Explicating Consumer Adoption of Wearable Technologies:

A Case of Smartwatches From the ASEAN Perspective

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ABSTRACT

This research aims to determine the key antecedent factors in consumers' adoption of and their intention to recommend smartwatch wearable technology. The proposed research model combines the current technology acceptance and innovation diffusion theories with perceived aesthetic and perceived privacy risk to explain individuals' smartwatch adoption and subsequent recommendation to other people. Based on a sample of 299 completed individual online surveys, the research employed partial least squares (a variance-based analysis method) for the model and hypotheses testing. The results showed some similarities as well as differences from the previous literature. The study found that performance expectancy, habit, and perceived aesthetic were the main predictors of smartwatch adoption. Compatibility was the antecedent factor of performance expectancy, and innovativeness directly influenced user adoption and effort expectancy. Consequently, user smartwatch adoption usually led to recommendation.

KEYWORDS

Diffusion of Innovation, Intention to Recommend, Smartwatch, UTAUT2, Wearable Technology

1. INTRODUCTION

Scholars define the term "wearable technology" in different ways. Nascimento et al. (2018) defined it as electrical devices that can be worn on people's bodies. Buenaflor and Kim (2013) defined wearable technology as an electronic device that functions as a computer and can be worn, carried, or attached to the body. Typical wearable devices are eyewear, clothes, and wristwear; of the latter, a smartwatch is a portable intelligent accessory that significantly improves people's way of life and well-being (Kim & Shin, 2015). A smartwatch is an electronic device that has a shape similar to a watch, is worn on the wrist, is able to tell time, and is wirelessly connected to the internet on its own or through a smartphone (Rawassizadeh et al., 2015). This new technological device was launched slightly less than 5 years ago, but it has garnered a megatrend of acceptance and adoption (Shin, 2019). Worldwide smartwatch sales have exponentially increased, reportedly reaching 48 million units last year, of which 22.5 million units were Apple alone (Statista.com). The most well-known global players in the smartwatch market are Apple, Samsung, Huawei, Xiaomi, and Pebble. According to an IDC report (2019), the smartwatch's market share grew 54% in 2018 and accounted for almost

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30% of all wearable devices shipped in that year. Apple is the leader in the smartwatch category, controlling 28% of the total worldwide market share.

Leading manufacturers and device designers have continuously upgraded smartwatches to incorporate multiple functions in order to improve their performance. Some smartwatch brands recently added extra features for health monitoring and fitness functions; examples of the latter are step counters, exercise trackers, heart and calorie monitors, sleep monitors, goal setting software, exercise alerts, as well as data reporting by the day, week, or month via smartphone connectivity (Gao, 2015). As each smartwatch brand has continued to deliver new functions for users, the recent industry trend emphasizes developing and designing smartwatches to be more stand-alone and powerful (Visuri et al., 2017). The Association of Southeast Asian Nations (ASEAN) market has responded positively to the advancement of new smartwatches; Thailand, Vietnam, and Malaysia have the highest smartwatch adoption rates. According to a September, 2018 Rakuten Insight survey on wearables in Asia, the top smartwatch functions that are used most frequently are workout tracking, heart rate monitoring, message/schedule notifications, and playing music. Asian males prefer heart rate monitoring, whereas females desire the workout tracking mode.

Several previous studies have addressed how to determine consumer attitudes and behavior intention (Kim & Shin, 2015; Wu et al., 2016; Hsiao & Chen, 2018), and some studies have attempted to predict the antecedent factors of technology acceptance (Chu & Park, 2016; Choi & Kim, 2016, Dutot et al., 2019). Although there have been few empirical researches to extend the findings beyond smartwatch adoption intention, recent work on smartwatches has focused on technology adoption, purchase intention, and continuance intention (Chuah et al., 2016; Chu & Park, 2016; Dehgani et al., 2018; Nascimento et al., 2018). However, most manufacturers are interested in whether smartwatch users react positively and are willing to recommend their devices. Therefore, the significant of this study is twofold, first it extends the original empirical research model from adoption to intention to recommend, thereby validating post-acceptance behavior. Secondly, due to the unique and varying characteristics of wearable devices, the study conceptualized and added additional constructs to better measure specific devices like the smartwatch. The construct of "perceived aesthetic," studied by Choi and Kim (2016); Jeong et al. (2016a); Hsiao & Chen, 2018, was found to have a significant influence on purchase intention and adoption. The "perceived privacy risk construct," which deals with the possibility of data leakage (such as personal health records) when it is transferred and recorded in another application, was studied by Nasir and Yurder (2015) and was added to the model.

2. LITERATURE REVIEW

2.1 Growth Potential of the Smartwatch Market

The ASEAN population represents the third-largest smartwatch market, following China and India. Southeast Asia alone has more than 400 million internet users, and the trend continues to rise. Thailand is one of the six largest economies in the region, with a total population close to 70 million, of whom 57 million are internet users who have 92.33 million mobile subscriptions (aseanup.com, 2019). The country continues to invest in technological infrastructure to support its recent surge of urbanization, and the expansion of digitalization has opened a gateway for new wireless devices to assist modern lifestyles. The smartwatch supports the growing demands of consumers' health awareness in the ASEAN countries, especially Thailand. According to research data provided by Statista.com (2019), in Thailand the total sales in the wearable segment are forecast to reach US$36 million by year-end 2019 Even though the Thai smartwatch market is relatively small within the global market, average sales during 2019-2023 are expected to grow at a steady pace of 4.8% per year. This cumulative growth will consequently generate a future annual sales volume of US$44 million by year-end 2023.

This study makes noble attempt to explore consumer behavior towards smartwatch adoption and recommendation in the ASEAN. The results can be used as a reference for manufacturers and designers to capture ASEAN market share and retain customers' loyalty.

2.2 Consumer Acceptance and Adoption Studies

Dated back to the study of consumer behavior and technology adoption models proposed by Davis (1989) the technology acceptance model (TAM) and theory of planned behavior (TPB) by Ajzen (1991), a recent comparative study of smartwatch adoption by Dutot et al., (2019) also applied TAM with other additional constructs to examine the differences among people in three countries, China, Thailand and France. Nevertheless, we have witnessed the evolution of number of technology acceptance models such as UTAUT, UTAUT2 by Venkatesh et al. 2003 and Venkatesh et al. 2012. To examine up-to-date consumer psychology towards technology acceptance, Buenaflor and Kim (2013) proposed an interesting proposition to understand the human factors involved in accepting wearable computers and technology. Their study explained a range of factors, from fundamental human needs to a high level of user's experience.

(a) Fundamental needs: Adapted from Maslow's hierarchy of needs, the user adopts a wearable device to fulfill fundamental needs for safety.
(b) Cognitive attitude: User acceptance based on their belief that the technology is useful (perceived usefulness), easy to use (perceived ease of use), and addresses other cognitive attitudes such as perceived fear and risk.
(c) Social aspect: Wearable users might fear using technological devices as they can threaten personal privacy. On the other hand, adoption might take place due to social influences or cultural norms.
(d) Physical aspect: User acceptance can be based on physical comfort and safety. Some users purchase them because of aesthetics and appearance as well as mobility.
(e) Demographic characteristics: Age and gender are also considered key influencing factors of user acceptance and adoption.
(f) Technical experience: The user's level of technological experience is another crucial factor in their willingness to accept wearable devices.

The proposition by Buenaflor and Kim (2013) summarized and shared similar constructs from the two leading theoretical technology models: the unified theory of acceptance and use of technology 2 (UTAUT2) by Venkatesh et al. (2012), and the diffusion of innovation theory by Rogers (2003). In addition, a recent study by Kalantari (2017) also categorized the factors influencing consumers' adoption of wearable technology into five areas: perceived benefits, technology characteristics, social influences, individual characteristics, and perceived risks. Thus, after reviewing extensive model for the study, we employed two theoretical models to examine consumer acceptance and adoption: UTAUT2 by Venkatesh et al. (2012), and diffusion of innovation theory by Rogers (2003). We used two additional constructs, perceived aesthetics and perceived privacy risk, to confirm consumers' adoption and recommendation of smartwatch devices.

2.3 Theoretical Models

2.3.1 Unified Theory of Acceptance And Use Of Technology 2 (Utaut2)

The original UTAUT model proposed by Venkatesh et al. (2003) provided a comprehensive assessment of antecedent factors: performance expectancy, effort expectancy, social influence, and facilitating conditions towards behavioral intention and use behavior. The first generation of the UTAUT model was a combination of the leading technology acceptance theories and models, namely, diffusion of innovation (DOI), the theory of reasoned action (TRA), and the theory of planned behavior (TPB) (Huang & Kao, 2014). The second generation of UTAUT was reviewed and extended by Venkatesh et al. (2012) to examine consumer acceptance and use of technology by incorporating variables such as habit, hedonic motivation, and price value to become UTAUT2.

Rondan-Cataluña et al. (2015) claimed that UTAUT2 has better "explanation power" compared to the other technology acceptance models. Accordingly, the model has become the main line of research in the literature on information systems uptake. For example, Wong et al. (2014) supported the use of UTAUT2 as the model for technology acceptance and use, and it has been used to test the adoption of wearable technology in many empirical studies. The study of Kranthi and Ahmed (2018) employed UTAUT2 together with other constructs to determine smartwatch adoption among IT professionals. Talukder et al. (2018) explored the acceptance and use predictors of fitness wearable technology and intention to recommend, and Gu et al. (2016) studied the factors influencing consumers' trust towards wearable commerce. Research by Gao at al. (2015) also employed UTAUT2 to investigate the factors associated with consumers' intention to adopt wearable technology in healthcare.

2.3.2 Diffusion Of Innovation Theory (DOI)

This model was first proposed by Rogers and is considered the first theory to study technology innovation and adoption. It identifies the factors that affect dissemination of innovations and new technologies in society, proposing four main elements to explain consumer behavior: innovation, communication channels, time, and social system (Rogers, 2003). Rogers's five attributes of innovation are: relative advantage, compatibility, complexity, trialability, and observability. These indicators influence individuals' behaviors and explain the pace of innovation adoption. Momani and Jamous (2017) reported that some variables under DOI, namely, compatibility, relative advantage (performance expectancy), and complexity (effort expectancy), are the most significant factors for individual acceptance, while demonstrability, image, visibility, and trialability do not influence individuals' use and adoption of new technology. A study by Wu et al. (2016) adopted the technology acceptance model (TAM) and DOI to explore consumers' intention to accept the smartwatch. Hsiao (2017) applied the DOI model to examine smartwatch adoption intention by comparing Apple and non-Apple watches. Similarly, Jeong et al. (2016b) tested DOI for purchase intention of wearable devices.

2.3.3 Perceived Aesthetic

Perceived aesthetic has been widely discussed as applicable to wearable technology, particularly in smart clothes, smart glasses, and smartwatches, as these are often considered fashion items (Kalantari, 2017). The design, shape, color, and texture of these technological devices are important attributes and can be seen as visual communication (Chuah et al., 2016). The unique design of a smartwatch can encourage consumers to develop a positive attitude and can support their self-expression of taste and style (Kranthi & Ahmed, 2018). Recent empirical studies also included perceived aesthetic in their models. Research by Yang et al. (2016) included a perceived aesthetic construct in the model by defining it as "visual attractiveness." Jeong et al. (2016a) also used the construct to determine smartwatch acceptance and adoption, and work by Hsiao & Chen (2018) examined the effect of perceived aesthetic on adoption intention of the smartwatch. Dehghani, Kim & Dangelico (2018) used aesthetic appeal to explore factors contributing to keep using smart wearable technology. The latter two studies found aesthetic as a major driver toward to use and continuance of use.

2.3.4 Perceived Privacy Risk

Mills et al. (2016) emphasized the need for security and concern with data privacy when evaluating wearable devices. A smartwatch offers various functions with its applications, recently including health monitoring and fitness tracking. Some applications allow a smartwatch to remotely link health information to a doctor for tracking and monitoring personal health status, but this introduces the possibility of data leakage or information hacking. To examine this argument, perceived privacy was added into the DOI model, and consumers' decisions to adopt health-related wearable must be examined to investigate concerns on data privacy (Gao et al., 2015). According to Nasir and Yurder

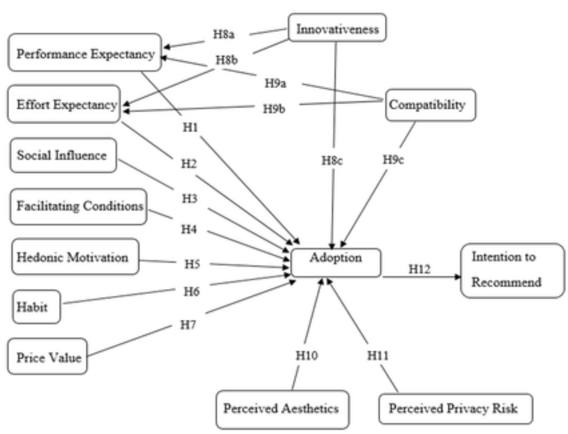
(2015), privacy risk has become an important component when assessing wearable technologies, and Shin (2010) found that perceived privacy risk is interrelated with trust and security in the context of consumers' data dependency. Gu et al, (2016) demonstrated that privacy concern can decrease consumers' trust and affect their adoption intention.

3. RESEARCH MODEL AND HYPOTHESIS DEVELOPMENT

3.1 Research Model

Recent studies on technology acceptance and smartwatch adoption found significant relationship between the two constructs under DOI, innovativeness and compatibility and performance expectancy and effort expectancy under UTAUT2 (Koenig-Lewis et al., 2010; Oliveira et al., 2016; Talukder et al., 2018). Innovativeness and compatibility become key antecedent factors toward performance expectancy and effort expectancy. The results, later, lead to adoption behavior. Thus, the research aims to explore technology acceptance, adoption, and intention to recommend smartwatch wearable devices. Figure 1 represents our research model by integrating the two currently predominant theoretical models, UTAUT2 and DOI. We added two more constructs, perceived aesthetic and perceived privacy risk, to fit with smartwatch characteristics. This research model was adapted from Oliveira et al. (2016).

Figure 1. Research model



3.2 Hypothesis Development

3.2.1 Performance Expectancy

"Performance expectancy" refers to the degree to which adopting a technology will bring effectiveness to users in performing certain activities (Vankatesh et al., 2003; 2012). In the context of smartwatch wearable devices, the effectiveness can be measured through the degree to which smartwatch use can help users to organize tasks and monitor fitness workouts and health. It is a utilitarian value perspective from consumers (Yuan et al., 2015). Performance expectancy is defined similarly to other technology acceptance models, such as "perceived usefulness" in the TAM model and "relative advantage" in the DOI model (Kalantari, 2017). Previous research found performance expectancy to be a major predictor of adoption intention (Gao et al., 2015; Kim & Shin, 2015; Gu et al., 2016; Wu et al., 2016; Talukder et al., 2018; Kranthi & Ahmed, 2018). Thus, it is concluded that performance expectancy was one of the main significant factors in other empirical research, such as by Kranthi and Ahmed (2018), Gao et al. (2015), Gu et al. (2016), and Yuan et al. (2015). Therefore, we hypothesize that:

H1. Performance expectancy positively influences the adoption of the smartwatch

3.2.2 Effort Expectancy

"Effort expectancy" refers to the degree of ease linked to consumers' use of technology (Vakatesh et al., 2012). Effort expectancy shares a common definition with "perceived ease-of-use (PEOU)" in the TAM model, in which it tries to determine people's beliefs in the freedom of effort in technology use (Davis, 1989). Kalantari (2017) also suggested that when examining the use of new technology, PEOU is considered a major technical factor to understand attitudes about use. In this study, effort expectancy is used to examine how simple and convenient the functions of smartwatch displays are to smartwatch users. In many earlier studies, effort expectancy was a key influence on consumers' adoption of wearable technology (Gao et al., 2015; Kim & Shin, 2015; Chuah et al., 2016). Therefore, we hypothesize that:

H2. Effort expectancy positively influences the adoption of the smartwatch

3.2.3 Social Influence

"Social influence" refers to consumers' perceptions that "important others," such as family and friends, believe they should use a particular technology (Vankatesh et al., 2003; 2012). People tend to pay close attention to the opinions and beliefs of people close to them (Buenaflor & Kim, 2013). According to Yuan et al. (2015), social influence under UTAUT was adapted from Ajzen's theory of planned behavior (Ajzen, 1985) as a subjective norm towards behavioral intention. Social influence has a significant impact on an individual's intention to use technology (Wu et al., 2016; Oliveira et al., 2016). Therefore, we hypothesize following relationships:

H3. Social influence positively influences the adoption of the smartwatch

3.2.4 Facilitating Conditions

Vankatesh et al. (2012) defined "facilitating conditions" as consumers' perceptions of resources or infrastructure that can support the use of technology. It is assumed that the more supported facilities are provided to smartwatch users, the greater the chance they will increase their use and thus recommend it to others (Talukder et al., 2018). Other research has found that facilitating conditions play a vital role in wearable device adoption (Spagnolli et al., 2014); if a smartwatch operation provides a support infrastructure and a help system for users, it will increase the likelihood of adopting the device (Taluker et al., 2018). Therefore, we hypothesize that:

H4. Facilitating conditions positively influence the adoption of the smartwatch

3.2.5 Hedonic Motivation

Whether the use of a smartwatch is fun or pleasurable is a significant factor in determining the user's intention (Vankatesh, et al., 2012; Brown & Vankatesh 2005). "Hedonic motivation" refers to perceived enjoyment as one of the influencing factors for consumer acceptance of technology in various devices. People who purchase a smartwatch may expect to feel fun and pleasure when using it, and some smartwatch producers also add entertaining features, introducing the concept of "gamification" to make the interfaces look joyful and attractive (Yuan et al., 2015). Hedonic motivation has often been found to be a key driver of consumers' adoption (Choi & Kim, 2016; Hong et al., 2016). Therefore, we hypothesize that:

H5. Hedonic motivation positively influences the adoption of the smartwatch

3.2.6 Price Value

"Price value" represents consumers' perceptions of the tradeoff between perceived benefits and monetary cost (Vankatesh et al., 2012). The greater the perceived benefits from the monetary expenditure, the more likely will consumers use the technology. Jung et al. (2016) found that price is more important than the design and other attributes of a smartwatch, so price value is a good predictor of behavioral intention to use technology that could be considered unnecessary goods. Manufacturers thus need to incorporate useful features to make consumers appreciate the distinct advantages of adopting a given device (Kalantari, 2017). Therefore, we hypothesize that:

H6 Price value positively influences the adoption of the smartwatch

3.2.7 Habit

According to Limayem et al. (2007), "habit" refers to automatic and repetitive behaviors based on learning. People tend to perform certain acts repeatedly over a certain period; Kim et al. (2005) advocated that the "automaticity factor" be described as habit. Moreover, Vankatesh et al. (2012) suggested experience does provide different degrees of habit for a user's intention to use technology. Nascimento et al. (2018) suggested that the earlier the stage of habit, when there has been little experience of the smartwatch device, the greater satisfaction and appreciation of its functions and usefulness to users, and vice versa. In a smartwatch context, repetitive behavior eventually leads to routine behavior; habit is thus a key predictor for adoption. Habit was also a significant factor, indicating that users make a habit of wearing the devices 24/7. Nascimento et al. (2018) found that habit was predictive of smartwatch continuance intention.

Therefore, we hypothesize that:

H7 Habit positively influences the adoption of the smartwatch

3.2.8 Innovativeness

"Innovativeness" has a profound impact on technology adoption. Among the early studies of innovation characteristics, Agarwal and Pravda (1997) suggested that the construct affects the intention to accept and use technology. In later studies, innovativeness also proved to be a key influencer, both directly and indirectly, of behavior intention and adoption of a new technology; it is also an antecedent variable of performance expectancy and effort expectancy (Oliveria et al., 2016; Miltgen et al., 2013). The higher the level of innovativeness, the greater the chance that consumers will understand the benefits of the new technology (Talukder et al., 2018). Therefore, we hypothesize that:

H8. Consumers' innovativeness positively influences (a) performance expectancy, (b) effort expectancy, and (c) adoption of the smartwatch

3.2.9 Compatibility

According to Rogers (1995), "compatibility" refers to "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters." This construct is used to examine how well new technology fits into consumers' lifestyles. Various studies have examined compatibility as a key predictor of performance expectancy and effort expectancy, particularly for wearable smartwatches and wearable health technologies (Choi & Kim, 2016; Wu et al., 2016; Nasir & Yurder, 2015). All of these studies have consistently found that compatibility positively influenced perceived usefulness, perceived ease of use or performance expectancy, and effort expectancy under UTAUT2, and an individual's adoption and use technology. Therefore, we hypothesize that:

H9. Compatibility positively influences (a) performance expectancy (b) effort expectancy, and (c) adoption of the smartwatch

3.2.10 Perceived Aesthetics

Wearable devices such as smartwatches, smart glasses, or smart clothes can be treated as fashion items, and consumers weigh their buying decision on aesthetic attributes such as design, color, or shape (Kalantari, 2017). A study by Jeong et al. (2016a) found that perceived aesthetics had a positive effect on acceptance intention of smartwatches. This result was also confirmed by Choi and Kim (2016), who argued that the smartwatch was inherently a piece of luxury jewelry, and suggested this had a significant effect on adoption intention. The beauty of a product's appearance has a positive influence on consumers' desires and purchases. Hsiao and Chen (2017) also reported on the significant direct effect of design aesthetic on intention to use and, later, the indirect effect on the purchase intention. Thus, we hypothesize that:

H10. Perceived aesthetics positively influences the adoption of the smartwatch

3.2.11 Perceived Privacy Risk

"Perceived privacy risk" is part of perceived risk theory that tries to understand users' behavior towards potential loss when desiring certain results (Featherman & Pavlou, 2003). A study by Nasir and Yurder (2015) attempted to demonstrate another facet of an individual's technology adoption using perceived privacy risk to measure. Perceived privacy risk can measure the disadvantages of an individual's technology adoption (Lao et al., 2010). A study by Shin (2010) supported the importance of perceived privacy when using online applications. Since smartwatch functions can include a health tracking feature, there arises the possible loss of control of private health data. Thus, we hypothesize that:

H11. Perceived privacy risk positively influences the adoption of the smartwatch

3.2.12 Adoption Intention

A meaningful consequence after adoption of a new technology is whether the user ultimately intends to recommend its use to others. Smartwatch manufacturers and designers continue to wonder about customers' reactions after new technology is adopted (Kalantari, 2017), and subsequent recommendation has proven to be a key success indicator. A study by Miltgen et al. (2013) demonstrated the significant effect of adoption intention on intention to recommend, and other studies on technology acceptance, such as mobile payment and wearable fitness technology, also confirmed similar results (Oliveria et al., 2016; Talukder et al., 2018). Therefore, we hypothesize that:

H12. Adoption intention positively influences intention to recommend the smartwatch to others

4. METHODOLOGY

Data collection was conducted in Thailand between October to November 2018

4.1 Measurement Instrument

All of the following measurement constructs were adapted with minor modifications from previous literature and are listed in Appendix A. Constructs under the UTAUT2 model were adapted from Vankatesh et al. (2012), whereas innovativeness and compatibility under the DOI model were adapted from Oliveira et al. (2016) and Talukder et al. (2018). Perceived aesthetic was applied from Jeong et al. (2016a) and Yang et al. (2016), and perceived privacy risk was adapted from Ernst and Ernst (2016), Li et al. (2015), and Gao et al. 2015. All the questionnaires were written in English and created through an online survey program. Each item was measured on five-point Likert scales where 5 represented “strongly agree” through 1 being “strongly disagree” (Premkumar & Ramamurthy, 1995). All of the questionnaires were adopted from previous literatures (see appendix A). Three professional experts, two from the management information systems field and one from the business management field examined their meaning, consistency, terminology, and contextual relevance. In addition, a pilot study was distributed to 30 respondents as a screening stage. There were some modifications following the experts’ advice and suggestions about wording and meaning of the sentences. Finally, the researcher was able to re-launch the complete questionnaire after final adjustments. All questionnaires were translated into the local language (Thai) by faculty from the Department of Linguistics, Panyapiwat Institute of Management and then were translated back into English by another linguistic expert from the same institution to confirm the thoroughness of meaning and consistency.

4.2 Data Collection

A structured questionnaire was launched via www.surveymonkey.com. From the 356 smartwatch users who replied, only 299 questionnaires were completely answered and used for data analysis. Table 1 presents details of the demographic data.

5. DATA ANALYSIS AND RESULTS

This study used partial least squares-based structural equation modeling (PLS-SEM), which is suitable for conducting research based on a causal model. Specifically, this study aimed, first, to determine influencing factors of smartwatch adoption in Thailand as an ASEAN’s representative country, and second, to explore additional constructs beyond UTAUT2 and DOI theoretical models as a new contribution. As recommended by Henseler and Dijkstra (2015), this research applied new software, ADANCO v.2.1.0, to calculate variance-based SEM that included PLS path modeling.

5.1 Measurement Model

The measurement model was assessed to determine the following conditions. First, the reliability of each construct was examined using composite reliability (CR) and Cronbach’s alpha. According to Hair et al. (2006), both the CR and the Cronbach’s alpha value should exceed 0.7 for each construct in order to confirm its reliability. Table 2 presents the CR and Cronbach’s alpha values of the model, showing that the CR ranges between 0.80 and 0.91, and Cronbach’s alpha values range between 0.77 and 0.91, suggesting good internal reliability.

Secondly, to assess convergent validity, loadings and average variance extracted (AVE) were used as the main indicators. Henseler et al. (2009) suggested that all loadings must be higher than 0.70, and any item loading that is less than 0.4 should be deleted. In this study, one item under innovativeness (IN3) was eliminated due to its low factor loading value; this item was also deleted in the study by Oliveria et al. (2016). All other loading values were higher than the 0.70 criterion. The AVE of each construct must be higher than 0.50 in order to allow latent variables to explain more than half of the

Table 1. Demographic Information

Variable	Description	Frequency	Percentage
Gender	Male	106	35.45
	Female	193	64.55
Age	Generation X 1965-1979	116	38.8
	Generation Y 1980-1997	163	54.5
	Generation Z 1997 onwards	20	6.7
Education	Below bachelor	18	6
	Bachelor	148	49.5
	Master	117	39.1
	Higher than Master	16	5.4
Income (฿32: US$1)	Below 30,000	91	30.4
	30,001-60,000	104	34.8
	60,001-100,000	55	18.4
	More than 100,000	49	16.4
Use experience (years)	Less than 1 year	145	48.5
	1-3 years	98	32.8
	3-5 years	29	9.7
Channel of recommendation	More than 5 years Word of mouth Social media	27 202 97	9.0 67.42 32.58

variance of its indicators (Fornell & Larcker, 1981). The AVE of each construct in this study met this criterion, as shown in Table 2.

Thirdly, to determine the discriminant validity of the constructs, the Fornell-Larcker criterion and cross loading were used to test the data. It is extremely important to assess discriminant validity in order to check multicollinearity. The Fornell-Larcker criterion advises that the square root of AVE should be greater than all the correlations with the other constructs (Henseler et al., 2015). Table 3 presents the values of the square root of AVE, indicated in bold on the diagonal, which are greater than the correlations between the constructs (off-diagonal values), suggesting that the discriminant validity of the data was satisfactory (Henseler et al., 2015).

In conclusion, our assessment of the measurement model determined that its construct reliability, convergent validity, and discriminant validity were satisfactory. This indicated that all constructs were ready to test the structural model.

5.2 Structural Model

Figure 2 illustrates the conceptual model with R^2 and path coefficients. The results showed that 48.2% of the intention to recommend smartwatch was explained by adoption, of which 57.8% influenced by four driven factors. . In order to test the hypotheses, we used a bootstrapping method to calculate at a significance level of 0.05 ($p < 0.05$), and the impact between independent and dependent variables was tested by path coefficients. Critical t-values for a two-tailed test were applied at the 1.96 significance level at 5% (Hair et al., 2014). Performance expectancy, habit, innovativeness, and

Table 2. The measurement model

Construct	Items	Loadings	Composite reliability	Cronbach's alpha (α)	AVE
Performance expectancy	PE1	0.85	0.85	0.77	0.59
	PE2	0.80			
	PE3	0.70			
	PE4	0.73			
Effort expectancy	EE1	0.90	0.93	0.88	0.81
	EE2	0.91			
	EE3	0.89			
Social influence	SI1	0.90	0.92	0.88	0.80
	SI2	0.90			
	SI3	0.89			
Facilitating conditions	FC1	0.86	0.89	0.82	0.73
	FC2	0.87			
	FC3	0.84			
Hedonic motivation	HM1	0.92	0.94	0.91	0.84
	HM2	0.94			
	HM3	0.90			
Price value	PV1	0.89	0.93	0.88	0.80
	PV2	0.91			
	PV3	0.89			
Habit	HB1	0.91	0.92	0.86	0.78
	HB2	0.88			
	HB3	0.87			
Innovativeness	IN1	0.84	0.88	0.80	0.71
	IN2	0.84			
	IN4	0.85			
Compatibility	COMP1	0.89	0.93	0.88	0.81
	COMP2	0.91			
	COMP3	0.89			
Aesthetics	AES1	0.88	0.92	0.89	0.75
	AES2	0.91			
	AES3	0.88			
	AES4	0.78			
Perceived privacy risk	PPR1	0.87	0.91	0.85	0.76
	PPR2	0.87			
	PPR3	0.88			
Adoption	AD1	0.91	0.93	0.88	0.81
	AD2	0.90			
	AD3	0.88			
Recommendation	REC1	0.92	0.89	0.76	0.80
	REC2	0.87			
Note: AVE, average variance extracted					

Table 3. Fornell-Larcker criterion: Matrix of correlation constructs and the square root of AVE

Construct	PE	EE	SI	FC	HM	PV	HB	IN	COMP	AES	PPR	AD	REC
PE	**0.77**												
EE	0.15	**0.68**											
SI	0.20	0.06	**0.90**										
FC	0.22	0.33	0.11	**0.86**									
HM	0.30	0.23	0.17	0.26	**0.92**								
PV	0.23	0.16	0.15	0.15	0.22	**0.90**							
HB	0.39	0.19	0.16	0.25	0.26	0.24	**0.89**						
IN	0.11	0.22	0.06	0.15	0.14	0.10	0.16	**0.84**					
COMP	0.34	0.23	0.13	0.35	0.30	0.23	0.48	0.22	**0.90**				
AES	0.17	0.18	0.12	0.25	0.26	0.14	0.28	0.15	0.34	**0.86**			
PPR	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.01	**0.87**		
AD	0.35	0.17	0.18	0.20	0.25	0.22	0.47	0.19	0.37	0.30	0.00	**0.90**	
REC	0.36	0.10	0.19	0.20	0.25	0.21	0.39	0.15	0.36	0.28	0.00	0.48	**0.89**

aesthetics were found to directly influence the intention to buy a smartwatch and were statistically significant toward intention to adopt a smartwatch. Innovativeness as well as compatibility were also significant predictors, being the antecedent factors toward performance expectancy and effort expectancy that later were the leading factors in the adoption of smartwatch technology. Therefore, our hypothesis testing supported H1, H7, H8b, H8c, H9a, H9b, and H10, and rejected H2-H6, H8a, H9c, and H11 towards the adoption of a smartwatch. In addition, the final construct also supported H12, stating that the adoption would lead to recommendation. All the results are summarized in Table 4.

Note: Path coefficients that were statistically insignificant are presented as dashed lines

6. DISCUSSION

The smartwatch market has continuously expanded since its introduction years ago. Majority of respondents were educated females in generation Y (those who were born during 1980-1997). Consumers in Thailand are at the stage of early adopters, as observed from their years of user

Figure 2. Structural model results

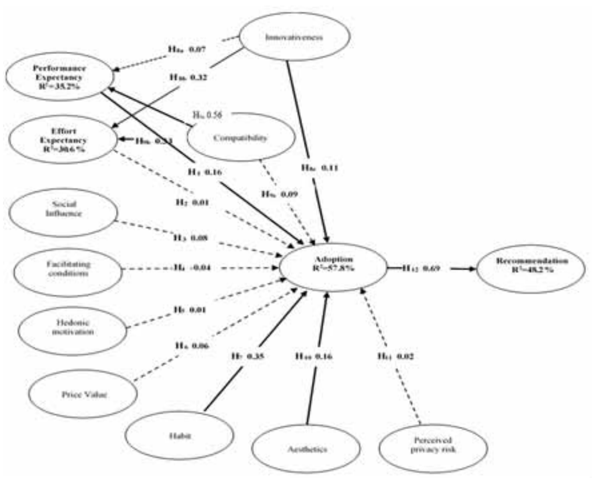


Table 4. Summary of structural model results

Hypothesis	Path	Coefficient	*t*-Statistics	Comments
H_1	PE AD	0.16	2.64	Supported
H_2	EE AD	0.01	0.14	Not Supported
H_3	SI AD	0.08	1.53	Not Supported
H_4	FC AD	-0.04	-0.69	Not Supported
H_5	HM AD	0.01	0.21	Not Supported
H_6	PV AD	0.06	1.14	Not Supported
H_7	HB AD	0.35	5.42	Supported
H_{8a}	IN PE	0.07	1.34	Not Supported
H_{8b}	IN EE	0.32	4.31	Supported
H_{8c}	IN AD	0.11	2.40	Supported
H_{9a}	COMP PE	0.56	9.34	Supported
H_{9b}	COMP EE	0.33	3.73	Supported
H_{9c}	COMP AD	0.09	1.25	Not Supported
H10	AES AD	0.16	2.58	Supported
H11	PPR AD	0.02	0.41	Not Supported
H12	AD REC	0.69	18	Supported
Note: R^2 for PE = 35.2%, R^2 for EE = 30.6%, R^2 for AD = 57.8%, and R^2 for REC = 48.2%, Significant at $p < 0.05$				

experience. Users' experience is considered crucial to the interpretation and understanding of adoption intention and recommendation. Smartwatch early and later adopters have different characteristics and make different perception decisions (Shin & Biocca, 2018), but in general, smartwatch users feel the device is very useful and beneficial to use, particularly with a health tracking function. In this study, under the UTAUT2 constructs, we found that performance expectancy and habit are the two most significant factors driving the adoption of smartwatches in Thailand.

Our finding that effort expectancy did not play a significant role in technology adoption, agreed with previous studies of Oliveira et al. (2016) and Wu et al. (2016), and partially agreed with Gao et al. (2015). In addition, the study of Dutot et al.(2019) could support the behavior of smartwatch users in Thailand market as perceived ease of use was found not significant toward adoption of smartwatch. We also found that social influence did not predict individual adoption behavior, the same outcome as in the study of Hsiao and Chen (2017). This was further supported by a study of Shin and Biocca (2018), which explained smartwatch early adopters' motives. That study suggested that smartwatch users at the early adoption stage have the desire to distinguish themselves from others, which is why social influence failed to predict adoption intention.

We also found that facilitating conditions did not have significant effects, which could suggest that users need to accumulate a certain amount of experience in the use of wearable devices (Gu et al., 2016). The constructs of hedonic motivation and price value were also rejected, as the Thai respondents did not feel that it was fun to use a smartwatch, nor were they sensitive to the monetary value of the device. These responses may have been related to self-motivation to use wearable devices for specific purposes, regardless of price and enjoyment of use. These results were similar to the findings of Talukder et al. (2018).

Two constructs of the DOI model, innovativeness and compatibility, showed very interesting outcomes. On the one hand, innovativeness significantly influenced effort expectancy and directly influenced individual adoption, but failed to influence performance expectancy. On the other hand, compatibility significantly influenced performance expectancy and effort expectancy, but was not directly influential on smartwatch adoption. These outcomes were similar to the study of Choi and Kim (2016), and were not sufficient to influence an individual's adoption. One reason could stem from the lack of experience in using a new technological device: Consumers might require deep understanding of the process and operation of smartwatch functions. Evidence of this is clearly shown in Table 1, where the majority of smartwatch users in Thailand have had a smartwatch for less than one year, and it might require a certain amount of time to get familiar with the system. Limayem et al. (2007) suggested that repetitive action will foster the necessary cognitive process, causing the habit construct to significantly influence users' adoption.

The two final variables tested in the model were perceived aesthetic and privacy risk. Karahanoglu and Erbug (2011) found that perceived aesthetic is significant in smartwatch adoption, and this was confirmed in our study, that perceived aesthetic positively influences smartwatch adoption. This result was also in line with previous literature demonstrating that design and aesthetics are significant drivers in individual adoption of wearable devices (Haiso & Chen, 2018; Jeoung et al., 2016; Yang et al., 2016). Perceived privacy risk was insignificant, suggesting that smartwatch users are not sensitive toward potential loss of private information. To measure smartwatch users' intention to recommend, our results supported that adoption leads to recommendation, with R^2 as well as adjusted R^2 values of 48%. This result aligned with previous studies (Oliveira et al., 2016; Taluker et al., 2018). In addition, with regard to the recommendation channels used by smartwatch users in Thailand, the majority prefer word-of-mouth instead of social media.

6.1 Theoretical Implications

The theoretical implications of this study are three-fold. First, to the best of our knowledge, this conceptual model is the first to determine the influencing factors of individuals' technology acceptance behavior in Thailand which is one of representative countries in the ASEAN. The outcomes revealed that the model fairly well explained users' adoption intention and recommendation toward smartwatches. The predictive power regarding intention to recommend, $R^2 = 48\%$, was substantial and was stronger than in the earlier study of Miltgen et al. (2013). This study shares the ASEAN perspective and is the first to elucidate users' adoption and recommendation of smartwatches.

Second, this study combined two well-known theoretical models, UTAUT2 and DOI, and we further attempted to improve the predictive power by adding two new constructs, perceived aesthetic and perceived privacy risk. Our study successfully demonstrated that perceived aesthetic is a key predictor of adoption. Chuah et al. (2015) also reviewed a similar construct, calling it "visibility," and tested it in the Malaysian market. These arguments resonate with the argument that performance expectancy and design aesthetic are the main predictors of smartwatch adoption. We firmly assume ASEAN consumers perceive smartwatches as technological devices as well as fashion accessories.

Finally, from a cognitive-psychological perspective, we confirmed that habit and innovativeness also directly influence consumers' adoption of smartwatches. Consumers in the early adopter stage require knowledge input and training to gain experience and feel comfortable when using these devices.

6.2 Practical Implications

This study attempted to draw consumers' perspectives with smartwatch wearable technology in the ASEAN countries. We used Thailand as a representative country to gain consumer insights and psychological perspectives. As stated earlier, from a consumer psychology standpoint we found that innovativeness is the key driver of effort expectancy and directly impacts the adoption of smartwatches. The strategic recommendation of this outcome is to create good experiences and educational platforms for new tech gadgets to target customers. Local vendors must emphasize building proper knowledge through free training or workshops, which could enhance buyers' confidence and willingness to try out new technological devices. This approach will no doubt increase consumers' experience and comfort.

Second, compatibility enables consumers to realize a device's usefulness and convenience. A demo session with a free trial period could help customers gain experience and recognize the compatibility of the gadget. Third, we found that design is important in the selection of wearable technology. This result affirms the consumers' mindset in the ASEAN countries of Thailand and Malaysia, which places emphasis on the aesthetics/visibility of smartwatches. And finally, we concluded that expanding the smartwatch's ecosystem as well as enhancing users' experience should be considered top priorities for manufacturers. They could focus on increasing app functionality and battery life, for example, or even add smartwatch functions similar to those on smartphones. Building more users' experience through education, workshops, training, and/or product free trials will provide greater opportunities for people to try out and consequently adopt the smartwatches.

6.3 Limitations and Future Research

Even though the goals of this study were to spotlight antecedent factors to the adoption and recommendation of wearable technology, certain limitations remain. First, since most smartwatch users in Thailand are in an early stage of adoption, their knowledge and understanding of wearable technology consequently reflects a somewhat shallow view of user behavior. Secondly, the survey took place in Thailand, which may differ from other ASEAN countries in terms of culture and knowledge background. Conducting comparative or multiple studies would enhance our findings in future research. Thirdly, the study employed mainly the constructs from UTAUT2 and DOI models which may provide limitation to the findings. The future research may consider applying TAM model with different constructs from the most up-to-date literature.

7. CONCLUSION

Previous empirical researches on the smartwatch emphasized acceptance and purchase intention (Wu et al., 2016; Hong et al., 2016; and Hsiao & Chen, 2017). In contrast, this study sought to identify the key predictors of smartwatch adoption and ultimate recommendation to other people. To this end, we used two prominent theoretical models, UTAUT2 and DOI, as our main conceptual models. Two other constructs from past literature were added to support the thoroughness and validity of the model: perceived aesthetic and perceived privacy risk. The ASEAN smartwatch market has gained popularity in recent years witnessing from double-digit annual sales growth (Rakuten Insight, 2018). It gets wider acceptance particularly among the young generation who have an urban lifestyle and have high health-awareness. ASEAN consumers' adoption intention and recommendation has not yet been thoroughly explored, but our results here shed some light on what the key predictors are and how vendors can apply this information to formulate selling strategies. Key constructs such as innovativeness, compatibility, performance expectancy, habit, and perceived aesthetic are here proved to be directly and indirectly influential in the purchase of smartwatches in Thailand. We here also confirm that the preferred means of user recommendations is still word-of-mouth; Thai people still prefer face-to-face contact when demonstrating new technologies.

The key takeaways in this study are, first, that Thailand is still at an early stage of smartwatch adoption. Thai consumers need to learn more about smartwatches to be familiar and comfortable with them. Second, once consumers acquire sufficient information and feel in control of a new technology, they are eager to use it and tend to easily grow acclimated to it. This leads to adoption behavior. Third, consumers in ASEAN countries emphasize and are concerned with the design aesthetic or product visibility, as it gives them a feeling of uniqueness and expresses their self-identity. Lastly, consumers are willing to recommend their product to others once they use or experience it. Vendors and manufacturing brands can use this research as reference in to order to help formulate selling strategies that are suitable to local potential buyers. Creating a seamless ecosystem for smartwatches will undoubtedly enable consumers to become loyal to the devices and will enhance users' experience and interaction.

REFERENCES

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In J. Kuhl & J. Beckmann (Eds.), Action-control: From Cognition to Behavior (pp. 11-39). Springer. doi:10.1007/978-3-642-69746-3_2

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. doi:10.1016/0749-5978(91)90020-T

Brown, S. A., & Venkatesh, V. (2005). Model of adoption of technology in the household: A baseline model test and extension incorporating household life Cycle. *Management Information Systems Quarterly*, *29*(4), 399–426. doi:10.2307/25148690

Buenaflor, C., & Kim, H. (2013). Six human factors to acceptability of wearable computers. *International Journal of Multimedia and Ubiquitous Engineering*, *8*(3), 103–113.

Cho, I., & Park, H. (2016). The influential factors on the diffusion of smartwatches in Korea. *International Journal of Technology Management*, *72*(1/2/3), 230–251. doi:10.1504/IJTM.2016.080537

Choi, J., & Kim, S. (2016). Is the smartwatch an IT product or a fashion product? A study on factors affecting the intention to use smartwatches. *Computers in Human Behavior*, *63*, 777–786. doi:10.1016/j.chb.2016.06.007

Chuah, H. S., Rauschnabel, P., Krey, N., Nguyen, B., Ramayah, T., & Lade, S. (2016). Wearable technologies: The role of usefulness and visibility in smartwatch adoption. *Computers in Human Behavior*, *65*, 276–284. doi:10.1016/j.chb.2016.07.047

Cyr, D., Head, M., & Ivanov, A. (2006). Design aesthetics leading to m-loyalty in mobile commerce. *Information & Management*, *43*(8), 950–963. doi:10.1016/j.im.2006.08.009

Davis, F. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *Management Information Systems Quarterly*, *13*(3), 319–340. doi:10.2307/249008

Dehghani, M. (2018). Exploring the motivational factors on continuous usage intention of smartwatches among actual users. *Behaviour & Information Technology*, *37*(2), 145–158. doi:10.1080/0144929X.2018.1424246

Dehghani, M., Kim, K. J., & Dangelico, R. M. (2018). Will smartwatches last? Factors contributing to intention to keep using smart wearable technology. *Telematics and Informatics*, *35*(2), 480–490. doi:10.1016/j.tele.2018.01.007

Dutot, V., Bhatiasevi, V. & Bellallahom, N. (2019). Applying the technology acceptance model in a three countries study of smartwatch adoption. *Journal of High Technology Management Research, 30*, 1-14.

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies*, *59*(4), 451–474. doi:10.1016/S1071-5819(03)00111-3

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *JMR, Journal of Marketing Research*, *18*(1), 39–50. doi:10.1177/002224378101800104

Gao, Y., Li, H., & Luo, Y. (2015). An empirical study of wearable technology acceptance in healthcare. *Industrial Management & Data Systems*, *115*(9), 1704–1723. doi:10.1108/IMDS-03-2015-0087

Gu, Z., Wei, J., & Xu, F. (2016). An empirical study on factors influencing consumers' initial trust in wearable commerce. *Journal of Computer Information Systems*, *56*(1), 79–85. doi:10.1080/08874417.2015.11645804

Hair, J., Anderson, R., Tatham, R., & Black, W. (2006). *Multivariate data analysis* (6th ed.). Prentice Hall.

Hair, J., Ringle, C., & Sarstedt, M. (2014). PLS-SEM: Indeed a Silver Bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152. doi:10.2753/MTP1069-6679190202

Henseler, J., & Dijkstra, T. K. (2015). *ADANCO 2.0. Composite Modeling*. Available at: www.compositemodeling.com

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management & Data Systems*, *116*(1), 2–20. doi:10.1108/IMDS-09-2015-0382

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. doi:10.1007/s11747-014-0403-8

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modelling in international marketing. *Advanced in International Market*, *20*, 277–319. doi:10.1108/S1474-7979(2009)0000020014

Hong, J., Lin, P., & Hsieh, P. (2017). The effect of consumer innovativeness on perceived value and continuance intention to use smartwatch. *Computers in Human Behavior*, *67*, 264–272. doi:10.1016/j.chb.2016.11.001

Hsiao, K. (2017). What drives smartwatch adoption intention? Comparing Apple and non-Apple watches. *Library Hi Tech*, *35*(1), 186–206. doi:10.1108/LHT-09-2016-0105

Hsiao, K., Lun, L., & Chen, C. (2018). What drives smartwatch purchase intention? Perspectives from hardware, software, design and value. *Telematics and Informatics*, *35*(1), 103–113. doi:10.1016/j.tele.2017.10.002

Huang, C., & Kao, Y. (2015). UTAUT2 Based Predictions of Factors Influencing the Technology Acceptance of Phablets by DNP. *Mathematical Problems in Engineering*, *21*, 1–23. doi:10.1155/2015/603747

Jeong, S. C., Byun, J. S., & Jeong, Y. J. (2016a). The effect of user experience and perceived similarity of smartphone on acceptance intention for smartwatch. *ICIC Express Letters*, *10*(7), 1613–1619.

Jeong, S. C., Kim, S., Park, J. Y., & Choi, B. (2016b). Domain-specific innovativeness and new product adoption: A case of wearable devices. *Telematics and Informatics*, *21*, 1–19. doi:10.1016/j.tele.2016.09.001

Jung, Y., Kim, S., & Choi, B. (2016). Consumer valuation of the wearables: The case of smartwatches. *Computers in Human Behavior*, *63*, 899–905. doi:10.1016/j.chb.2016.06.040

Kalantari, M. (2017). Consumers' adoption of wearable technologies: Literature review, synthesis, and future research agenda. *International Journal of Technology Marketing*, *12*(3), 274–307. doi:10.1504/IJTMKT.2017.089665

Karahanoglu, A., & Erbug, C. (2011). Perceived qualities of smart wearables: determinants of user acceptance. In *Proceedings of the 2011 Conference on Designing Pleasurable Products and Interfaces* (pp. 1–8). doi:10.1145/2347504.2347533

Kim, K. J., & Shin, D. H. (2015). An acceptance model for smart watches: Implications for the adoption of future wearable technology. *Internet Research*, *25*(4), 527–541. doi:10.1108/IntR-05-2014-0126

Koenig-Lewis, N., Palmer, A., & Moll, A. (2010). Predicting young consumers' take up of mobile banking services. *International Journal of Bank Marketing*, *28*(5), 410–432. doi:10.1108/02652321011064917

Kranthi, A. K., & Ahmed, K. A. A. (2018). Determinants of smartwatch adoption among IT professionals – an extended UTAUT2 model for smartwatch enterprise. *International Journal of Enterprise Network Management*, *9*(3), 294–316. doi:10.1504/IJENM.2018.094669

Llamas, R., Ubrani, J., & Shirer, M. (2019). *IDC Reports Strong Growth in the Worldwide Wearables Market, Led by Holiday Shipments of Smartwatches, Wrist Bands, and Ear-Worn Devices*. Retrieved from https://www.idc.com/getdoc.jsp?containerId=prUS44901819

Luo, X., Li, H., Zhang, J., & Shim, J. P. (2010). Examining multi-dimensional trust and multi-faceted risk in initial acceptance of emerging technologies: An empirical study of mobile banking services. *Decision Support Systems*, *49*(2), 222–234. doi:10.1016/j.dss.2010.02.008

Mills, A. J., Watson, R. T., Pitt, L., & Kietzmann, J. (2016). Wearing safe: Physical and informational security in the age of the wearable device. *Business Horizons*, *59*(6), 615–622. doi:10.1016/j.bushor.2016.08.003

Miltgen, C. L., Popovic, A., & Oliveira, T. (2013). Determinants of end-user acceptance of biometrics: Integrating the "Big 3" of technology acceptance with privacy context. *Decision Support Systems*, *56*, 103–114. doi:10.1016/j.dss.2013.05.010

Momani, A., & Jamous, M. (2017). The evolution of technology acceptance theories. *International Journal of Contemporary Computer Research*, *1*(1), 51–58.

Nascimento, B., Oliveira, T., & Tam, C. (2018). Wearable technology: What explains continuance intention in smartwatches? *Journal of Retailing and Consumer Services*, *43*, 157–169. doi:10.1016/j.jretconser.2018.03.017

Oliveira, T., Thomas, M., Baptista, G., & Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Computers in Human Behavior*, *61*, 404–414. doi:10.1016/j.chb.2016.03.030

Premkumar, G., & Ramamurthy, K. (1995). The role of interorganizational and organizational factors on the decision mode for adoption of interorganizational systems. *Decision Sciences*, *26*(3), 303–336. doi:10.1111/j.1540-5915.1995.tb01431.x

Rakuten Insight Survey. (2018). *Wearable in Asia*. September 2018. Retrieved from https://insight.rakuten.com/wearables-in-asia/

Rawassizadeh, R., Price, B.A., & Petre, M. (2015). Wearable: Has the age of smartwatches finally arrived? *ACM, 58*(1), 45–47. .10.1145/2629633

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). The Free Press.

Rondan-Cataluña, F., Arenas-Gaitán, J., & Ramírez-Correa, P. (2015). A comparison of the different versions of popular technology acceptance models: A non-linear perspective. *Kybernetes*, *44*(5), 788–805. doi:10.1108/K-09-2014-0184

Shin, D. (2019). How do technological properties influence user affordance of wearable technologies? *Interaction Studies: Social Behaviour and Communication in Biological and Artificial Systems*, *20*(2), 307–338. doi:10.1075/is.16024.shi

Spagnolli, A., Guardigli, E., Orso, V., Varotto, A., & Gamberini, L. (2014). Measuring user acceptance of wearable symbiotic devices: validation study across application scenarios. In *International Workshop on Symbiotic Interaction*. Springer International Publishing. doi:10.1007/978-3-319-13500-7_7

Talukder, M., Bao, Y., & Malik, B. (2018). Acceptance and use predictors of fitness wearable technology and intention to recommend. *Industrial Management & Data Systems*, *119*(1), 170–188. doi:10.1108/IMDS-01-2018-0009

Vankatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *Management Information Systems Quarterly*, *27*(3), 425–478. doi:10.2307/30036540

Vankatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending unified theory of acceptance and use of technology. *Management Information Systems Quarterly*, *36*(1), 157–178. doi:10.2307/41410412

Wright, R., & Keith, L. (2014). Wearable technology: If the tech fits, wear it. *Journal of Electronic Resources in Medical Libraries*, *11*(4), 204–216. doi:10.1080/15424065.2014.969051

Wu, L. H., Wu, L. C., & Chang, S. C. (2016). Exploring consumers' intention to accept smartwatch. *Computers in Human Behavior*, *64*, 383–392. doi:10.1016/j.chb.2016.07.005

Yuan, S., Kanthawala, S., & Peng, W. (2015). Keep using my health apps: Discover users' perception of health and fitness. *Telemedicine Journal and e-Health*, *21*(9), 735–741. doi:10.1089/tmj.2014.0148 PMID:25919238

APPENDIX A. QUESTIONNAIRE

Table 5.

Constructs	Items Measurement items	Sources
Performance Expectancy (PE)	PE1 - I find smartwatch useful in my daily life PE2 - Using smartwatch helps accomplish things more quickly PE3 – Using smartwatch improves the quality of my daily healthcare activities PE4 - Using smartwatch increases my chances of achieving things that are important to me	Talukder et al. (2018), Gao et al. (2015), Venkatesh et al. (2012)
Effort Expectancy (EE)	EE1 - Learning how to use smartwatch is easy for me EE2 - I find smartwatch easy to use EE3 - It is easy for me to become skillful at using smartwatch	Venkatesh et al. (2012)
Social Influence (SI)	SI1 - People who are important to me would think that I should use smartwatch SI2 - People who influence me would think I should use smartwatch SI3 - People whose opinions are valuable to me would prefer that I use smartwatch	Venkatesh et al. (2012), Yuan et al. (2015)
Facilitating Conditions (FC)	FC1 - I have the resources necessary to use smartwatch FC2 - I have the knowledge necessary to use smartwatch FC3 – Smartwatch is compatible with other systems I use	Spagnolli et al. (2014), Venkatesh et al. (2012)
Hedonic Motivation (HM)	HM1 – Using smartwatch is fun HM2 – Using smartwatch is enjoyable HM3 – Using smartwatch is very entertaining	Venkatesh et al. (2012), Wu et al. (2016)
Price value (PV)	PV1 – Smartwatch is reasonably priced PV2 – Smartwatch is good value for money PV3 – At the current price, smartwatch provides a good value for money	Venkatesh et al. (2012), Oliveira et al. (2016)
Habit (HB)	HB1 – The use of smartwatch has become a habit for me HB2 – I am addicted to using smartwatch HB3 – Using smartwatch has become natural to me	Nascimento et al. (2018), Venkatesh et al. (2012)
Innovativeness (IN)	IN1 – If I heard about a new information technology, I would look for ways to experiment with it IN2 – Among my peers, I am usually the first to try out	Oliveira et al. (2016), Hong et al. (2016)
Compatibility (COM)	new information technologies IN3 – In general, I am hesitant to try out new information technologies IN4 – I like to experiment with new information technologies COM1 – Using smartwatch is compatible with all aspects of my lifestyle COM2 – Using smartwatch is complete compatible with my current situation COM3 – Using smartwatch fits into my lifestyle	Hsiao (2017), Oliveira et al. (2016)
Perceived Aesthetics (AES) Perceived Privacy Risk (PPR) Adoption behavior	AES1: The design of smartwatch is attractive to me AES2: The appearance of smartwatch is visually appealing to me AES3: User interface of smartwatch (i.e., colors, boxes, menus, etc.) is attractive AES4: The smartwatch looks professionally designed PPR1: Overall, I see a privacy threat linked to smartwatch usage PPR2: There would be high potential for loss associated with disclosing my personal information to a smartwatch's system operator PPR3: Using smartwatch allows others to misuse my personal data AD1 – I will use smartwatch at every opportunity in the future AD2 – I always use smartwatch in my daily life AD3 – I am increasing my use of smartwatch	Jeong et al. (2016a) and Yang et al. (2016) Ernst and Ernst (2016), Nasir and Yurder (2015), Gao et al. (2015) Venkatesh et al. (2012), Li et al. (2015)
Intention to Recommend (REC)	REC1 – I will recommend to my friends to use smartwatch REC2 – If I have a good experience with smartwatch, I will recommend my friends by word of mouth or social networking sites to use the technology	Miltgen et al. (2013), Talukder et al. (2018), Oliveira et al. (2016)

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