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Phaik Khee Beh

Yuvaraj Ganesan

Mohammad Iranmanesh
Edith Cowan University

Behzad Foroughi

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Using Smartwatches for Fitness and Health Monitoring: The UTAUT2 Combined with Threat Appraisal as Moderators

Beh Phaik Khee^a, Yuvaraj Ganesan^a, Mohammad Iranmanesh^{b*}, Behzad Foroughi^a

^a Graduate School of Business, Universiti Sains Malaysia (USM), Penang, Malaysia;

^b School of Business and Law, Edith Cowan University, Joondalup, Australia

Abstract

Recent advancements in smartwatch technology have led to several applications in continuous fitness and health monitoring. Considering the benefits of smartwatches, their low level of usage for fitness and health monitoring purposes, and the limited understanding of determinants of their usage, this study advances the body of knowledge by developing an innovative and comprehensive research model that integrates the extended unified theory of acceptance and use of technology (UTAUT2) with perceived vulnerability and perceived severity as moderators. The model was tested using partial least squares (PLS), in a quantitative study with data from 271 respondents from Malaysia. The results showed that performance expectancy, effort expectancy, facilitating conditions and hedonic motivation have positive impacts on behavioural intentions towards using smartwatches for health and fitness monitoring. Perceived vulnerability moderates positively the impacts of effort expectancy. Perceived severity moderates positively the impacts of social influence and negatively the influence of hedonic motivation. The findings provide useful insights for smartwatch technology developers, marketers and managers in developing more effective devices and strategies and consequently promoting smartwatches as health monitoring devices. These outcomes extend the UTAUT2 and provide new insights into drivers of the use of smartwatches for fitness and health monitoring.

Keywords: Smartwatch; Fitness and Health Monitoring; UTAUT2; Perceived Vulnerability; Perceived Severity

1. Introduction

The burgeoning of non-communicable diseases, better known as chronic diseases, is now becoming a serious global social issue (Huzooree *et al.*, 2019). The World Health Organization (WHO) reported that non-communicable diseases take 40 million people's precious lives each year, representing 70% of all deaths throughout the world (WHO, 2018a).

Cardiovascular diseases contributed to most of these deaths from chronic disease, killing 17.9 million people per year. Cancer, respiratory illness and diabetes mellitus accounted for 9.0 million, 3.9 million and 1.6 million, respectively. According to the WHO (2018b), the population of people aged 60 and above is estimated to almost double from approximately 900 million in 2015 to about 2.0 billion in 2050. Aging populations are more prone to chronic diseases and they require regular monitoring of parameters to ensure good health (Kekade *et al.*, 2018). Even though chronic diseases are usually associated with older people, age alone is not the only risk factor for these diseases. Statistics reveal that 15 million people aged between 30 and 69 years old lose their lives to chronic diseases each year, and this fact implies that each individual, regardless of age, is susceptible to the risk factors attributed to chronic diseases (WHO, 2018b). Failure to control these chronic diseases will severely affect the individual's quality of life, causing inability to work and loss of employment as well as incurring undesirable expenses which impact the household income in the long term (Jan *et al.*, 2018). At the same time, government and private sectors also have to bear the tremendous cost of medical treatment as well as other expenses associated with premature death and disability caused by chronic diseases (Lehnert *et al.*, 2011; Sambamoorthi *et al.*, 2015).

Personal fitness and health monitoring is an integral component of today's healthcare systems. Such monitoring mechanisms act as predictors of certain chronic diseases (Nordregren, 2013; Whelton *et al.*, 2017; American Diabetes, 2018). Wearable devices have emerged as a new technology with a significant role in continuous health monitoring. These devices are useful for measuring physiological parameters, such as heart rate and arterial blood pressure, as well as human movement and daily activities (King and Sarrafzadeh, 2018), and have shown potential in cutting healthcare costs and enhancing healthcare efficiency (Li *et al.*, 2017). Despite the potential benefits that wearable devices offer, their usage for personal fitness and health monitoring remains limited and has fallen short of expectations (Sultan, 2015). As such, research on wearable devices has attracted increasing attention from academics.

There are various types of wearable devices meant for healthcare, such as smartwatches, fitness trackers, smart wristbands and bracelets, wearable patches, glaucoma sensors, glucose sensors, body movement sensors and smart footwear, which have different health purposes (Bloss, 2015; King *et al.*, 2017). As such, the factors that may motivate individuals to use them are varied. However, the limited studies on the use of healthcare wearable devices (e.g., Gao *et al.*, 2015; Marakhimov and Joo, 2017) have not restricted their research focus to any

specific type of wearable device, such as the smartwatch, despite its popularity. The smartwatch, a cutting-edge wearable technology, successfully combines the features of a smartphone with continuous data monitoring functions such as step-counting, heart rate tracking, energy consumption as well as physical activity monitoring, which are able to help in health promotion (Glowacki *et al.*, 2016). They can provide prompt feedback to users that allows them to monitor their health condition, perform timely interventions such as advising the right medication use based on the user's symptoms, and allow effective communication between healthcare providers and caregivers (Reeder and David, 2016). Smartwatches have been specifically selected as the subject of this study rather than other types of wrist-wearable devices because smartwatches have experienced a surge in popularity in recent years, especially since the launch of the Apple smartwatch in 2015 (Jung *et al.*, 2016). According to recent research from Mintel (2018) covering the UK consumer market, smartwatches sales increased by 23 percent in 2016, with an estimated 1.96 million smartwatches sold in 2017. As such, in this study, the factors that motivate individuals to use smartwatches for fitness and health monitoring purposes were investigated. Studies on smartwatches have examined individuals' adoption of smartwatches based on technology and fashion perspectives (e.g., Choi and Kim, 2016; Chuah *et al.*, 2016) but there is a lack of research on acceptance of smartwatches from a health perspective.

Previous studies have investigated the individuals' technology acceptance by applying various theories, such as the Technology Acceptance Model (TAM) (Nasir and Yurder, 2015; Lunney *et al.*, 2016), the Innovation Diffusion Theory (IDT) (Wu *et al.*, 2016), the Theory of Reasoned Action (TRA) (Hsiao and Chen, 2018), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Gu *et al.*, 2015), and UTAUT2 (Gao *et al.*, 2015). According to Baptista and Oliveira (2017), UTAUT2, which is built based on eight prominent theories, has strong explanatory power in explaining individuals' adoption of innovative technologies. As such, in this study, UTAUT2 was used as the most comprehensive theory to elucidate individuals' intention to use smartwatches for fitness and health monitoring.

The focus of UTAUT2 theory is largely on technological factors. Given that smartwatches involve an application of innovative technology which can be used for healthcare purposes, both technological and healthcare factors are predicted to significantly influence individuals' adoption decisions (Karahoca *et al.*, 2018; Sun *et al.*, 2013). Previous research has shown that threat appraisals (perceived vulnerability and perceived severity) are health-related factors that have significant effects on individual health behaviour (Gao *et al.*,

2015; Zhao *et al.*, 2018). Perceived vulnerability is described as the probability that an individual will experience health threat, while perceived severity is explained as the degree of health threat due to individual unhealthy behaviours (Rogers, 1975). It is expected that the likelihood of using a smartwatch for fitness and healthcare purposes is higher among individuals who have higher perceptions of vulnerability and severity. Therefore, incorporating perceived vulnerability and perceived severity as moderators in this context may enhance the power of the UTAUT2 model in explaining individuals' intention to use smartwatches for fitness and health monitoring purposes.

This study makes three main contributions to the literature. First, the determinants of using smartwatches, as an example of healthcare wearable devices, for fitness and healthcare monitoring purpose are tested. Second, according to the suggestion of Venkatesh *et al.* (2012) that the UTAUT2 model can be extended through identifying the relevant factors in countries with different cultural settings, different age groups and new technology, we test this theory in the context of using smartwatches for fitness and healthcare monitoring purposes in Malaysia. Third, perceived vulnerability and perceived severity are included in the model to test their moderating effect. This is important because individuals' perceptions of vulnerability and severity are different and the industry needs to know the factors that may motivate each type of individual.

The remainder of this paper is structured as follows. The next section presents the theoretical background of the study. Then, the theoretical framework and hypotheses will be illustrated. Next, the research methodology and data analysis will be addressed. Finally, the findings of the study will be discussed and the implications of the study, limitations, and avenues for future research will be provided.

2. Theoretical Background

2.1 Smartwatches for Fitness and Health Monitoring

A smartwatch can be defined as “a mini device that is worn like a traditional watch with computational power, that can connect to other devices via short range wireless connectivity such as Bluetooth, Wi-Fi and GPS; provides alert notifications; collects personal data through a range of sensors and stores them; and has a clock function” (Cecchinato *et al.*, 2015). Smartwatches have proven to be useful in a wide range of healthcare applications and their most common applications are focused on health and fitness monitoring (King *et al.*, 2017; Lim *et al.*, 2018; Lu *et al.*, 2016; Tison *et al.*, 2018). With their functionality of miniaturized

biosensors and computing technology, smartwatches are designed to be portable, non-invasive and unobtrusive monitoring devices with capability of continuously and automatically transmitting massive amounts of users' physiological data to other smart devices such as smartphones and tablets. Unlike other smart devices such as smartphones, smartwatches are considered truly wearable without interrupting users' daily lives (Lu *et al.*, 2016). The introduction and development of healthcare smartwatches have made it easy for people to monitor their fitness and health at any time and anywhere (Lunney *et al.*, 2016). In conventional practice, it has been difficult for people to track their basic physical health attributes by themselves. They had to visit healthcare settings to monitor their blood pressure, heart rate and other physiological data. Besides the need to spend a long time in the hospital for monitoring of their vital signs, another weakness of this one-time momentary test is that healthcare providers were unable to capture patients' day-to-day conditions. Patient conditions could vary dramatically over time, but once a patient leaves the clinical setting, healthcare providers no longer have a way to monitor them. Today, the emergence of healthcare smartwatches is changing all of this. Smartwatches which collect near-real-time continuous data are able to provide complementary information to existing monitoring devices and ultimately give a complete view of the patient's condition. Smartwatches can monitor one or more criteria continuously, store and later generate the data to assist healthcare providers in the delivery of their healthcare services (Bloss, 2015).

Health and fitness smartwatches generally have the features of tracking users' calories burned, step count and heart rate, and the latest versions even have the additional features of tracking sleep patterns, stress levels, blood pressure and blood oxygen saturation (SpO₂). Measurement of physiological parameters, such as heart rate, arterial blood pressure and body temperature, are important to reflect an individual's physical health status. Deviation of these parameters from the normal range can be of concern. For instance, heart rate is a predictor of cardiovascular fitness, while daily movement data are able to provide a general view of an individual's physical activity level. These two metrics are closely correlated with cardiovascular and metabolic disorders (CVMDs) (Lim *et al.*, 2018). SpO₂, which represents oxygen saturation of haemoglobin, is one of the important physiological parameters that help in the diagnosis of chronic pulmonary disease (COPD) and sleep apnoea (Amalakanti and Pentakota, 2016; Bostanci *et al.*, 2015). Even though changes in these physiological parameters cannot be used to confirm disease or illness, the findings are helpful in giving early warning signals to the users. Besides, health and fitness smartwatches are devices which

could motivate the users to be actively engaged in a healthy lifestyle and other health improvement activities. For instance, users are motivated to do more exercise because smartwatches provide continuous data to reflect users' fitness condition (Dehghani, 2018). Inactivity has been linked to an increased risk of all-cause mortality, including cardiovascular death. Hence, modifying a sedentary lifestyle by using health and fitness smartwatches as a motivator to increase daily activity can contribute to health benefits (Lim *et al.*, 2016).

A systematic review conducted by Lu *et al.* (2016) revealed that smartwatches are also found to be useful for patients with neurological diseases, such as epilepsy, Alzheimer's disease and Parkinson's disease. One of the major complications of neurological diseases is patients' inability to perform their daily activities. These groups of vulnerable patients who need to be scrupulously monitored potentially benefit from the help of smartwatches. The first FDA-approved epilepsy smartwatch – the Embrace smartwatch – has recently been released onto the market for seizure tracking and epilepsy management (Empatica, 2018). More medical-grade smartwatches are expected to be released to the consumer market in the near future, such as Omron's blood pressure smartwatch (Omron, 2018) which will benefit large numbers of hypertension patients. Application of smartwatches for fitness and health monitoring, therefore, enable faster and more convenient preventive care, reduces overall healthcare costs and will help to provide much better medical care in the future (Zhang *et al.*, 2017).

2.2 UTAUT2

A variety of theoretical models have been established to explore consumers' usage intentions and actual usage of new technology. One well known model, the TAM, introduced by Davis (1989), has been widely used in estimating the likelihood that consumers will accept or reject an innovative technology. The TAM consists of two main constructs to predict technological acceptance, namely perceived usefulness and perceived ease of use (Gilani *et al.*, 2017; Weng *et al.*, 2017)(Weng *et al.*, 2017; Gilani *et al.*, 2017. This model has been validated repeatedly in the mobile and healthcare context (Ahadzadeh *et al.*, 2015; Becker, 2016; Nasir and Yurder, 2015; Park *et al.*, 2016). The TAM is a simple but robust model which can explain the key factors of consumers' adoption of new technologies. However, the TAM alone is insufficient to posit determinants of the adoption of new technologies because the model leaves out certain crucial determinants, such as social impact in real situations. Hence,

many researchers have tried to integrate other theories into the TAM to better explain individuals' acceptance towards new technology (Wu *et al.*, 2016).

Venkatesh *et al.* (2003) proposed the UTAUT as a new IT acceptance theory. The UTAUT is a unified attempt to integrate eight prominent theories, including the TRA, TAM, motivational model (MM), Theory of Planned Behaviour (TPB), combined TAM-TPB (C-TAM-TPB), model of PC utilization (MPCU), IDT and social cognitive theory (SCT). The UTAUT is broadly used to examine individuals' acceptance and use of technologies, including technologies related to healthcare (Gao *et al.*, 2015; Pal *et al.*, 2018). There are four independent variables, namely performance expectancy, effort expectancy, social influence and facilitating conditions, posed in the UTAUT model as direct determinants of behavioural intentions. Performance expectancy and effort expectancy are closely associated with perceived usefulness and perceived ease of use, respectively, as suggested by the TAM model.

Although the UTAUT model achieved a higher explanatory power, scholars criticized that it overlooks certain critical determinants that could lead to incompatibilities of the framework with new predictors. In addition, the UTAUT model only considered factors relevant to the prediction of employees' behavioural intention to use new technology in organizational settings, which makes the UTAUT model unfavourable for the prediction of consumer-graded innovations such as smartwatches. Hence, Venkatesh *et al.* (2012) extended the original organization-oriented UTAUT model to the UTAUT2 model in regard to customers' perspectives. Along with the four original constructs: performance expectancy, effort expectancy, social influence and facilitating conditions, there are three additional constructs, namely price value, hedonic motivation and habit are integrated into this new model to examine consumers' acceptance and use of technology.

Hedonic value, which is conceptualized as perceived enjoyment, is added to the UTAUT2 model in order to highlight intrinsic motivations of users in accepting consumer products. Price value is integrated into UTAUT2 model because, unlike in the organizational context, it is users who bear the costs of these innovations: thus, costs can influence consumers' behavioural intention (Venkatesh *et al.*, 2012). Rondan-Cataluña *et al.* (2015) validated the UTAUT2 as having better predictive power in a consumer use context compared with other technology acceptance models in a study using a sample of mobile internet users. Therefore, this study used the UTAUT2 model to explain consumers' intention

to use smartwatches for fitness and health monitoring purposes. Habit, according to Venkatesh *et al.* (2012), is considered as prior behaviour and measured as the extent to which an individual tends to perform behaviours automatically. Experience is thought to be a prerequisite of habit formation. Since smartwatches are still in their infancy and the majority of the respondents of this study are potential users who probably have no experience of using a smartwatch and have not formed any habits regarding their use, habit was dropped from this study. Furthermore, we integrated perceived vulnerability and perceived severity as moderators in our model, as they appear to be important factors in health behaviour (Zhao *et al.*, 2018).

2.3 Threat Appraisal

Health is a state that encompasses not merely the absence of illness but also complete physical and mental well-being (WHO, 2018a). ‘Perception’ is a significant determinant of individual behaviour in the field of health promotion. A number of health behaviour theories (Rogers, 1975; Rosenstock, 1974) posit that perception is an important individual level concept in explaining health behaviour and alternatives. Although assessment of individuals’ health perception is subjective, perceived health is a good general indicator that predicts an individual’s health care use (OECD, 2018). Individuals’ state of perceived health is significantly related to their daily health practices, such as consuming a balanced diet, regular physical activity, sufficient sleep, moderate or no alcohol intake and maintaining a normal weight to protect them from disease or improve health (Noguchi *et al.*, 2015; Blázquez Abellán *et al.*, 2016). However, most past studies often disregard the healthcare perspective when predicting consumers’ acceptance of smartwatches as a healthcare product. Hence, the present study introduced health-driven factors as moderators in the research model to examine whether the relationship between technology-driven factors and customers’ adoption of healthcare smartwatches differs as a function of these health-driven factors.

Threat appraisal (perceived vulnerability and perceived severity), which was first introduced by Rogers (1975) in protection motivation theory, was proposed to explain how fear appeals could drive an individual towards healthy behaviours. Perceived vulnerability is defined as the probability that one will feel threatened by health problems, whereas perceived severity represents how seriously the individual considers the health threats. An individual will be inclined to adopt certain health behaviour that can protect him/her from the health threat when s/he feels that s/he is very likely to suffer from a health threat (high perceived

vulnerability) or that the harm caused by the threat is severe (high perceived severity) (Rogers, 1975). The current study, which focuses on personal health monitoring, emphasizes perceived health threat because we expect people who perceive themselves to be at higher risk of suffering from chronic diseases and believe that the consequences of having chronic diseases are significant will be more willing to engage in personal health monitoring. In other words, before anyone decides to use health monitoring tools regularly, perceived health threat will strengthen or weaken the behavioural intention towards such use. Therefore, it is assumed that perceived health threat can act as a moderator for the relationship between UTAUT2 constructs and individuals' intention to use smartwatches for health and fitness monitoring.

3. Theoretical Framework and Hypotheses Development

To fill the gaps in the literature, in the present study, the UTAUT2 was used to examine the determinants of individual intention to use smartwatches for fitness and health monitoring (Figure 1). Perceived vulnerability and severity were also introduced as moderators. The specific hypotheses are discussed as follows.

Figure 1. Theoretical Framework

3.1 Performance Expectancy

PE refers to the extent to which the individual believes that usage of a particular new technology will provide benefits to him or her in performing certain activities (Venkatesh *et al.*, 2012). According to the original UTAUT, performance expectancy is the strongest predictor of behavioural intention (Venkatesh *et al.*, 2003). Performance expectancy has consistently been shown to be a pivotal determinant of new technology acceptance and use in various sectors such as agriculture (Engotoit *et al.*, 2016), tourism (Gupta *et al.*, 2018), education (Farooq *et al.*, 2017), banking and finance (Baptista and Oliveira, 2017; Foroughi *et al.*, 2019) and healthcare (Iranmanesh *et al.*, 2017; Zailani *et al.*, 2015). With respect to individuals' intention to use healthcare smartwatches, performance expectancy may be explained as the extent to which the device is able to assist the individual to continuously monitor his or her daily physical health condition and ultimately improve his or her health. Previous studies also indicate that performance expectancy (which is similar to perceived usefulness) has a significant effect on individuals' behavioural intention to use technology innovations in the healthcare sector. Reyes-Mercado (2018) shows that performance expectancy has the strongest influence on behavioural intention to use fitness wearables for adopters. Pal *et al.* (2018) indicate that performance expectancy affects intention to use smart home and home telehealth services respectively in an elderly population. Gao *et al.* (2015) analysed wearable technology acceptance in healthcare and obtained a quite different finding from the previous studies. They found that although performance expectancy has a contribution to behavioural intention, the impact of performance expectancy is less significant if compared to other factors in UTAUT2 model on users (both fitness wearable users and medical wearable users). If the individuals feel that using a smartwatch to continuously monitor physiological parameters will enable them to manage their health in a better manner and improve their overall quality of life, then they are more likely to use this technology. Accordingly, a hypothesis is presented as follows:

H1: Performance expectancy has a positive effect on individuals' behavioural intention to use smartwatches for fitness and health monitoring.

3.2 Effort Expectancy

Effort expectancy represents the extent of the ease associated with individuals' use of a new technology (Saghapour *et al.*, 2018; Venkatesh *et al.*, 2012). Within this study, effort expectancy is introduced to measure individuals' perceived ease of use of smartwatches

for health and fitness monitoring. That is, the easier the individuals believe the smartwatch is to use, the higher their intention to use it. This determinant is similar to the perceived ease of use found in the TAM and TAM 2, ease of use in the MPCU and complexity in the IDT. In term of technology adoption, like performance expectancy, effort expectancy is another strong predictor for analysing behavioural intention and actual technology usage (Venkatesh *et al.*, 2003, 2012). Prior studies reveal a significant positive relationship between effort expectancy and behavioural expectancy in the context of mobile banking services (Baptista and Oliveira, 2017), mobile app-based shopping (Tak and Panwar, 2017) and lecture capture systems (Farooq *et al.*, 2017). In the healthcare context, several studies reveal that effort expectancy significantly and positively influences individuals' behavioural intention to accept and use healthcare technology. Reyes-Mercado (2018) shown that effort expectancy positively impacts consumers' intention to use healthcare wearable technology, which is consistent with the findings of the original UTAUT model. Therefore, it is feasible to assume that high effort expectancy would be associated with more positive intention to use a smartwatch for health and fitness monitoring. The study therefore hypothesizes that:

H2: Effort expectancy has a positive effect on the individual's behavioural intention to use smartwatch for fitness and health monitoring.

3.3 Social Influence

Social influence is defined as how individual decision-making is influenced by important others' perceptions (Venkatesh *et al.*, 2003; Sun *et al.*, 2013). Researchers have widely explored the idea of social influence and demonstrated its impacts on shaping individuals' intention to use and accept different types of technology innovations such as electronic library services (Awwad and Al-Majali, 2015), internet banking (Bashir and Madhavaiah, 2015); mobile shopping apps (Tak and Panwar, 2017) and mobile wallets (Madan and Yadav, 2016), wearable technology (Gao *et al.*, 2015; Lunney *et al.*, 2016), and mobile devices (Sun *et al.*, 2013). Social influence plays a crucial role, particularly for products or services in the early stages of development where the technology products are entirely new to them and they lack information regarding utilization of this new technology (Adapa *et al.*, 2018; Pal *et al.*, 2018). Thus, it is assumed that individuals are more prone to consider other people's opinions when forming their intention to use smartwatches. Therefore, the study hypothesizes that:

H3. Social influence has a positive effect on individuals' behavioural intention to use smartwatches for fitness and health monitoring.

3.4 Facilitating Conditions

Facilitating conditions refer to the extent to which an individual believes that the technical infrastructure is provided to advocate the use of new technology (Venkatesh *et al.*, 2003). Facilitating conditions, in the present study, reflect the effect of necessary resources (internet connectivity and compatibility with other smart devices such as smartphones) and required knowledge to engage in health and fitness monitoring through a smartwatch. Extant literature has verified the significant relationship between facilitating conditions and behavioural intention across different technology contexts, such as intentions to adopt mobile wallet solutions (Madan and Yadav, 2016), mobile apps (Hew *et al.*, 2015) and mobile app-based shopping (Tak and Panwar, 2017). Phichitchaisopa and Naenna (2013) found that facilitating conditions have a significant positive effect among healthcare employees in the adoption of healthcare information technology. Therefore, it is proposed that facilitating conditions positively affect individuals' intention to use smartwatches. Accordingly, a hypothesis is presented as follows:

H4. Facilitating conditions have a positive effect on individuals' behavioural intention to use smartwatches for fitness and health monitoring.

3.5 Price Value

In contrast to organizational settings, the financial cost of new technology usage is borne by consumers. Thus, an individual will cognitively compare the utilities that will be gained with the financial cost that should be sacrificed before making the decision to use the new technology. Price value has a positive effect towards behavioural intention if an individual perceives that the advantages offered by technology usage outweigh the monetary cost incurred (Venkatesh *et al.*, 2012). The relationship between price value and intention to use technology has been discussed over the relevant research (Baptista and Oliveira, 2017; Tak and Panwar, 2017; Madan and Yadav, 2016). In the healthcare wearable technology context, Kim and Shin (2015) demonstrated the significant effects of perceived cost on users' intention to use wearable devices. Consistent with Venkatesh *et al.* (2012), this study presumes that if the individual perceives the value he or she will receive when using a smartwatch for personal health monitoring to be greater than the monetary cost paid to

avail such healthcare technology, the price value is expected to have a positive impact on behavioural intention. Thus, the following hypotheses are posited:

H5. Price value has a positive effect on individuals' behavioural intention to use smartwatches for fitness and health monitoring.

3.6 Hedonic Motivation

Hedonic motivation refers to the individual's degree of fun and enjoyment derived from adopting a new technology (Venkatesh *et al.*, 2012). Hedonic motivation is correlated with the individual's intrinsic nature which can be aroused by either personal traits or cognitive states (Magni *et al.*, 2010). Previous studies in different settings clearly establish a positive relationship between hedonic motivation and behavioural intention (Gu *et al.*, 2016; Farooq *et al.*, 2017). In the healthcare context, Gao *et al.* (2015) postulated that hedonic motivation has a significant effect on the individual's intention to adopt healthcare wearables. Analysing an individual's intrinsic perception towards technology innovation is necessary with regard to consumer-graded devices, as consumers not only focus on utilitarian aspects but also consider the hedonic aspects of using a technology. This study suggests that if the individual is able to gain a feeling of pleasure using a smartwatch for personal health monitoring through its functions and features, they will be intrinsically motivated to accept and use the device. Therefore, the study hypothesizes that:

H6. Hedonic motivation has a positive effect on individuals' behavioural intention to use smartwatches for fitness and health monitoring.

3.7 Perceived Vulnerability and Perceived Severity

There are inconsistent findings between the relationships of independent variables (performance expectancy, effort expectancy, social influence, facilitating condition, price value and hedonic motivation) and dependent variables (behavioural intention) in the past literature. These differences in findings are likely to be due to the moderating effects of some other important factors being overlooked in previous studies, such as individuals' age, gender, past experience of using health technology and so on. According to Baron and Kenny (1986), moderator variables are generally applied in the situation when the relationship between dependent and independent variables are found to be weak, inconsistent or non-existent. Moderators can be considered in these kinds of cases to either further weaken or strengthen the existing relationship. The present study introduces perceived vulnerability and

perceived severity of individuals to examine its moderating effect on the proposed relationships.

A growing body of literature reveals perceived health threat as a major determinant of health behaviours. Although perceived vulnerability and vulnerability are often combined to measure health threat, researchers have also examined each construct individually with health behaviour (McKinley and Ruppel, 2014). Perceived vulnerability has been shown to positively influence women's decision to take or not selective oestrogen receptor modulators (SERMs) (Ralph *et al.*, 2014) and affect individuals' safe food choices (Chen, 2016). Plotnikoff *et al.* (2010) revealed that perceived severity is significantly related to intention to engage in physical activity among individuals with type 2 diabetes mellitus. In terms of using healthcare technology, some studies (Sun *et al.*, 2013; Gao *et al.*, 2015; Guo *et al.*, 2015) reported that individual with high perceived health threat (high perceived vulnerability and perceived severity) exhibited those health behaviours at a higher rate than did those with low perceived threat. When individuals feel that they are at heightened risk of experiencing a health threat, they will be more likely to use the health innovation to protect themselves from the threat. Similarly, individuals will be more likely to adopt the health innovation to protect themselves from the health threat if they perceive that the consequences of the threat are serious. Based on the aforementioned discussion, therefore, we hypothesize that:

H7. The positive relationships between (a) performance expectancy, (b) effort expectancy, (c) social influences, (d) facilitating conditions, (e) price value, and (f) hedonic motivation with individuals' behavioural intention to use smartwatches for fitness and health monitoring will be higher for individuals with high perceived vulnerability levels.

H8. The positive relationships between (a) performance expectancy, (b) effort expectancy, (c) social influence, (d) facilitating condition, (e) price value, and (f) hedonic motivation with individuals' behavioural intention to use smartwatches for fitness and health monitoring will be higher for individuals with high perceived severity levels.

4. Research Methodology

4.1 Measurement instrument

To test the hypotheses presented in the theoretical model, a survey that includes items for all constructs in the model was conducted. The measurement instrument consisted of 28 items and measured nine research constructs: performance expectancy, effort expectancy, social influence, facilitating conditions, price value, hedonic motivation, perceived vulnerability, perceived severity and behavioural intention. Performance expectancy, effort expectancy, social influence and perceived vulnerability were measured using three items derived from Gao *et al.* (2015). For measuring hedonic motivation, both items were adapted from Gu *et al.* (2015). The four items for FC and three items for price value were adapted from Venkatesh *et al.* (2012). The construct perceived severity, having four items, was adapted from Henson *et al.* (2010). Finally, for measuring the dependent variable (behavioural intention), all three items were taken from Wu *et al.* (2016). Minor modifications in wording of items were made to suit the healthcare smartwatch context. All items were measured on a seven-point Likert scale where “1” stands for “strongly disagree” and “7” stands for “strongly agree”.

4.2 Sample and Data Collection

The survey was conducted in Penang, Malaysia to gather information from both users and non-users of smartwatches. Respondents from various socio-cultural and economic backgrounds were approached in different locations (e.g., hospitals, healthcare clinics, university, and restaurants) using a convenience sampling method. Data were collected using a printed version of the questionnaire. The screening question: “Have you heard of smartwatches before?” was used in order to minimize the hypothetical response biases from respondents who had no idea at all about smartwatches. Respondents who answered “no” were filtered out from the remaining questions of the survey. A total of 300 questionnaires were distributed and 282 questionnaires were completed and returned. Out of 282 collected responses, 11 respondents were excluded through the screening questions because they had never heard about smartwatches, resulting in an effective response rate of 90.3%. The questionnaire used in the study was short, which encouraged individuals to participate in this study and consequently led to a high response rate. The sample consisted of 271 participants, of whom approximately 58.9% were females, and most of the respondents were bachelor’s degree holders (57.1%). Participants’ ages ranged from 18 to 56, with the majority of respondents being aged 18 to 30 (52.0%). Based on BMI, 25.2% of respondents were

overweight. In total, 37 percent of respondents had experience of using smartwatches, of whom more than 80 percent used smartwatches for health and fitness monitoring.

Podsakoff *et al.* (2003) suggested that common method variance should be examined when the data are collected through self-reported questionnaires and all variables are answered by the same respondents. Harman's single factor test is one of the most common methods used in previous studies to evaluate common method bias. If a single factor carries the majority of the explained variance, then common method bias is problematic (Podsakoff *et al.*, 2003). According to the results of the unrotated factor analysis, the first factor accounted for 33.5% of the total of 82.1% variance, which indicates that common method bias is not a serious problem in this study.

4.3 Data analysis

The normality of the data was evaluated using software available on the Webpower website¹ as recommended by Hair *et al.* (2019). According to the results, the p-value was lower than 0.5 and the data was not normal. Hair *et al.* (2019) stated that data is almost always abnormal in social science. The research model is tested using the partial least squares structural equation modelling (PLS-SEM) approach. The PLS-SEM approach is considered as an appropriate tool for this study for various reasons. PLS-SEM can test complex cause-effect relationships (Chin *et al.*, 2003; Reinartz *et al.*, 2009), and is particularly useful for testing the moderating effect of the relationship between independent and dependent variables (Chin *et al.*, 2003). As the study examined the moderating effects of perceived vulnerability and perceived severity, PLS-SEM was an appropriate analysis technique. Furthermore, PLS-SEM has a higher robustness in comparison to covariance-based SEM (CB-SEM) for abnormal data (Hair *et al.*, 2019). The study employed a two-step approach, as suggested by Hair *et al.* (2017), to analyse the empirical data collected from the survey. The first stage involved validation of the measurement model, while the second stage examined the structural relationships of the latent variables. This two-step approach was utilized to establish the reliability and validity of the measures before evaluating the structural relationship of the research model.

¹. <https://webpower.psychstat.org/models/kurtosis>

5. Results

5.1 Measurement model

In order to evaluate the measurement model of reflective constructs, this study examined their internal reliability, convergent validity and discriminant validity criteria (Hair *et al.*, 2017). In the present study, composite reliability (CR) from all constructs ranged from 0.915 to 0.980, which exceeds the value of 0.70 suggested by Hair *et al.* (2017), indicating a strong internal consistency reliability. The average variance extracted (AVE) and factor loadings (FL) were used to test for convergent validity: all estimated FL values and AVE of each construct should be greater than 0.7 and 0.5, respectively (Hair *et al.*, 2017). The results demonstrated that the FL of each item in the measurement model, varying from 0.819 to 0.981, fulfilled the rule of thumb of Hair *et al.* (2010). AVE of all constructs in this study varied from 0.730 to 0.961, which is greater than 0.50, indicating a construct's ability to explain 50 percent of the variation of its indicators: hence the measures exhibit good convergent validity.

Table 1. Measurement model

Constructs	Items	Factor loadings	CR	AVE
Performance expectancy (PE)	I find smartwatch useful for health and fitness monitoring in my daily life.	0.906	0.939	0.837
	Using smartwatch for health and fitness monitoring would enable me to take action related to my health more quickly.	0.926		
	Using smartwatch improves the quality of my daily healthcare seeking.	0.913		
Effort expectancy (EE)	Learning how to use smartwatch for health and fitness monitoring is easy for me.	0.931	0.956	0.879
	I find easy to use smartwatch for health & fitness monitoring.	0.950		
	It is easy for me to become skillful at using smartwatch for health and fitness monitoring.	0.931		
Social influence (SI)	People who are important to me would think that I should use smartwatch for health and fitness monitoring.	0.953	0.969	0.913
	People who influence me would think that I should use smartwatch for health and fitness monitoring.	0.962		
	People whose opinions are valued to me would prefer that I should use smartwatch for health& fitness monitoring.	0.952		
Facilitating condition (FC)	I have the resources necessary to use smartwatch for health and fitness monitoring.	0.857	0.915	0.730
	I have the knowledge necessary to use smartwatch for health and fitness monitoring.	0.884		
	Smartwatch is compatible with other technologies I use.	0.858		
	I can get help from others when I have difficulties using smartwatch for health and fitness monitoring.	0.819		
Price value (PV)	Smartwatch is reasonably priced.	0.925	0.961	0.891
	Smartwatch is good value for money.	0.951		
	At the current price, smartwatch is provide good value.	0.955		
Hedonic motivation (HM)	Using smartwatch for health and fitness monitoring is fun.	0.979	0.980	0.961
	Using smartwatch for health and fitness monitoring is enjoyable.	0.981		
Perceived vulnerability	I am at risk for suffering the chronic diseases.	0.951	0.969	0.913
	It is likely that I will suffer chronic diseases.	0.973		

(VUL)	It is possible for me to suffer the chronic diseases.	0.941		
Perceived severity (PS)	If I suffered the chronic disease, my quality of life would be severely affected.	0.884	0.947	0.816
	If I suffered the chronic disease, my career would be seriously affected.	0.916		
	If I suffered the chronic disease, my quality of life would be significantly reduced.	0.924		
	If I suffered the chronic disease, my financial situation would be seriously affected.	0.888		
Behavioural intention (BI)	I would be willing to use a smartwatch for health and fitness monitoring.	0.949	0.966	0.906
	I would be willing to use a smartwatch for health and fitness monitoring, if I possess one.	0.956		
	I would be willing to let a smartwatch help me to monitor my health and fitness.	0.950		

Notes: CR: Composite Reliability; AVE: Average Variance Extracted.

We examined discriminant validity by assessing the outer loadings, the Fornell-Larcker criterion (Fornell and Larcker, 1981), and the heterotrait-monotrait (HTMT) criteria (Henseler *et al.*, 2015). Firstly, there were no cross-loadings among the measurement items. Secondly, the square roots of AVE were greater than the relevant inter-construct correlations in the construct correlation matrix, providing evidence for discriminant validity (Table 2). Thirdly, as a more conservative measure (Henseler *et al.*, 2015), discriminant validity was examined through the heterotrait-monotrait (HTMT) criteria. HTMT refers to “the mean value of the item correlations across constructs relative to the (geometric) mean of the average correlations for the items measuring the same construct” (Hair *et al.*, 2019, p. 9). Discriminant validity problems are present when HTMT values are high. The HTMT values were revealed to be less than 0.85 (Table 3), thus confirming the discriminant validity of all given variables (Kline, 2016).

Table 2. Fornell and Larcker

	BI	EE	FC	HM	PE	PS	PV	SI	VUL
BI	0.952								
EE	0.580	0.938							
FC	0.556	0.586	0.855						
HM	0.562	0.461	0.527	0.980					
PE	0.620	0.642	0.483	0.422	0.915				
PS	0.305	0.239	0.228	0.120	0.257	0.921			
PV	0.306	0.230	0.431	0.399	0.326	0.080	0.944		
SI	0.469	0.421	0.446	0.375	0.549	0.164	0.301	0.955	
VUL	0.104	0.038	-0.009	0.043	0.155	0.124	0.045	0.146	0.955

Note: Diagonal terms (in bold) are square roots of the AVE

Table 3. Hetrotrait-Monotrait Ratio (HTMT_{.85})

	BI	EE	FC	HM	PE	PS	PV	SI	VUL
BI									
EE	0.615								
FC	0.605	0.645							
HM	0.589	0.487	0.571						
PE	0.669	0.699	0.541	0.452					
PS	0.323	0.252	0.254	0.130	0.292				
PV	0.321	0.242	0.474	0.418	0.351	0.093			
SI	0.493	0.447	0.487	0.392	0.592	0.175	0.318		
VUL	0.109	0.041	0.039	0.046	0.167	0.144	0.047	0.154	

5.2 Structural model

After assessing the validity of the measurement model, the study tested the hypotheses using the structural model. The research model's explained variance (R^2) value was 0.60, indicating that the model has the ability to explain 60.0 percent of the variance in behavioural intention associated with healthcare smartwatch adoption. In addition to assessing the R^2 values, effect size (f^2) is used to examine whether a specific independent variable has a substantive impact on a dependent variable. Based upon Cohen's (1988) guideline, the results show that the f^2 for the supported hypotheses was acceptable (Table 4). Predicted relevance (Q^2) value was also evaluated by running the blindfolding procedure and calculated using the cross-validated redundancy approach. Chin (2010) suggested that a Q^2 value bigger than zero indicates that the model has predictive relevance. This study's dataset exhibits satisfactory predictive relevance, as the Q^2 value was 0.485 (i.e. above zero).

A nonparametric bootstrapping process with 5000 iterations was employed to examine the significance levels of path coefficients (Hair *et al.*, 2017). The results indicate that performance expectancy ($\beta = 0.280$; $p < 0.001$), effort expectancy ($\beta = 0.133$; $p < 0.05$), facilitating condition ($\beta = 0.150$; $p < 0.05$), and hedonic motivation ($\beta = 0.267$; $p < 0.001$) had significant relationships with behavioural intention, while social influence ($\beta = 0.076$; $p > 0.05$) and price value ($\beta = -0.022$; $p > 0.05$) were not significant predictors of behavioural intention (Figure 2). Hence, H1, H2, H4, and H6 were supported, while H3 and H5 were not supported (Table 4).

Table 4. Path coefficients and hypotheses testing

Hypotheses	Relationship	Std. Beta	t-value	P-value	f ²	Decision
H1	PE → BI	0.280	4.357	0.000***	0.081	Supported
H2	EE → BI	0.133	1.768	0.039*	0.018	Supported
H3	SI → BI	0.076	1.279	0.101	0.008	Not supported
H4	FC → BI	0.150	2.330	0.010**	0.025	Supported
H5	PV → BI	-0.022	0.055	0.401	0.001	Not supported
H6	HM → BI	0.267	4.290	0.000***	0.103	Supported

Notes: * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

BI, behavioural intention; EE, effort expectancy; FC, facilitating factor; HM, hedonic motivation; PC, privacy concern; PE, performance expectancy; PS, perceived severity; PV, price value; SI, social influence; VUL, perceived vulnerability.

A two-stage PLS approach was employed to examine the moderating effects of perceived vulnerability and perceived severity on the relationships between independent variables and the dependent variable after testing the main model. The results demonstrated that perceived vulnerability only moderated the relationship between effort expectancy and behavioural intention ($\beta = 0.147$; $p < 0.05$), while perceived severity only moderated the relationship between social influence and behavioural intention ($\beta = 0.146$; $p < 0.05$). Thus, H7b and H8c were supported (Table 5).

Table 5. Moderating effect

Hypotheses	Relationship	Path Coefficient	t-value	P-value	Decision
H7a	PE x Vul → BI	-0.099	1.458	0.073	Not supported
H7b	EE x Vul → BI	0.147	1.920	0.027*	Supported
H7c	SI x Vul → BI	0.102	1.540	0.062	Not supported
H7d	FC x Vul → BI	-0.090	1.196	0.115	Not supported
H7e	PV x Vul → BI	0.016	0.302	0.382	Not supported
H7f	HM x Vul → BI	-0.023	0.386	0.350	Not supported
H8a	PE x PS → BI	-0.056	0.799	0.213	Not supported
H8b	EE x PS → BI	-0.075	1.031	0.152	Not supported
H8c	SI x PS → BI	0.146	2.768	0.003**	Supported
H8d	FC x PS → BI	0.067	0.920	0.178	Not supported
H8e	PV x PS → BI	0.049	0.839	0.201	Not supported
H8f	HM x PS → BI	-0.135	2.303	0.011*	Not supported

Notes: ** $p < 0.01$, * $p < 0.05$

Figure 2. Structural Model

Subsequently, we plotted the interaction effect in order to observe how the moderator changes the relationships, as stated by Dawson (2014). The results are illustrated in Figures 3 and 3. As shown in Figure 3, the findings suggested that the higher the effort expectancy of smartwatches, the greater the tendency of individuals' intention to use them for health and fitness monitoring, for the group with high perceived vulnerability than those with low perceived vulnerability. As demonstrated in Figure 4, the positive relationship between social influence and intention to use smartwatches for health and fitness monitoring is stronger when individuals' perceived severity is high.

Figure 3. Moderating effect of perceived vulnerability in the relation between effort expectancy and behavioural intention

Figure 4. Moderating effect of perceived severity in the relation of social influence and behavioural intention

As shown in Figure 5, the findings suggested that the higher the hedonic motivation, the greater the possibility the individual's intention to use a smartwatch for health monitoring in which the group with low perceived severity has higher intention than does the group with high perceived severity.

Figure 5. Moderating effect of perceived severity in the relation of hedonic motivation and behavioural intention

6. Discussion

Among the proposed factors, performance expectancy was the strongest predictor of intention to use smartwatches. This result is in line with the findings of Reyes-Mercado (2018), Hoque and Sorwar (2017) and Gupta *et al.* (2017), indicating that in the healthcare wearable

environment, performance expectancy plays a prominent role in consumers' behavioural intention to use smartwatches. As expected, effort expectancy showed a significant positive relationship with behavioural intention, which is consistent with the findings of Gao *et al.* (2015), Cimperman *et al.* (2016) and Hoque and Sorwar (2017). This indicates that to make consumers more willing to use smartwatches for health and fitness monitoring, it is insufficient to improve the performance of the smartwatch; instead, it is crucial to make the smartwatch easy to use. Besides, the results also indicated hedonic motivation as an important predictor in the context of healthcare smartwatch adoption. Earlier studies have also supported the relationship between hedonic motivation and new technology adoption (Gao *et al.*, 2015; Madan and Yadav, 2018; Tak and Panwar, 2017). Likewise, facilitating condition exerted a significance effect upon behavioural intention, consistent with previous research (Cimperman *et al.*, 2016; Reyes-Mercado, 2018).

Quite strangely, in contrast to the original UTAUT2 model and findings of earlier research (Hoque and Sorwar, 2017; Gao *et al.*, 2015), the role of social influence on consumers' intention to use smartwatches for health and fitness monitoring was not confirmed. This implies that opinions from members of consumers' immediate social circle, such as peers and family members, have no influence towards their intention to use smartwatches for health monitoring. One possible explanation for the insignificance of social influence found in this study may be that some of the respondents are early adopters of new technology who do not require opinions from their social groups, as in fact, they themselves are the influential people for other potential adopters. Early adopter consumers tend to be younger individuals and have a higher education level (Läpple and Van Rensburg, 2011), like most of the respondents in the current study (18 to 30 years old: 52.1%; bachelor's degree and above: 66%). Second, social influence plays a lesser role in the decision related to healthcare as individuals may be more likely to rely on the opinions of experts such as doctors, pharmacists and nurses.

The study also revealed an interesting fact, whereby price value had no significant relationship with the use of smartwatches for health and fitness monitoring. This result is contrary to the UTAUT2 model and to the findings of Baptista and Oliveira (2017), Tak and Panwar (2017) and Madan and Yadav (2016), which established a significant positive relationship between price value and behavioural intention. This result is consistent with the findings of Park *et al.* (2016). One potential reason is that the price of available smartwatches varies in the market and customers can select one of them based on their perception of its

price value. As such, price value is not the individuals' concern in using smartwatches for health and fitness monitoring. Furthermore, most of the respondents in this study are educated people who know that prevention is the key to both better health and lower healthcare costs. As the use of smartwatches for health and fitness monitoring is related to their health and may reduce their future potential healthcare costs, price value plays an insignificant role in their decision to use smartwatches.

Further, the study found that perceived vulnerability moderates the relationship between effort expectancy and intention to use smartwatches for health and fitness monitoring. As mentioned earlier, in order to achieve the health benefits promised by smartwatches, ease of use is also a crucial factor. Individuals who perceive themselves as being at high risk of suffering from chronic disease in the future are more likely to find an easier way to avoid such chronic diseases compared with individuals with low perceived risk. This means that, individuals with high perceived vulnerability are more likely to use smartwatches for self-monitoring purposes if the smartwatch can be easily used to manage their health condition.

According to the results, the effects of performance expectancy, social influence, facilitating conditions, price value and hedonic motivation on intention to use smartwatches for health and fitness monitoring are not significantly different between individuals with low and high perceived vulnerability. This indicates that performance expectancy, facilitating conditions and hedonic value are important drivers of intention to use for both groups, while social influence and price value are not. As such, smartwatch technology developers, marketers and managers should give special attention to the usefulness of smartwatches for health and fitness monitoring, and should also develop their features in a way that is compatible with other common use technologies and give a feeling of pleasure, as these factors play a critical role in using smartwatches regardless of the extent of individuals' perceived vulnerability.

Besides, this finding demonstrated that perceived severity acts as a moderator strengthening the relationship between social influence and intention to use smartwatches for health and fitness monitoring. Perceived severity originates from the feeling of fear: hence, individuals with high perceived severity are expected to have higher fear of illness and even death anxiety compared to those with low perceived severity. This group of people is more likely to seek family members' and friends' opinions over their health issues. Social support

from family members and friends may act as a protective factor to lower individuals' anxiety and fear. Therefore, an individual who has high awareness towards the consequences of chronic diseases, in order to reduce his or her fear and anxiety, may communicate with trusted people to address the possible healthy behaviour to prevent himself or herself from suffering the chronic diseases, such as using the self-monitoring health device.

The study also postulated that perceived severity moderated negatively the relationship between hedonic motivation and behavioural intention. Instead of emphasizing the utilitarian aspect of healthcare smartwatches, individuals with low perceived severity are more concerned with the enjoyment they will gain when using smartwatches for health monitoring. This group of people might be younger individuals who think chronic diseases are not applicable to them. On the other hand, the group with high perceived severity are more likely to anticipate health performance of healthcare smartwatches instead of using them for fun.

The results also indicated that perceived severity does not moderate significantly the impacts of performance expectancy, effort expectancy, facilitating conditions and price value on intention to use smartwatches for health and fitness monitoring. As such, performance expectancy, effort expectancy and facilitating conditions are important drivers of smartwatch use for both individuals with low and high severity perceptions, and price value is not an important driver. As such, smartwatch developers should understand the potential needs of smartwatch users and develop user-friendly and useful functions that are compatible with other technologies that are commonly used by others. Both perceived vulnerability and perceived severity do not moderate the impacts of performance expectancy, facilitating conditions and price value. As the direct effects of performance expectancy and facilitating conditions on intention to use are significant, these are the two critical factors in successfully promoting smartwatches for health and monitoring purposes, and smartwatch developers and marketers should pay special attention to these two factors.

7. Implications

7.1 Theoretical implications

This study provides several meaningful theoretical contributions to the extant literature. The emergence of healthcare smartwatches represents a paradigm shift in health monitoring, as

the technology can be worn discreetly and applied as a device to monitor personal health and fitness. However, academic research on healthcare smartwatches is still in a very nascent state, so this study adds to the limited body of research. Besides this, the current study tested the UTAUT2 in the context of smartwatches and the results showed that of six selected factors from this theory, four factors have significant effects. Social influence and price value play insignificant roles due to the context of the study. Furthermore, in this study, UTAUT2 was extended by integrating perceived vulnerability and perceived severity, two variables that were predictors of individual behaviour in previous research, as moderators in the original research model. This integrated research model is capable of demonstrating greater explanatory power in predicting intention to use smartwatches for health monitoring. It is noteworthy that both moderators had moderating effects: perceived vulnerability moderated the relationship between effort expectancy and behavioural intention, while perceived severity moderated the relationship between social influence and behavioural intention.

7.2 Practical implications

A practical value of this research lies in the fact that the findings provide significant implications for the promotion of healthcare smartwatches as part of a broader strategy to reduce morbidity and mortality due to chronic diseases. The empirical findings of this study will provide useful information to help smartwatch technology developers, marketers and managers to design more attractive and effective devices as well as to seek to regulate better policies and strategies to promote smartwatches as health monitoring devices. First, performance expectancy is the critical determinant, so enhancing smartwatch features and applications for healthcare monitoring will increase consumers' acceptance. For example, a smartwatch will be considered more useful if it not only collects health data but also automatically connects to the nearest healthcare centre if any abnormalities are detected. Hence, technology developers should attempt to improve the performance of healthcare smartwatches. Besides, technology developers should design smartwatches that are easy to operate by creating a user-friendly interface to increase their usability. A robust technical infrastructure is also needed to support the usage of smartwatches to deliver the promised health benefits. One issue is that most of the smartwatches in the current market are not standalone products, but are indirectly connected to wireless connectivity through smartphones. As well as this, they have interoperability problems with other smart devices which have different operating systems, and these problems will make it difficult for users to transfer health-related data collected from smartwatches to their other smart devices. To

enhance consumers' usage of smartwatches for health and monitoring, companies will need to resolve these incompatibility weaknesses or emphasize standalone features of smartwatches in the future. Level of enjoyment is another key factor to predict usage of smartwatches for health and fitness monitoring. Consumers can gain a feeling of enjoyment when wearing a smartwatch to continuously check their own physiological conditions, such as sleep pattern and heart rate. This implies that smartwatch developers should not only focus on the utilitarian dimension (performance expectancy) of smartwatches, but also take into consideration the hedonic dimension (hedonic motivation), as this will amplify consumers' adoption. Moreover, since perceived vulnerability and perceived severity can strengthen the influence between the relationship of effort expectancy and social influence and consumers' adoption, respectively, marketers can also make use of both perceived health threat factors to raise the awareness of consumers regarding their personal risk and complications of chronic diseases to further enhance their adoption.

8. Limitations and Future Studies

The study is constrained by a few limitations. First, the study is cross-sectional, and thus is unable to demonstrate changes in behaviour over time. Hence, longitudinal analysis should be considered in future studies to elucidate how temporal changes affect consumers' acceptance of smartwatches for health monitoring purposes. Second, the survey was only conducted in Malaysia, so the results may not be generalizable to other countries with different cultures and levels of acceptance of smartwatches. Thus, there is a need to test whether the proven relationships are still held in other countries. Third, the majority of the respondents in this study were aged below 40. Though younger individuals are the dominant users of smartwatches (Persistence market report, 2017), older individuals who are less technologically savvy should be considered in future research. Lastly, the present study only considered consumers' perspectives: future research may consider examining healthcare providers' smartwatch adoption behaviour as well as their intention to recommend the use of smartwatches for health purposes to their patients.

9. Conclusions

Utilizing smartwatches for health and fitness monitoring has great potential to motivate individuals to be more engaged in a healthy lifestyle as well as to help them to detect chronic disease in its early stages and ultimately to improve their general health. This

study thoroughly investigated factors that influence consumers' intention to use smartwatches for personal fitness and health monitoring purposes by considering perceived vulnerability and severity as moderators. The results showed that performance expectancy, effort expectancy, facilitating conditions, and hedonic motivation have positive effects on behavioural intention to adopt smartwatches for health and fitness monitoring. Furthermore, the results demonstrated that perceived vulnerability moderates positively the impact of effort expectancy on behavioural intention. Perceived severity moderates positively the impact of social influence and moderates negatively the impact of hedonic motivation on behavioural intention to adopt smartwatches for health and fitness monitoring. The findings of this research not only contribute to the literature on smartwatch adoption, but also provide valuable information to enable smartwatch technology developers, marketers and managers to understand the factors that may motivate individuals to adopt smartwatches for health and fitness monitoring purposes.

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