designing devices that are user-friendly enough for the elderly and that they are able to learn to use the devices very quickly and easily. For example, the designers could make the devices with a simpler interface so that the elderly can quickly pick up and learn how to use such devices.

In addition, social influence is also one of the considerations of the elderly on perceiving the usefulness of the smart wearable technology before they intend to use the technology. Which means that the marketers should educate the family members of the elderly on the importance of using smart wearable technology as well as the benefits of using the technology in order to convince the elderly to use it. As the opinions of a stranger can never be as convincing as the opinions of your surrounding friends and family. Therefore, marketers can be shifting their focus on the friends and family members of the users first to boost up the awareness and knowledge of smart wearable technology. For example, they could target the interest of their friends and family on the advantages of using such technology and how it helps to enhance their everyday life to influence the elderlies in their families in using it.

6.2 Study Limitations

While this study is one of the first few studies on exploring the factors of the behavioral intention on smart wearable technology in developing countries, this study has its own limitation. The first limitation of this study is that the data collected from the survey is through social media platforms. The facial expression of the participants while answering the survey cannot be seen and thus, we will never know if they fully understood the questions of the survey and answered them accurately. Therefore, we can only assume that our participants understood the context of the questions in the survey and answered them correctly based on their own thoughts. The insights might be different if the survey was conducted face-to-face.

In the aspect of the data collection, although Iacobucci's [205] stated that a 100 sample size is typically sufficient for convergence, while a 150 sample size is better sufficed for convergence as well as proper solution. He also stated that in some cases, some models can exhibit good performance with small sample size which are in the range of 50 to 100. In this study, a total 300 of participants were collected for our data, 266 of them were kept as our final data after data filtering. Even though 266 is far from enough based on the statement by Iacobucci [205], it is possible that different results can be obtained when the sample size of the data collection is bigger.

The next limitation is that due to smart wearable technology in Malaysia is not a very commonly used technology yet, the findings of this study could not be generalized to bigger region such as Asia. More studies should be performed in the aspect of Asia region by collecting more data across countries in Asia to gain more insights in this perspective. Therefore, the results obtained in this research are only reflective to the elderly in Malaysia. Hence, different results may be obtained when data is collected from different countries in the Asia region.

Furthermore, the current study was conducted as a cross-sectional study, which also indicated as one of the limitations to this study. A cross-sectional study may not be able to capture the dynamic and is harder to predict user behavior in regards of the new technology acceptance behavior. It can be argued that the results may be slightly biased. This is because the selected respondents do not have the actual smart wearable technology device for usage testing prior to answering the questionnaire. The result could vary if the data were collected after the respondents have tested using an actual smart wearable technology device instead of just answering the questions based on imagination. An actual usage of the smart wearable technology device will influence the users' intention as they are able to evaluate whether the technology is really useful to them.

6.3 Recommendations for Future Research

Based on the limitations mentioned above, this research provides several recommendations for future research as elaborated below:

- Longitudinal data: Firstly, future research could explore the factors on behavioral intention in smart wearable technology by using longitudinal data. It would be interesting to examine whether the elderly's decision to use smart wearable technology device changes over time. It would be interesting to understand how could repeated exposure influence behavioral intentions. It can be hypothesized that even though the elderly may not have the intention to use the device at first, prolonged interaction and exposure with the device may increase their confidence towards the usefulness of the technology. Consequently, this will increase the elderly's willingness to use the smart wearable technology.
- Design and Implementation: This study did not address the issues linked to the design and implementation of the smart wearable technology. Hence, future studies should examine the effect of interface design towards the elderly's perception, attitude, and behavior on intention to use. Examining additional constructs of design structures such as weight, screen size, color scheme, and the interface will enrich the knowledge of smart wearable technology designers and its link to customers' attitude towards the technology.
- Experimental Research: Future studies can be done by repeating this study using a controlled experiment setting. Experimental research can be done with individuals to explore the actual usage of the technology within a timeframe and

what impact experience can have on intention and actual behavior. This will help with the accuracy verification of the research model. The findings may not be sufficiently conclusive for all the variables because this study only accounts for 64.20% of the variation in the intention to use the technology. Future studies could therefore be conducted to broaden the study and gain more knowledge about the underlying causes of behavioral intention in smart wearable technology.

- Functions and Features: It is also suggested that future studies should include functions and features in their variables. This is to gauge whether the users enjoy using the functions and features of the smart wearable technology and will it influence the user's behavioral intention. Future studies can also focus on what are the functions and features the elderly prefer to have before intending to use the smart wearable technology. As this might increase the technology's perceived usefulness and eventually the users' willingness.

7. REFERENCES

[1] J. T. Erber, *Aging and older adulthood*. John Wiley & Sons, 2012.

[2] K. Chen and A. H. S. Chan, "A review of technology acceptance by older adults.," *Gerontechnology*, 2011.

[3] M. McCann, M. Donnelly, and D. O'Reilly, "Living arrangements, relationship to people in the household and admission to care homes for older people," *Age Ageing*, vol. 40, no. 3, pp. 358–363, 2011.

[4] A. Abdullah, A. Ismael, A. Rashid, A. Abou-ElNour, and M. Tarique, "Real time wireless health monitoring application using mobile devices," *Int. J. Comput. Networks Commun.*, vol. 7, no. 3, pp. 13–30, 2015.

[5] E. L. Murnane *et al.*, "Self-monitoring practices, attitudes, and needs of individuals with bipolar disorder: implications for the design of technologies to manage mental health," *J. Am. Med. Informatics Assoc.*, vol. 23, no. 3, pp. 477–484, 2016.

[6] S. Stowe and S. Harding, "Telecare, telehealth and telemedicine," *Eur. Geriatr. Med.*, vol. 1, no. 3, pp. 193–197, 2010, doi: https://doi.org/10.1016/j.eurger.2010.04.002.

[7] M. Niemelä, R. G. Fuentetaja, E. Kaasinen, and J. L. Gallardo, "Supporting independent living of the elderly with mobile-centric ambient intelligence: user evaluation of three scenarios," in *European Conference on Ambient Intelligence*, 2007, pp. 91–107.

[8] H. Li, J. Wu, Y. Gao, and Y. Shi, "Examining individuals' acceptance of healthcare wearable devices: An empirical study from privacy calculus perspective," *Int. J. Med. Inform.*, vol. 88, pp. 8–17, 2016, doi: https://doi.org/10.1016/j.ijmedinf.2015.12.010.

[9] S. T. Rosenbloom, "Person-generated health and wellness data for health care," *J. Am. Med. Informatics Assoc.*, vol. 23, no. 3, pp. 438–439, 2016, doi: 10.1093/jamia/ocw059.

[10] M. Chan, D. Estève, J.-Y. Fourniols, C. Escriba, and E. Campo, "Smart wearable systems: Current status and future challenges," *Artif. Intell. Med.*, vol. 56, no. 3, pp. 137–156, 2012, doi: https://doi.org/10.1016/j.artmed.2012.09.003.

[11] J. A. Fraile, J. Bajo, J. M. Corchado, and A. Abraham, "Applying wearable solutions in dependent environments," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 6, pp. 1459–1467, Nov. 2010, doi: 10.1109/TITB.2010.2053849.

[12] N. A. Kalogriopoulos, J. Baran, A. J. Nimunkar, and J. G. Webster, "Electronic medical record systems for developing countries," in *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2009, pp. 1730–1733.

[13] P. Lukowicz, T. Kirstein, and G. Tröster, "Wearable systems for health care applications," *Methods Inf. Med.*, vol. 43, no. 03, pp. 232–238, 2004.

[14] N. Maglaveras, I. Chouvarda, V. Koutkias, S. Meletiadis, K. Haris, and E. A. Balas, "Information technology can enhance quality in regional health delivery," *Methods Inf. Med.*, vol. 41, no. 05, pp. 393–400, 2002.

[15] T. Rault, A. Bouabdallah, Y. Challal, and F. Marin, "A survey of energy-efficient

context recognition systems using wearable sensors for healthcare applications," *Pervasive Mob. Comput.*, vol. 37, pp. 23–44, 2017, doi: https://doi.org/10.1016/j.pmcj.2016.08.003.

[16] M. Hakonen, H. Piitulainen, and A. Visala, "Current state of digital signal processing in myoelectric interfaces and related applications," *Biomed. Signal Process. Control*, vol. 18, pp. 334–359, 2015, doi: https://doi.org/10.1016/j.bspc.2015.02.009.

[17] H. Ehmen, M. Haesner, I. Steinke, M. Dorn, M. Gövercin, and E. Steinhagen-Thiessen, "Comparison of four different mobile devices for measuring heart rate and ECG with respect to aspects of usability and acceptance by older people," *Appl. Ergon.*, vol. 43, no. 3, pp. 582–587, 2012, doi: https://doi.org/10.1016/j.apergo.2011.09.003.

[18] Y.-D. Lee and W.-Y. Chung, "Wireless sensor network based wearable smart shirt for ubiquitous health and activity monitoring," *Sensors Actuators B Chem.*, vol. 140, no. 2, pp. 390–395, 2009, doi: https://doi.org/10.1016/j.snb.2009.04.040.

[19] C.-S. Lin, H. C. Hsu, Y.-L. Lay, C.-C. Chiu, and C.-S. Chao, "Wearable device for real-time monitoring of human falls," *Measurement*, vol. 40, no. 9, pp. 831–840, 2007, doi: https://doi.org/10.1016/j.measurement.2007.04.001.

[20] A. Alaiad and L. Zhou, "The determinants of home healthcare robots acceptance: An empirical investigation," *Int. J. Med. Inform.*, vol. 83, no. 11, pp. 825–840, 2014, doi: https://doi.org/10.1016/j.ijmedinf.2014.07.003.

[21] T. R. F. Postema, J. M. Peeters, and R. D. Friele, "Key factors influencing the implementation success of a home telecare application," *Int. J. Med. Inform.*, vol. 81, no. 6, pp. 415–423, 2012, doi: https://doi.org/10.1016/j.ijmedinf.2011.12.003.

[22] C. Liddy, J. J. Dusseault, S. Dahrouge, W. Hogg, J. Lemelin, and J. Humber, "Telehomecare for patients with multiple chronic illnesses: Pilot study," *Can. Fam. Physician*, vol. 54, no. 1, pp. 58–65, 2008.

[23] A. Spagnolli, E. Guardigli, V. Orso, A. Varotto, and L. Gamberini, "Measuring user acceptance of wearable symbiotic devices: validation study across application scenarios," in *International Workshop on Symbiotic Interaction*, 2015, pp. 87–98.

[24] A. Borders, M. Earleywine, and S. Huey, "Predicting problem behaviors with multiple expectancies: Expanding expectancy-value theory," *Adolescence*, vol. 39, no. 155, pp. 539–550, 2004.

[25] M. B. Mazis, O. T. Ahtola, and R. E. Klippel, "A comparison of four multi-attribute models in the prediction of consumer attitudes," *J. Consum. Res.*, vol. 2, no. 1, pp. 38–52, 1975.

[26] I. Ajzen and M. Fishbein, "A Bayesian analysis of attribution processes.," *Psychol. Bull.*, vol. 82, no. 2, p. 261, 1975.

[27] M. Fishbein, J. Jaccard, A. R. Davidson, I. Ajzen, and B. Loken, "Predicting and understanding family planning behaviors," in *Understanding attitudes and predicting social behavior*, Prentice Hall, 1980.

[28] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Q.*, pp. 319–340, 1989.

[29] F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, "User Acceptance of Computer

Technology: A Comparison of Two Theoretical Models," *Manage. Sci.*, vol. 35, no. 8, pp. 982–1003, 1989, doi: 10.1287/mnsc.35.8.982.

[30] R. J. Holden and B.-T. Karsh, "The technology acceptance model: its past and its future in health care," *J. Biomed. Inform.*, vol. 43, no. 1, pp. 159–172, 2010.

[31] M. Fishbein and I. Ajzen, "Belief, attitude, intention, and behavior: An introduction to theory and research," 1977.

[32] P. J. Hu, P. Y. K. Chau, O. R. L. Sheng, and K. Y. Tam, "Examining the technology acceptance model using physician acceptance of telemedicine technology," *J. Manag. Inf. Syst.*, vol. 16, no. 2, pp. 91–112, 1999.

[33] V. Venkatesh and F. D. Davis, "A theoretical extension of the technology acceptance model: Four longitudinal field studies," *Manage. Sci.*, vol. 46, no. 2, pp. 186–204, 2000.

[34] I. Ajzen and others, "The theory of planned behavior," *Organ. Behav. Hum. Decis. Process.*, vol. 50, no. 2, pp. 179–211, 1991.

[35] S. Taylor and P. Todd, "Assessing IT usage: The role of prior experience," *MIS Q.*, pp. 561–570, 1995.

[36] R. Safeena, H. Date, N. Hundewale, and A. Kammani, "Combination of TAM and TPB in internet banking acceptance," *Int. J. Comput. Theory Eng.*, vol. 5, no. 1, p. 146, 2013.

[37] H. C. Triandis, "Values, attitudes, and interpersonal behavior.," in *Nebraska symposium on motivation*, 1979.

[38] R. L. Thompson, C. A. Higgins, and J. M. Howell, "Personal computing: Toward a conceptual model of utilization," *MIS Q.*, pp. 125–143, 1991.

[39] L. G. Tornatzky and K. J. Klein, "Innovation characteristics and innovation acceptance-implementation: A meta-analysis of findings," *IEEE Trans. Eng. Manag.*, no. 1, pp. 28–45, 1982.

[40] E. M. Rogers, *Diffusion of innovations*. Simon and Schuster, 2010.

[41] R. Ibrahim, S. M. Hilles, S. M. Adam, and Y. El-Ebiary, "Methodological Process for Evaluation of E-government Services base on the Federal Republic of Nigerian Citizen's E-government Services usage," *Indian J. Sci. Technol.*, vol. 9, no. 28, 2016.

[42] E. P. Udeh, "Exploring user acceptance of free wireless fidelity public hot spots: An empirical study," *Hum. Technol. An Interdiscip. J. Humans ICT Environ.*, 2008.

[43] E. L. Deci and R. M. Ryan, "The general causality orientations scale: Self-determination in personality," *J. Res. Pers.*, vol. 19, no. 2, pp. 109–134, 1985.

[44] R. P. Bagozzi, F. D. Davis, and P. R. Warshaw, "Development and test of a theory of technological learning and usage," *Hum. relations*, vol. 45, no. 7, pp. 659–686, 1992.

[45] C. Koo, N. Chung, and K. Nam, "Assessing the impact of intrinsic and extrinsic motivators on smart green IT device use: Reference group perspectives," *Int. J. Inf. Manage.*, vol. 35, no. 1, pp. 64–79, 2015.

[46] F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, "Extrinsic and intrinsic motivation

to use computers in the workplace 1," *J. Appl. Soc. Psychol.*, vol. 22, no. 14, pp. 1111–1132, 1992.

[47] A. Bandura, "Human agency in social cognitive theory.," *Am. Psychol.*, vol. 44, no. 9, p. 1175, 1989.

[48] D. R. Compeau and C. A. Higgins, "Application of social cognitive theory to training for computer skills," *Inf. Syst. Res.*, vol. 6, no. 2, pp. 118–143, 1995.

[49] D. Compeau, C. A. Higgins, and S. Huff, "Social cognitive theory and individual reactions to computing technology: A longitudinal study," *MIS Q.*, pp. 145–158, 1999.

[50] A. Weeger and H. Gewald, "Examining Social And Cognitive Aspects Determining Physician's Acceptance Of Electronic Medical Records," 2013.

[51] B. H. Sheppard, J. Hartwick, and P. R. Warshaw, "The theory of reasoned action: A meta-analysis of past research with recommendations for modifications and future research," *J. Consum. Res.*, vol. 15, no. 3, pp. 325–343, 1988.

[52] I. Ajzen, "From intentions to actions: A theory of planned behavior," in *Action control*, Springer, 1985, pp. 11–39.

[53] S. Taylor and P. Todd, "Decomposition and crossover effects in the theory of planned behavior: A study of consumer acceptance intentions," *Int. J. Res. Mark.*, vol. 12, no. 2, pp. 137–155, 1995.

[54] S. Taylor and P. A. Todd, "Understanding information technology usage: A test of competing models," *Inf. Syst. Res.*, vol. 6, no. 2, pp. 144–176, 1995.

[55] I. Ajzen, "Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior 1," *J. Appl. Soc. Psychol.*, vol. 32, no. 4, pp. 665–683, 2002.

[56] P. A. Pavlou and M. Fygenson, "Understanding and predicting electronic commerce acceptance: An extension of the theory of planned behavior," *MIS Q.*, pp. 115–143, 2006.

[57] F. D. Davis, "A technology acceptance model for empirically testing new end-user information systems: Theory and results," Massachusetts Institute of Technology, 1985.

[58] V. Venkatesh, "Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model," *Inf. Syst. Res.*, vol. 11, no. 4, pp. 342–365, 2000.

[59] Y. Kim and K. Crowston, "Technology acceptance and use theory review for studying scientists' continued use of cyber-infrastructure," *Proc. Am. Soc. Inf. Sci. Technol.*, vol. 48, no. 1, pp. 1–10, 2011.

[60] E. Karahanna, D. W. Straub, and N. L. Chervany, "Information technology acceptance across time: a cross-sectional comparison of pre-acceptance and post-acceptance beliefs," *MIS Q.*, pp. 183–213, 1999.

[61] G. C. Moore and I. Benbasat, "Development of an instrument to measure the perceptions of adopting an information technology innovation," *Inf. Syst. Res.*, vol. 2, no. 3, pp. 192–222, 1991.

[62] R. M. Ryan and E. L. Deci, "Intrinsic and extrinsic motivations: Classic definitions

and new directions," *Contemp. Educ. Psychol.*, vol. 25, no. 1, pp. 54–67, 2000.

[63] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Q.*, pp. 425–478, 2003.

[64] A. Bandura, "Social foundations of thought and action," *Englewood Cliffs, NJ*, vol. 1986, no. 23–28, 1986.

[65] D. R. Compeau and C. A. Higgins, "Computer self-efficacy: Development of a measure and initial test," *MIS Q.*, pp. 189–211, 1995.

[66] R. D. Johnson and G. M. Marakas, "The role of behavioral modeling in computer skills acquisition: Toward refinement of the model," *Inf. Syst. Res.*, vol. 11, no. 4, pp. 402–417, 2000.

[67] H. P. Profita, "Social acceptability of wearable technology use in public: an exploration of the societal perceptions of a gesture-based mobile textile interface," Georgia Institute of Technology, 2011.

[68] L. Dunne, "The design of wearable technology: addressing the human-device interface through functional apparel design," 2004.

[69] M. Kurwa, A. Mohammed, and W. Liu, "Wearable Technology, Fashioning the Future. Flextronics. Retrieved May 13, 2014." 2008.

[70] K. Chen and A. H. S. Chan, "Gerontechnology acceptance by elderly Hong Kong Chinese: a senior technology acceptance model (STAM)," *Ergonomics*, vol. 57, no. 5, pp. 635–652, 2014, doi: 10.1080/00140139.2014.895855.

[71] D. Gefen, E. Karahanna, and D. W. Straub, "Trust and TAM in online shopping: An integrated model," *MIS Q.*, pp. 51–90, 2003.

[72] V. P. Aggelidis and P. D. Chatzoglou, "Using a modified technology acceptance model in hospitals," *Int. J. Med. Inform.*, vol. 78, no. 2, pp. 115–126, 2009, doi: 10.1016/j.ijmedinf.2008.06.006.

[73] P. Y. K. Chau and P. J.-H. Hu, "Investigating healthcare professionals' decisions to accept telemedicine technology: an empirical test of competing theories," *Inf. Manag.*, vol. 39, no. 4, pp. 297–311, 2002.

[74] W. G. Chismar and S. Wiley-Patton, "Does the extended technology acceptance model apply to physicians," in *36th Annual Hawaii International Conference on System Sciences, 2003. Proceedings of the*, 2003, pp. 8--pp.

[75] R. Jayasuriya, "Determinants of microcomputer technology use: implications for education and training of health staff," *Int. J. Med. Inform.*, vol. 50, no. 1–3, pp. 187–194, 1998.

[76] H. Yang, J. Yu, H. Zo, and M. Choi, "User acceptance of wearable devices: An extended perspective of perceived value," *Telemat. Informatics*, vol. 33, no. 2, pp. 256–269, 2016, doi: https://doi.org/10.1016/j.tele.2015.08.007.

[77] E. Park and K. J. Kim, "User acceptance of long-term evolution (LTE) services: An application of extended technology acceptance model," *Program*, 2013.

[78] C. K. L. Or, B.-T. Karsh, D. J. Severtson, L. J. Burke, R. L. Brown, and P. F. Brennan, "Factors affecting home care patients' acceptance of a web-based interactive self-management technology," *J. Am. Med. Informatics Assoc.*, vol. 18, no. 1, pp. 51–59, 2011.

[79] M.-H. Ryu, S. Kim, and E. Lee, "Understanding the factors affecting online elderly user's participation in video UCC services," *Comput. Human Behav.*, vol. 25, no. 3, pp. 619–632, 2009, doi: https://doi.org/10.1016/j.chb.2008.08.013.

[80] S. Pan and M. Jordan-Marsh, "Internet use intention and acceptance among Chinese older adults: From the expanded technology acceptance model perspective," *Comput. Human Behav.*, vol. 26, no. 5, pp. 1111–1119, 2010, doi: https://doi.org/10.1016/j.chb.2010.03.015.

[81] C. K. L. Or and B.-T. Karsh, "A systematic review of patient acceptance of consumer health information technology," *J. Am. Med. Informatics Assoc.*, vol. 16, no. 4, pp. 550–560, 2009.

[82] B. Kaplan, "Evaluating informatics applications—clinical decision support systems literature review," *Int. J. Med. Inform.*, vol. 64, no. 1, pp. 15–37, 2001.

[83] M.-P. Gagnon *et al.*, "An adaptation of the theory of interpersonal behaviour to the study of telemedicine acceptance by physicians," *Int. J. Med. Inform.*, vol. 71, no. 2–3, pp. 103–115, 2003.

[84] L. Chen, M. L. Gillenson, and D. L. Sherrell, "Enticing online consumers: an extended technology acceptance perspective," *Inf. Manag.*, vol. 39, no. 8, pp. 705–719, 2002, doi: https://doi.org/10.1016/S0378-7206(01)00127-6.

[85] F.-C. Tung and S.-C. Chang, "Nursing students' behavioral intention to use online courses: A questionnaire survey," *Int. J. Nurs. Stud.*, vol. 45, no. 9, pp. 1299–1309, 2008, doi: https://doi.org/10.1016/j.ijnurstu.2007.09.011.

[86] J.-H. Wu and S.-C. Wang, "What drives mobile commerce?: An empirical evaluation of the revised technology acceptance model," *Inf. Manag.*, vol. 42, no. 5, pp. 719–729, 2005, doi: https://doi.org/10.1016/j.im.2004.07.001.

[87] L. Xue *et al.*, "An exploratory study of ageing women's perception on access to health informatics via a mobile phone-based intervention," *Int. J. Med. Inform.*, vol. 81, no. 9, pp. 637–648, 2012, doi: https://doi.org/10.1016/j.ijmedinf.2012.04.008.

[88] J.-H. Wu, S.-C. Wang, and L.-M. Lin, "Mobile computing acceptance factors in the healthcare industry: A structural equation model," *Int. J. Med. Inform.*, vol. 76, no. 1, pp. 66–77, 2007, doi: https://doi.org/10.1016/j.ijmedinf.2006.06.006.

[89] K. Mathieson, "Predicting user intentions: comparing the technology acceptance model with the theory of planned behavior," *Inf. Syst. Res.*, vol. 2, no. 3, pp. 173–191, 1991.

[90] R. Fensli, J. G. Dale, P. O'Reilly, J. O'Donoghue, D. Sammon, and T. Gundersen, "Towards improved healthcare performance: examining technological possibilities and patient satisfaction with wireless body area networks," *J. Med. Syst.*, vol. 34, no. 4, pp. 767–775, 2010.

[91] R. Fensli, P. E. Pedersen, T. Gundersen, and O. Hejlesen, "Sensor acceptance model - Measuring patient acceptance of wearable sensors," *Methods Inf. Med.*, vol. 47, no. 1, pp. 89–95, 2008, doi: 10.3414/ME9106.

[92] S. Chatterjee and A. Price, "Healthy Living with Persuasive Technologies: Framework, Issues, and Challenges," *J. Am. Med. Informatics Assoc.*, vol. 16, no. 2, pp. 171–178, 2009, doi: https://doi.org/10.1197/jamia.M2859.

[93] P. Valdastri, A. Menciassi, A. Arena, C. Caccamo, and P. Dario, "An implantable telemetry platform system for in vivo monitoring of physiological parameters," *IEEE Trans. Inf. Technol. Biomed.*, vol. 8, no. 3, pp. 271–278, 2004.

[94] A. Bandura, "Self-efficacy: toward a unifying theory of behavioral change.," *Psychol. Rev.*, vol. 84, no. 2, p. 191, 1977.

[95] P. Y. K. Chau and P. J.-H. Hu, "Information technology acceptance by individual professionals: A model comparison approach," *Decis. Sci.*, vol. 32, no. 4, pp. 699–719, 2001.

[96] A. Durndell and Z. Haag, "Computer self efficacy, computer anxiety, attitudes towards the Internet and reported experience with the Internet, by gender, in an East European sample," *Comput. Human Behav.*, vol. 18, no. 5, pp. 521–535, 2002.

[97] J. Li, Q. Ma, A. H. Chan, and S. S. Man, "Health monitoring through wearable technologies for older adults: Smart wearables acceptance model.," *Appl. Ergon.*, vol. 75, pp. 162–169, Feb. 2019, doi: 10.1016/j.apergo.2018.10.006.

[98] J. Li, Q. Ma, A. H. Chan, and S. S. Man, "Health monitoring through wearable technologies for older adults: Smart wearables acceptance model," *Appl. Ergon.*, vol. 75, no. September 2018, pp. 162–169, 2019, doi: 10.1016/j.apergo.2018.10.006.

[99] R. Fensli, P. E. Pedersen, T. Gundersen, and O. Hejlesen, "Sensor acceptance model - measuring patient acceptance of wearable sensors.," *Methods Inf. Med.*, vol. 47, no. 1, pp. 89–95, 2008, doi: 10.3414/me9106.

[100] Q. Ma, A. H. S. Chan, and K. Chen, "Personal and other factors affecting acceptance of smartphone technology by older Chinese adults," *Appl. Ergon.*, vol. 54, pp. 62–71, 2016.

[101] M. Pagani, "Determinants of acceptance of third generation mobile multimedia services," *J. Interact. Mark.*, vol. 18, no. 3, pp. 46–59, 2004.

[102] Y.-M. Cheng, "Towards an understanding of the factors affecting m-learning acceptance: Roles of technological characteristics and compatibility," *Asia Pacific Manag. Rev.*, vol. 20, no. 3, pp. 109–119, 2015, doi: https://doi.org/10.1016/j.apmrv.2014.12.011.

[103] N. Corrocher, "The acceptance of Web 2.0 services: An empirical investigation," *Technol. Forecast. Soc. Change*, vol. 78, no. 4, pp. 547–558, 2011, doi: https://doi.org/10.1016/j.techfore.2010.10.006.

[104] T. P. LeBel, "Perceptions of and responses to stigma," *Sociol. Compass*, vol. 2, no. 2, pp. 409–432, 2008.

[105] E. Golberstein, D. Eisenberg, and S. E. Gollust, "Perceived stigma and mental health care seeking," *Psychiatr. Serv.*, vol. 59, no. 4, pp. 392–399, 2008.

[106] J. Polaha, S. L. Williams, C. A. Heflinger, and C. R. Studts, "The perceived stigma of mental health services among rural parents of children with psychosocial concerns," *J. Pediatr. Psychol.*, vol. 40, no. 10, pp. 1095–1104, 2015.

[107] C. M. Neal, P. G. Quester, and D. Hawkins, "Consumer Behaviour, Implication for Marketing Strategy (3rdedn.)," *Aust. McGraw Hill Publ.*, 2002.

[108] R. L. Horton, "The structure of perceived risk: Some further progress," *J. Acad.*

Mark. Sci., vol. 4, no. 4, pp. 694–706, 1976.

[109] D. M. I. Akhtar, “Research design,” *Res. Des. (February 1, 2016)*, 2016.

[110] D. Stockemer, *Quantitative Methods for the Social Sciences*. 2019.

[111] D. Soliño-Fernandez, A. Ding, E. Bayro-Kaiser, and E. L. Ding, “Willingness to adopt wearable devices with behavioral and economic incentives by health insurance wellness programs: results of a US cross-sectional survey with multiple consumer health vignettes,” *BMC Public Health*, vol. 19, no. 1, pp. 1–8, 2019.

[112] M. U. Mahidin, “Department of Statistics Malaysia Press Release: Current Population Estimates, Malaysia, 2018-2019,” *Dep. Stat. Malaysia*, no. July, pp. 2018–2019, 2019.

[113] M. A. Memon, H. Ting, J.-H. Cheah, R. Thurasamy, F. Chuah, and T. H. Cham, “Sample Size for Survey Research: Review and Recommendations,” *J. Appl. Struct. Equ. Model.*, vol. 4, no. 2, pp. i–xx, 2020, doi: 10.47263/jasem.4(2)01.

[114] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, “When to use and how to report the results of PLS-SEM,” *Eur. Bus. Rev.*, vol. 31, no. 1, pp. 2–24, 2019, doi: 10.1108/EBR-11-2018-0203.

[115] G. T. M. Hult, J. F. Hair Jr, D. Proksch, M. Sarstedt, A. Pinkwart, and C. M. Ringle, “Addressing endogeneity in international marketing applications of partial least squares structural equation modeling,” *J. Int. Mark.*, vol. 26, no. 3, pp. 1–21, 2018.

[116] C. M. Ringle, M. Sarstedt, R. Mitchell, and S. P. Gudergan, “Partial least squares structural equation modeling in HRM research,” *Int. J. Hum. Resour. Manag.*, vol. 31, no. 12, pp. 1617–1643, 2020.

[117] F. Faul, E. Erdfelder, A. Buchner, and A.-G. Lang, “Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses,” *Behav. Res. Methods*, vol. 41, no. 4, pp. 1149–1160, 2009.

[118] F. Faul, E. Erdfelder, A.-G. Lang, and A. Buchner, “G* Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences,” *Behav. Res. Methods*, vol. 39, no. 2, pp. 175–191, 2007.

[119] J. F. Hair Jr, G. T. M. Hult, C. M. Ringle, and M. Sarstedt, *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications, 2021.

[120] A. S. Acharya, A. Prakash, P. Saxena, and A. Nigam, “Sampling: why and how of it?,” *Indian J. Med. Spec.*, vol. 4, no. 2, 2013, doi: 10.7713/ijms.2013.0032.

[121] S. Y. Chyung, K. Roberts, I. Swanson, and A. Hankinson, “Evidence-based survey design: The use of a midpoint on the Likert scale,” *Perform. Improv.*, vol. 56, no. 10, pp. 15–23, 2017.

[122] N. S. Aziz and A. Kamaludin, “Using pre-test to validate the Questionnaire for Website Usability (QWU),” in *2015 4th International Conference on Software Engineering and Computer Systems (ICSECS)*, 2015, pp. 107–111.

[123] K. Miller, “To Do or Not to Do,” *J. Nurse Pract.*, vol. 15, no. 7, p. A8, 2019, doi: 10.1016/j.nurpra.2019.06.015.

[124] E. Bell, A. Bryman, and B. Harley, *Business research methods*. Oxford university press, 2018.

[125] A. Field, *Discovering statistics using IBM SPSS statistics*. sage, 2013.

[126] A. Bryman and E. Bell, *Business Research Methods*, Fourth Edi. Oxford, UK: Oxford University Press: Oxford, UK: Oxford University Press, 2011.

[127] U. Sekaran and R. Bougie, *Research methods for business: A skill building approach*. john wiley \& sons, 2016.

[128] J. Hair, G. T. M. Hult, C. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling*. 2014.

[129] M. Bradford and J. Florin, "Examining the role of innovation diffusion factors on the implementation success of enterprise resource planning systems," *Int. J. Account. Inf. Syst.*, vol. 4, no. 3, pp. 205–225, 2003, doi: https://doi.org/10.1016/S1467-0895(03)00026-5.

[130] R. N. Stone and K. Grønhaug, "Perceived risk: Further considerations for the marketing discipline," *Eur. J. Mark.*, vol. 27, no. 3, pp. 39–50, 1993.

[131] L. Zhao, Y. Lu, W. Huang, and Q. Wang, "Internet inequality: The relationship between high school students' Internet use in different locations and their Internet self-efficacy," *Comput. Educ.*, vol. 55, no. 4, pp. 1405–1423, 2010.

[132] M. Masrom, "Technology acceptance model and E-learning," *12th Int. Conf. Educ.*, no. May, pp. 21–24, 2007.

[133] M. Sarstedt, C. M. Ringle, J. F. Hair, and others, "Partial least squares structural equation modeling," *Handb. Mark. Res.*, vol. 26, no. 1, pp. 1–40, 2017.

[134] J. F. Hair, G. T. M. Hult, C. M. Ringle, M. Sarstedt, and K. O. Thiele, "Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods," *J. Acad. Mark. Sci.*, vol. 45, no. 5, pp. 616–632, 2017.

[135] D. L. Goodhue, W. Lewis, and R. Thompson, "Does PLS have advantages for small sample size or non-normal data?," *MIS Q.*, pp. 981–1001, 2012.

[136] G. A. Marcoulides, W. W. Chin, and C. Saunders, "When imprecise statistical statements become problematic: a response to Goodhue, Lewis, and Thompson," *Mis Q.*, vol. 36, no. 3, pp. 717–728, 2012.

[137] J. Henseler *et al.*, "Common beliefs and reality about PLS: Comments on Rönkkö and Evermann (2013)," *Organ. Res. methods*, vol. 17, no. 2, pp. 182–209, 2014.

[138] G. F. Khan, M. Sarstedt, W.-L. Shiau, J. F. Hair, C. M. Ringle, and M. P. Fritze, "Methodological research on partial least squares structural equation modeling (PLS-SEM): an analysis based on social network approaches," *Internet Res.*, 2019.

[139] J. F. Hair, B. Babin, and N. Krey, "An Assessment of structural equation modeling applications in the journal of advertising," *J. Advert.*, vol. 46, no. 1, pp. 163–177, 2017.

[140] J. F. Hair, M. Sarstedt, T. M. Pieper, and C. M. Ringle, "The use of partial least squares structural equation modeling in strategic management research: a review of past practices and recommendations for future applications," *Long Range Plann.*, vol. 45, no. 5–6, pp. 320–340, 2012.

[141] J. F. Hair, M. Sarstedt, C. M. Ringle, and J. A. Mena, "An assessment of the use of partial least squares structural equation modeling in marketing research," *J. Acad. Mark. Sci.*, vol. 40, no. 3, pp. 414–433, 2012.

[142] L. Lee, S. Petter, D. Fayard, and S. Robinson, "On the use of partial least squares path modeling in accounting research," *Int. J. Account. Inf. Syst.*, vol. 12, no. 4, pp. 305–328, 2011.

[143] C. M. Ringle, M. Sarstedt, and D. W. Straub, "A critical look at the use of PLS-SEM in MIS quarterly. MIS Q. Manag," *Inf. Syst*, vol. 36, 2012.

[144] J. Hair, C. L. Hollingsworth, A. B. Randolph, and A. Y. L. Chong, "An updated and expanded assessment of PLS-SEM in information systems research," *Ind. Manag. \& Data Syst.*, 2017.

[145] M. Sarstedt, C. M. Ringle, D. Smith, R. Reams, and J. F. Hair Jr, "Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers," *J. Fam. Bus. Strateg.*, vol. 5, no. 1, pp. 105–115, 2014.

[146] P. O. do Valle and G. Assaker, "Using partial least squares structural equation modeling in tourism research: A review of past research and recommendations for future applications," *J. Travel Res.*, vol. 55, no. 6, pp. 695–708, 2016.

[147] J. F. Hair Jr., L. M. Matthews, R. L. Matthews, and M. Sarstedt, "PLS-SEM or CB-SEM: updated guidelines on which method to use," *Int. J. Multivar. Data Anal.*, vol. 1, no. 2, p. 107, 2017, doi: 10.1504/ijmda.2017.10008574.

[148] T. S. Yin, A. R. Othman, S. Sulaiman, M. I. Mohamed-Ibrahim, and M. Razha-Rashid, "Application of mean and standard deviation in questionnaire surveys: Construct validation," *J. Teknol.*, vol. 78, no. 6–4, pp. 99–105, 2016, doi: 10.11113/jt.v78.8983.

[149] H. et al., "Multivariate Data Analysis. Seventh Edition. Prentice Hall," *Engl. Pearson*, 2010.

[150] K. R. Das and A. Imon, "A brief review of tests for normality," *Am. J. Theor. Appl. Stat.*, vol. 5, no. 1, pp. 5–12, 2016.

[151] D. G. Altman and J. M. Bland, "Statistics notes: the normal distribution," *Bmj*, vol. 310, no. 6975, p. 298, 1995.

[152] A. Ghasemi and S. Zahediasl, "Normality tests for statistical analysis: a guide for non-statisticians," *Int. J. Endocrinol. Metab.*, vol. 10, no. 2, p. 486, 2012.

[153] A. Indrayan and L. Satyanarayana, "Essentials of Biostatistics. 4. Numerical methods to summarize data," *Indian Pediatr.*, vol. 36, no. 11, pp. 1127–1134, 1999.

[154] Barbara G. Tabachnick; Linda S. Fidell, "Using Multivariate Statistics," *Res. Methods Polit. Sci.*, pp. 187–209, 2019, doi: 10.4324/9781003103141-17.

[155] D. Wulandari, S. Sutrisno, and M. B. Nirwana, "Mardia's Skewness and Kurtosis for Assessing Normality Assumption in Multivariate Regression," *Enthusiastic Int. J. Appl. Stat. Data Sci.*, vol. 1, no. 01, pp. 1–6, 2021, doi: 10.20885/enthusiastic.vol1.iss1.art1.

[156] M. K. Cain, Z. Zhang, and K.-H. Yuan, "Univariate and multivariate skewness and kurtosis for measuring nonnormality: Prevalence, influence and estimation," *Behav. Res. Methods*, vol. 49, no. 5, pp. 1716–1735, 2017.

[157] R. B. Kline, *Principles and practice of structural equation modeling*. Guilford publications, 2015.

[158] T. Ramayah, J. Cheah, F. Chuah, H. Ting, and M. A. Memon, "Partial least squares

structural equation modeling (PLS-SEM) using smartPLS 3.0," *An Updat. Guid. Pract. Guid. to Stat. Anal.*, 2018.

[159] H. A. Richardson, M. J. Simmering, and M. C. Sturman, "A tale of three perspectives: Examining post hoc statistical techniques for detection and correction of common method variance," *Organ. Res. Methods*, vol. 12, no. 4, pp. 762–800, 2009.

[160] P. M. Podsakoff, S. B. MacKenzie, and N. P. Podsakoff, "Recommendations for creating better concept definitions in the organizational, behavioral, and social sciences," *Organ. Res. Methods*, vol. 19, no. 2, pp. 159–203, 2016.

[161] S. Tehseen, T. Ramayah, S. Sajilan, and others, "Testing and controlling for common method variance: A review of available methods," *J. Manag. Sci.*, vol. 4, no. 2, pp. 142–168, 2017.

[162] N. Kock and G. Lynn, "Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations," *J. Assoc. Inf. Syst.*, vol. 13, no. 7, 2012.

[163] N. Kock, "Common method bias in PLS-SEM: A full collinearity assessment approach," *Int. J. e-Collaboration*, vol. 11, no. 4, pp. 1–10, 2015.

[164] J. C. Anderson and D. W. Gerbing, "Structural equation modeling in practice: A review and recommended two-step approach.," *Psychol. Bull.*, vol. 103, no. 3, p. 411, 1988.

[165] K. Sijtsma, "On the use, the misuse, and the very limited usefulness of Cronbach's alpha," *Psychometrika*, vol. 74, no. 1, pp. 107–120, 2009.

[166] D. McNeish, "Thanks coefficient alpha, we'll take it from here Psychological Methods," *Adv. online Publ. doi*, vol. 10, 2017.

[167] W. W. Chin, "Commentary: Issues and opinion on structural equation modeling," *MIS quarterly*. JSTOR, pp. vii--xvi, 1998.

[168] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *J. Mark. Res.*, vol. 18, no. 1, pp. 39–50, 1981.

[169] J. F. Hair, C. M. Ringle, and M. Sarstedt, "PLS-SEM: Indeed a silver bullet: The Journal of Marketing Theory and Practice, v. 19," 2011.

[170] N. Urbach, F. Ahlemann, and others, "Structural equation modeling in information systems research using partial least squares," *J. Inf. Technol. theory Appl.*, vol. 11, no. 2, pp. 5–40, 2010.

[171] W. W. Chin, "How to write up and report PLS analyses," in *Handbook of partial least squares*, Springer, 2010, pp. 655–690.

[172] M. R. Ab Hamid, W. Sami, and M. H. M. Sidek, "Discriminant validity assessment: Use of Fornell \& Larcker criterion versus HTMT criterion," in *Journal of Physics: Conference Series*, 2017, vol. 890, no. 1, p. 12163.

[173] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *J. Acad. Mark. Sci.*, vol. 43, no. 1, pp. 115–135, 2015.

[174] A. Diamantopoulos and J. A. Siguaw, "Formative versus reflective indicators in

organizational measure development: A comparison and empirical illustration," *Br. J. Manag.*, vol. 17, no. 4, pp. 263–282, 2006.

[175] S. Streukens and S. Leroi-Werelds, "Bootstrapping and PLS-SEM: A step-by-step guide to get more out of your bootstrap results," *Eur. Manag. J.*, vol. 34, no. 6, pp. 618–632, 2016.

[176] R. L. Wasserstein and N. A. Lazar, "The ASA statement on p-values: context, process, and purpose," *The American Statistician*, vol. 70, no. 2. Taylor \& Francis, pp. 129–133, 2016.

[177] E. D. Hahn and S. H. Ang, "From the editors: New directions in the reporting of statistical results in the Journal of World Business," *J. World Bus.*, vol. 52, no. 2, pp. 125–126, 2017.

[178] M. I. Aguirre-Urreta and M. Rönkkö, "Statistical inference with PLSc using bootstrap confidence intervals," *MIS Q.*, vol. 42, no. 3, pp. 1001–1020, 2018.

[179] J. Cohen, *Statistical power analysis for the behavioral sciences*. Routledge, 2013.

[180] G. M. Sullivan and R. Feinn, "Using effect size—or why the P value is not enough," *J. Grad. Med. Educ.*, vol. 4, no. 3, pp. 279–282, 2012.

[181] G. Shmueli and O. R. Koppius, "Predictive analytics in information systems research," *MIS Q.*, pp. 553–572, 2011.

[182] E. E. Rigdon, "Rethinking partial least squares path modeling: In praise of simple methods," *Long Range Plann.*, vol. 45, no. 5–6, pp. 341–358, 2012.

[183] J. Henseler, C. M. Ringle, and R. R. Sinkovics, "The use of partial least squares path modeling in international marketing," in *New challenges to international marketing*, Emerald Group Publishing Limited, 2009.

[184] S. Raithel, M. Sarstedt, S. Scharf, and M. Schwaiger, "On the value relevance of customer satisfaction. Multiple drivers and multiple markets," *J. Acad. Mark. Sci.*, vol. 40, no. 4, pp. 509–525, 2012.

[185] Ipsos Affluent Intelligence, "Who are the World's Biggest Wearable Tech Buyers?," *Technol. Telecoms*, 2018.

[186] M. M. Baig, H. Gholamhosseini, and M. J. Connolly, "A comprehensive survey of wearable and wireless ECG monitoring systems for older adults.," *Med. Biol. Eng. Comput.*, vol. 51, no. 5, pp. 485–495, May 2013, doi: 10.1007/s11517-012-1021-6.

[187] A. R. Ahlan and B. I. Ahmad, "User Acceptance of Health Information Technology (HIT) in Developing Countries: A Conceptual Model," *Procedia Technol.*, vol. 16, pp. 1287–1296, 2014, doi: 10.1016/j.protcy.2014.10.145.

[188] R. Cheung and D. Vogel, "Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for e-learning," *Comput. Educ.*, vol. 63, pp. 160–175, 2013, doi: 10.1016/j.compedu.2012.12.003.

[189] S. Mallenius, M. Rossi, and V. K. Tuunainen, "Factors affecting the acceptance and use of mobile devices and services by elderly people--results from a pilot study," *6th Annu. Glob. Mobil. Roundtable*, vol. 31, p. 12, 2007.

[190] U. Akturan and N. Tezcan, "Mobile banking acceptance of the youth market: Perceptions and intentions," *Mark. Intell. \& Plan.*, 2012.

[191] T. D. Nguyen and T. C. H. Nguyen, “The role of perceived risk on intention to use online banking in Vietnam,” in *2017 international conference on advances in computing, communications and informatics (ICACCI)*, 2017, pp. 1903–1908.

[192] H.-P. Lu, C.-L. Hsu, and H.-Y. Hsu, “An empirical study of the effect of perceived risk upon intention to use online applications,” *Inf. Manag. \& Comput. Secur.*, 2005.

[193] S. Arora and S. Kaur, “Perceived risk dimensions and its impact on intention to use E-banking services: A conceptual study,” *J. Commer. Account. Res.*, vol. 7, no. 2, p. 18, 2018.

[194] M. Dehghani, K. J. Kim, and R. M. Dangelico, “Will smartwatches last? Factors contributing to intention to keep using smart wearable technology,” *Telemat. Informatics*, vol. 35, no. 2, pp. 480–490, 2018.

[195] S. Seol, D. Ko, and I. Yeo, “UX analysis based on TR and UTAUT of sports smart wearable devices,” *KSII Trans. Internet Inf. Syst.*, vol. 11, no. 8, pp. 4162–4179, 2017.

[196] R. Chandrasekaran, V. Katthula, and E. Moustakas, “Too old for technology? Use of wearable healthcare devices by older adults and their willingness to share health data with providers,” *Health Informatics J.*, vol. 27, no. 4, p. 14604582211058072, 2021.

[197] M. Dehghani, “Exploring the motivational factors on continuous usage intention of smartwatches among actual users.,” *Behav. Inf. Technol.*, vol. 37, no. 2, pp. 145–158, Feb. 2018.

[198] M. Lin, H. C. Lucas Jr, and G. Shmueli, “Research commentary—too big to fail: large samples and the p-value problem,” *Inf. Syst. Res.*, vol. 24, no. 4, pp. 906–917, 2013.

[199] A. Ahmad, T. Rasul, A. Yousaf, and U. Zaman, “Understanding factors influencing elderly diabetic patients’ continuance intention to use digital health wearables: Extending the technology acceptance model (TAM),” *J. Open Innov. Technol. Mark. Complex.*, vol. 6, no. 3, pp. 1–15, 2020, doi: 10.3390/JOITMC6030081.

[200] D. Claudio, M. A. Velázquez, W. Bravo-Llerena, G. E. Okudan, and A. Freivalds, “Perceived usefulness and ease of use of wearable sensor-based systems in emergency departments,” *IIE Trans. Occup. Ergon. Hum. Factors*, vol. 3, no. 3–4, pp. 177–187, 2015.

[201] K. Y. Chau *et al.*, “Smart technology for healthcare: Exploring the antecedents of acceptance intention of healthcare wearable technology,” *Heal. Psychol. Res.*, vol. 7, no. 1, 2019.

[202] T.-H. Tsai, W.-Y. Lin, Y.-S. Chang, P.-C. Chang, and M.-Y. Lee, “Technology anxiety and resistance to change behavioral study of a wearable cardiac warming system using an extended TAM for older adults.,” *PLoS One*, vol. 15, no. 1, p. e0227270, 2020, doi: 10.1371/journal.pone.0227270.

[203] A. Tarabasz and G. Poddar, “Factors influencing acceptance of wearable devices in Dubai,” *J. Econ. Manag.*, vol. 36, no. 2, pp. 123–143, 2019.

[204] A. Ometov *et al.*, “A survey on wearable technology: History, state-of-the-art and current challenges,” *Comput. Networks*, vol. 193, p. 108074, 2021.

[205] D. Iacobucci, “Structural equations modeling: Fit indices, sample size, and advanced topics,” *J. Consum. Psychol.*, vol. 20, no. 1, pp. 90–98, 2010.

Appendix A. Questionnaires

Title of the research: Health Monitoring through Smart Wearables for Elderly: A User Acceptance Model

Part A: Demographic Information

1. Gender:

☐Male
☐Female

2. Age:

☐Below 60
☐60 to 64
☐65 to 69
☐70 to 74
☐75 to 79
☐80 and above

3. What is your nationality?

☐Malaysian
☐Non-Malaysian

4. Are you currently living alone?

☐Yes
☐No

5. What is your education level?

☐High School Level or lower
☐Diploma Level
☐Bachelor's Degree Level or higher

6. Have you heard of Smart Wearable Technology (E.g., Smartwatch, Fitness Tracker, Fall detection sensors, etc.)?

☐Yes
☐No

7. Are you a user of Smart Wearable Technology (E.g., Smartwatch, Fitness Tracker, Fall detection sensors, etc.)?

☐Yes
☐No

Answer the following questions by circling the most appropriate answer.
(5 = Strongly Agree, 4 = Agree, 3 = Neutral, 2 = Disagree, 1 = Strongly Disagree)

Part B:

Facilitating Conditions					
Getting help from a person or group is important when I use wearable technologies.	1	2	3	4	5
The use of Smart Wearable Technology is very supportive towards my health monitoring.	1	2	3	4	5
Training provided before using Smart Wearable Technologies is important to me.	1	2	3	4	5
Compatibility					
Wearable technologies are compatible with my existing electronics (smartphone and others).	1	2	3	4	5
Using wearable technologies fits into all aspects of my work.	1	2	3	4	5
Using it would not affect my daily life (because of its weight, volume, and others).	1	2	3	4	5
Social Influence					
People who affect my behavior think that I should use wearable technologies.	1	2	3	4	5
My family members and friends support my decision to use it.	1	2	3	4	5
If the product has become a trend among people around me, I would consider using it.	1	2	3	4	5

Perceived Stigmatization					
People will look at me strangely if they see me using it.	1	2	3	4	5
I am embarrassed to wear health monitoring devices.	1	2	3	4	5
People around me would laugh at my wearable technology acceptance.	1	2	3	4	5
Performance Risk					
I’m concern about whether will it provide the expected benefits (functionalities and others).	1	2	3	4	5
Smart wearable technologies may not work satisfactorily (measuring accuracy and quality concerns, and others).	1	2	3	4	5
Such technologies may lead to privacy violation.	1	2	3	4	5

Anxiety					
Wearing this equipment is frightening.	1	2	3	4	5
I don’t want it to be seen by other people.	1	2	3	4	5
I am afraid that the equipment may suddenly stop functioning.	1	2	3	4	5
Self-efficacy					
I feel confident wearing smart wearable technologies even if it can be seen by other people.	1	2	3	4	5
I feel confident using smart wearable technologies.	1	2	3	4	5
Smart wearable technologies do not scare me at all.	1	2	3	4	5

Perceived Usefulness					
Using the technology will make one's life more effective.	1	2	3	4	5
My life will become more convenient when I use such technologies.	1	2	3	4	5
It is very useful to use wearable technologies in life.	1	2	3	4	5
Perceived Ease of Use					
I think wearable technologies are easy to use.	1	2	3	4	5
My interaction with smart wearable technologies is clear.	1	2	3	4	5
I can easily learn how to operate such technologies.	1	2	3	4	5
Intention to Use					
Using smart wearable technology is worthwhile	1	2	3	4	5
Using a smart wearable technology is a good idea.	1	2	3	4	5
I intend to use wearable technologies in the future.	1	2	3	4	5

Appendix B. Confidence Intervals Bias Corrected

	5.0%	95.0%
Compatibility -> Anxiety	0.248	0.482
Facilitating Condition -> Anxiety	0.238	0.468
Facilitating Condition -> Compatibility	0.392	0.617
Intention to use -> Anxiety	0.458	0.653
Intention to use -> Compatibility	0.392	0.587
Intention to use -> Facilitating Condition	0.449	0.651
Perceived Ease of Use -> Anxiety	0.507	0.703
Perceived Ease of Use -> Compatibility	0.496	0.667
Perceived Ease of Use -> Facilitating Condition	0.318	0.527
Perceived Ease of Use -> Intention to use	0.541	0.694
Perceived Stigmatization -> Anxiety	0.658	0.807
Perceived Stigmatization -> Compatibility	0.348	0.544
Perceived Stigmatization -> Facilitating Condition	0.432	0.611
Perceived Stigmatization -> Intention to use	0.575	0.721
Perceived Stigmatization -> Perceived Ease of Use	0.481	0.650
Perceived Usefulness -> Anxiety	0.378	0.605
Perceived Usefulness -> Compatibility	0.613	0.756
Perceived Usefulness -> Facilitating Condition	0.557	0.744
Perceived Usefulness -> Intention to use	0.731	0.831
Perceived Usefulness -> Perceived Ease of Use	0.573	0.712
Perceived Usefulness -> Perceived Stigmatization	0.566	0.699
Performance Risk -> Anxiety	0.206	0.455
Performance Risk -> Compatibility	0.268	0.485
Performance Risk -> Facilitating Condition	0.054	0.224
Performance Risk -> Intention to use	0.024	0.099
Performance Risk -> Perceived Ease of Use	0.086	0.289
Performance Risk -> Perceived Stigmatization	0.104	0.349
Performance Risk -> Perceived Usefulness	0.035	0.196
Self-Efficacy -> Anxiety	0.545	0.726
Self-Efficacy -> Compatibility	0.666	0.792
Self-Efficacy -> Facilitating Condition	0.458	0.672
Self-Efficacy -> Intention to use	0.618	0.761
Self-Efficacy -> Perceived Ease of Use	0.617	0.756
Self-Efficacy -> Perceived Stigmatization	0.573	0.726
Self-Efficacy -> Perceived Usefulness	0.704	0.843
Self-Efficacy -> Performance Risk	0.068	0.279
Social Influence -> Anxiety	0.076	0.247
Social Influence -> Compatibility	0.172	0.441
Social Influence -> Facilitating Condition	0.445	0.686
Social Influence -> Intention to use	0.426	0.624
Social Influence -> Perceived Ease of Use	0.208	0.437
Social Influence -> Perceived Stigmatization	0.318	0.526
Social Influence -> Perceived Usefulness	0.450	0.673
Social Influence -> Performance Risk	0.069	0.332
Social Influence -> Self Efficacy	0.297	0.554