Continuance intention to use smartwatches: An empirical study

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CHRONICLE	ABSTRACT
	This study aims at investigating the factors that determine the continuous intention to use smartwatches, one of the most prevalent types of wearable devices. The study extends the expectation confirmation model (ECM) by incorporating other variables (i.e., construct) which capture the unique context of smartwatches continuous usage, namely healthology, perceived aesthetics, habit, and social influence. Hypotheses were assessed using partial least square structural equation modeling (PLS-SEM) approach on data collected from 287 actual smartwatch users. The results reveal that performance expectancy, satisfaction, healthtology, perceived aesthetics and habit significantly influence the continuous usage of smartwatches, while social influence is non-significant. The research model of this study explains 65.7% of the variance in the continuous usage intention of smartwatches. The insights provided by this study suggest fruitful opportunities for future research. They can also help smartwatches companies, developers and marketers with strategies and directions for further development and growth by ensuring users' continuous usage of smartwatches.

1. Introduction

The use of "smart wearable technologies" or "wearable gadgets/devices" has recently increased exponentially (e.g., Chuah, 2019; Dehghani et al., 2018; Dehghani & Kim, 2019; Pal et al., 2020). Wearable devices come in 431 different forms, including fitness/wellness trackers, smartwatches, smart glasses, remote headsets, clothing, bracelets, rings, necklaces, and more (Vandrico, 2021), and are used in various industries, including entertainment, fitness, medical, gaming, industrial, and lifestyle sectors. Smartwatches, the most common type of wearable devices, offer a variety of features and tasks to its users, including timekeeping, music streaming, talking with friends, receiving notifications, and making phone calls (Krey et al., 2019). They can also foster a healthy lifestyle by encouraging users to eat wisely and exercise on a regular basis (Dehghani et al., 2018).

Smartwatches usage is expected to increase at a rapid rate in the next few years (Chuah, 2019; Sabbir et al., 2020). In 2020, the global smartwatch spending reached 21.76 billion dollars, up from 18.5 billion dollars in 2019, and is predicted to reach 31.34 billion dollars in 2022, with Apple Watch dominating the market (Statista, 2021). However, there are two issues associated with smartwatches. First, Gartner's survey pointed out that 29% of smartwatches' users have stopped using their devices because they neither find it to be useful nor interesting (Gartner, 2016). In fact, Angela McIntyre, research director at Gartner, stated that "dropout from device usage is a serious problem for the industry … the abandonment rate is quite high relative to the usage rate…" (Gartner, 2016). Second, though the increased competition in the smartwatches sector is beneficial for end-

users, as they have different choices to select from, it will "make retaining existing users difficult because they will always want to try out new technology, products, and services" (Pal et al., 2020, p. 262).

Information systems (IS) scholars (e.g., Adapa et al., 2018; Al-Emran, 2021; Basoglu et al., 2017; Beh et al., 2019; Rauschnabel et al., 2015; Sabbir et al., 2020; Yang et al., 2016) have explored the initial usage and acceptance variables of smartwatches, but they did not consider the "changes in use behaviors far into the future" (Dehghani et al., 2018, p. 481). Yet, "technology long-term effectiveness, success and viability are decided by the continuous use rather than early acceptance or utilization" (Foroughi et al., 2019, p. 1017). Only a few studies (Chuah, 2019; Dehghani et al., 2018; Hong et al., 2017; Ogbanufe & Gerhart, 2018; Pal et al., 2020) have examined the determinant factors that influence users' continuous usage of smartwatches. However, these studies reported contradicting as well as mixed findings and did not account for all variables that emphasize the distinctive context of smartwatches continuous usage.

The objectives of this study are fourfold. First, this study investigates users' continuance intention to use smartwatches, in the State of Kuwait, in the post-adoption phase. Studying smartwatches continuous usage is relevant to Kuwait, as "Kuwait is one of the most interesting markets in the Middle East and North Africa region, as it influences purchases all across the Gulf Council Countries (GCC) […] Despite being a small market, Kuwait has amongst the highest adoption rates of new technology and highest revenue per user for tech companies" (Global Finance, 2020). Second, "since successful scenarios of users' continued intention to use smartwatches cannot be straightforwardly applied in various social and cultural settings" (Rabaa'i, in press b); then examining this topic in the context of Kuwait, where to the best of the researchers' knowledge, no similar research study has been conducted, is a significant contribution. Third, this study attempts to enrich the Expectation-Confirmation Model (ECM) (Bhattacherjee, 2001a) literature, in the context of smartwatches, by including variables, which emphasize the distinctive context of smartwatches continuous usage, such as healthology, perceived aesthetics, habit, and social influence. Finally, in light of the increased competition in the smartwatches sector and the growing as well as unpredictable customer needs and demands, this study intends to aid smartwatch firms and designers in better understanding users' continuance usage. Therefore, the research question of this study is: *What are the main factors that influence users' continuous usage of smartwatches?*

This study is structured as follows. The literature review is introduced in the following section, followed by a discussion of the conceptual model and hypotheses development. Next, the research methodology, data analysis and results will be discussed. Finally, the study findings, implications, limitations and future research directions will be addressed.

2. Literature review

While information systems (IS) scholars have studied determinant variables that impact users' behavioral intention to adopt wearable gadgets in general and smartwatches in particular, very limited studies investigated their continuous usage intentions. This section summarizes previous adoption research conducted on these devices. Detailed literature review, regarding wearable devices, can be found in the studies by Kalantari (2017), Dehghani (2018), Chuah (2019) and Pal et al., (2020).

Yang et al., (2016) argued that perceived usefulness, joy, and social image positively influence customers' perceived benefits of wearable gadgets. Potnis et al., (2017) demonstrated that effort expectancy, social influence, facilitating conditions, and trusting beliefs are the key determinants to use such devices. In an effort to study the behavioral intentions to purchase smart bras and t-shirts, Turhan (2013) integrated the technology acceptance model (TAM) with the theory of planned behavior (TBP). The study results confirmed that perceived usefulness and behavioral control have indirect impacts on purchase intention, whereas subjective norms and perceived behaviors have a direct impact on purchase intention. Additionally, Rauschnabel et al.'s, (2015) study results affirm that functional benefit, ease of use, and brand positively impact users' attitudes toward using smart glasses. Moreover, Basoglu et al., (2017) found that usefulness, ease of use, involvement, self-efficacy, risk-task characteristics, anxiety and enjoyment were the main adoption factors of smart glasses. Adapa et al., (2018) found that compatibility, look and feel, and the availability of specific apps are the determinant factors that affect the adoption of both google glasses and smartwatches.

Rabaa'i and Zhu (2021) investigated the variables which affect user's behavioral intention to use smart wearables for payment purposes. Their study results pointed out that behavioral intention to adopt smart wearable for payments is influenced by attractiveness of alternatives, perceived usefulness, perceived ease of use, perceived security and trust. Additionally, Al-Emran (2021) integrated TAM, task-technology Fit (TTF) factors with quality features of smartwatches to investigate students' behavioral intention to adopt smartwatches for learning tasks. The study findings reveal that individual-technology fit and task-technology fit positively impact the perceived usefulness of smartwatches, while no positive effects were reported on the ease of use of these devices for academic purposes.

Kim and Chiu (2018) integrated TAM and technology readiness (TR) models to examine the influential factors that affect consumers' acceptance and use of sports and fitness wearable devices, according to the results, TR has a positive impact on perceived ease of use (PEOU) and perceived usefulness (PU), and negative TR had a negative impact on PEOU and PU. Both PEOU and PU promoted the intention to use sports wearable devices. With the objective to investigate the behavioral intentions to use smartwatches for fitness and health monitoring, Beh et al., (2019) combined the Unified Theory of Acceptance and Use of Technology (UTAUT2) with threat appraisal as moderators and reported that performance expectancy, effort expectancy, facilitating conditions and hedonic motivation have positive influence on behavioral intentions towards using smartwatches.

Rauschnabel et al., (2016) claimed that the vast majority of their study's survey respondents, (75%) considered wearable technology as a fashion product instead of a technology product. Hence, the authors suggest the importance of adding the 'fashnology' (a combination of fashion and technology aspect of wearable devices to complement technology acceptance theories with fashion-focused variables. The fashnology concept was supported by Chuah et al., (2016) who reported that "consumers who consider smartwatches as a technology product recognize usefulness more than visibility, whereas those who view smartwatches as a fashion product consider the product visibility more than usefulness in their adoption decision". Kim (2016) claimed that a round screen, compared to a square one, is more effective in enhancing device's hedonic qualities that further encourage smartwatch adoption.

Choi and Kim (2016) extended TAM to investigate the factors affecting consumers' intention to use smartwatches. The authors indicated that vanity and the need for uniqueness influence consumers' attitude toward using smartwatches through perceived enjoyment and perceived self-expressiveness. They concluded that considering a smartwatch as a fashion accessory is significant in explaining consumers' behavioral intentions. Similarly, Krey et al., (2019) demonstrated that product visibility will help in the expression of one's identity, and extroverts value the symbolic aspect of smartwatches more than do introverts. In their study to explore factors affecting consumers' intention to use Smartwatch in Bangladesh, Sabbir et al., (2020) pointed out that behavioral intention to use smartwatches is influenced by aesthetic appeal, attitude, and healthology. Their study also found that attitude has the strongest direct impact on behavioral intention. Studies by Hsiao and Chen (2018), Dehghani et al., (2018) and Dehghani and Kim (2019) investigated the design aesthetic of smartwatches. Their studies' findings confirmed that the size, shape, and uniqueness significantly influence both the purchase and continuance intentions towards smartwatches.

Hong et al., (2017) demonstrated that hedonic and utilitarian value mediated the relationship between personal innovativeness and continuance usage of smartwatches. Dehghani et al., (2018, p. 484) have developed a model to investigate the underlying factors affecting the intention to continue using smartwatches. The authors proposed the term "healthtology" (a combination of health and technology), and "claimed that the more the smartwatches can motivate users to stay healthy, the more intense is their actual usage". They found that the actual usage of smartwatches is influenced by aesthetic appeal, complementary goods and healthology. The results also indicated that smartwatches' continuous usage is impacted positively by hedonic motivation as well as aesthetic appeal and negatively by operational imperfection. However, complementary goods and healthology had no influence on continuous usage. Based on a study of 324 actual smartwatch users, Chuah (2019) reported that users' intentions to continue using smartwatches are impacted by perceived benefits and previous lifestyle incongruence, but not by perceived risks. The results also pointed out that the impact of perceived benefits and previous lifestyle incongruence on continuance intention is mediated by inspiration and well-being. Based on the expectation confirmation model (ECM) and with the objective of assessing users' continuous usage of smartwatches, Pal et al., (2020) studied 312 long-term smartwatch users in four Asian countries and found that perceived usefulness, hedonic motivation, perceived comfort and self-socio motivation have positive associations with continuous usage. The results also pointed out that perceived privacy, battery-life concern, perceived accuracy and functional limitations negatively influence continuous usage of smartwatches.

While these studies provide important findings related to wearable technology in general, and smartwatches in particular, the literature review clearly indicates a research gap that exists in investigating users' continuous intentions to use smartwatches. Apart from five studies, all studies investigated the behavioral usage intention of smartwatches rather than the continuous usage. However, initial technology acceptance or use has not always converted into continuous usage, as proven by the fact that some users utilized a technology but later stopped using it (Rabaa'i, 2022; Rabaa'i et al., 2021; Rabaa'i & Abu ALMaati, 2021). For instance, it is suggested that users' intention to utilize a technology indicates merely their positive attitude toward the technology and their associated need to use it (Huang, 2019), but does not imply that they would use it in the future (Wang et al., 2019a). Therefore, users will continue to use a technology as long as it meets their expectations (Huang, 2019), and "will stop using a technology when it does not meet their expectations or fulfill their needs" (Bhattacherjee, 2001a).

3. The conceptual model and hypotheses development

Adapted from the Expectation-Confirmation Theory (ECT) (Oliver, 1980) and developed by Bhattacherjee (2001a), the Expectation Confirmation Model (ECM) is concerned with post-acceptance and post-consumption expectation variables (e.g., Pal et al., 2020; Rabaa'i et al., 2021; Rabaa'i & Abu ALMaati, 2021). Unlike technology acceptance models, such as TAM, UTAUT, and TPB models, the ECM is focused on the factors that determine the continuous usage intention of a technology in the future. The ECM has been employed to assess individuals' continuous use intention in different technological contexts, for example: cloud services (Huang, 2016), massive open online courses (MOOC) (Zhou, 2017), mobile application use (Tam et al., 2018), smart wearables (Chuah, 2019; Hong et al., 2017; Ogbanufe & Gerhart, 2018), e-learning (Rabaa'i et al., 2021), and mobile banking (Rabaa'i & Abu ALMaati, 2021).

The ECM contains four constructs: confirmation, perceived usefulness (or performance expectancy), satisfaction, and continuance intention (Bhattacherjee, 2001a). Huang (2019, p. 25) stated that "when users are asserted that a technology matches their expectations, they are more likely to assume that it will not only save them time but also increase their performance and productivity, and they will find it satisfactory. Then, if they perceive the technology to be simple, they are more likely to feel that it will improve their effectiveness, and they will be satisfied with the technology and continue to use it as a result. Users

will feel satisfied with a technology if they believe it is beneficial, and they will want to continue using it. Finally, users' satisfaction with a technology will inspire them to continue using it, and prompt them to act accordingly".

This research suggests a new theoretical model, based on the ECM, to evaluate smartwatches' continuance usage intention. Thus, this study proposes to incorporate the ECM with four constructs, namely: healthtology, perceived aesthetics, habit, and social influence, which are significant in the context of smartwatches continuance usage intention. The model of this study is depicted in Fig. 1. Below, the definition of each construct is provided.
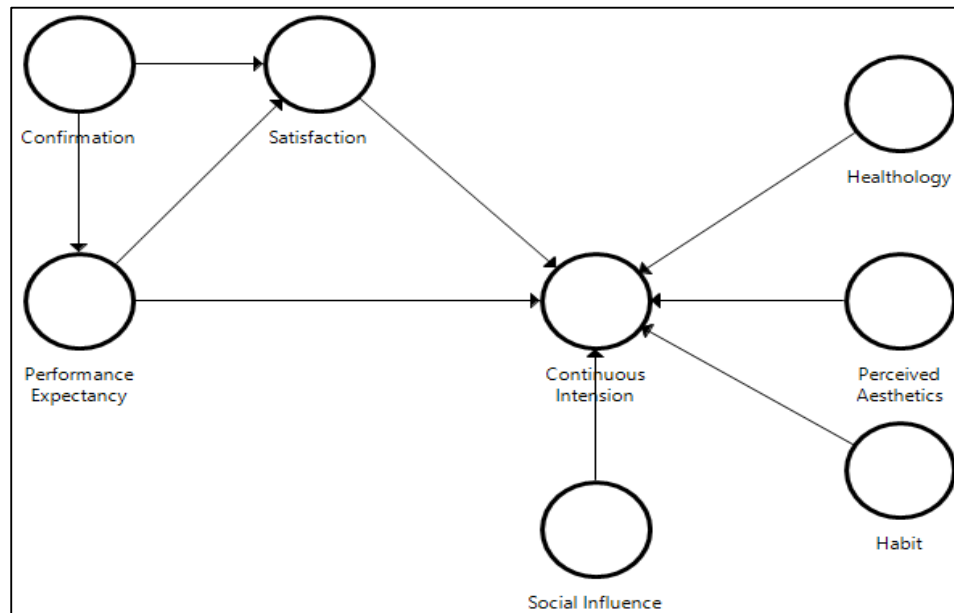

Fig. 1. The Research Model

Confirmation (CON)

Confirmation refers to the degree to which users believe their initial expectations are being fulfilled during the use of a technology (Rahi et al., 2018). Users' confirmation of expectations, according to the ECM, has a positive impact on both performance expectancy and satisfaction with a technology (Bhattacherjee, 2001a, 2001b). According to Tam et al., (2018), when users' expectations are met through the usage of a technology, they will have a positive attitude toward the technology's perceived benefits, which will, in turn, promote their satisfaction with it. Previous research studies confirmed the significant associations between confirmation and performance expectancy as well as satisfaction (e.g., Alraimi et al., 2015; Dai et al., 2020; Ding, 2019; Foroughi et al., 2019; S. Hong et al., 2006; Huang, 2019; Ifinedo, 2018; Pal et al., 2020; Rabaa'i et al., 2021; Rabaa'i & Abu ALMaati, 2021; Tam et al., 2018). As such, this study proposes that when users' expectations are confirmed, they tend to believe that smartwatches are advantageous, helpful, and valuable, and this, in turn, will stimulate their satisfaction with smartwatches. The study, therefore, hypothesizes that:

H1: *Confirmation has a positive effect on performance expectancy.*

H2: *Confirmation has a positive effect on individuals' satisfaction with smartwatches.*

Performance Expectancy (PE)

Similar to perceived usefulness and relative advantage (Huang, 2019; Venkatesh et al., 2003), performance expectancy refers to the extent to which an individual believes that using a specific technology would assist him or her in accomplishing certain activities or tasks (Venkatesh et al., 2012). PE is a significant variable to analyze user behavior at both the initial and post-adoption stages (Venkatesh et al., 2003). Dia et al., (2020) argued that a user's perceived PE, of a technology, is a crucial factor of satisfaction and intention to continue using it. Bhattacherjee (2001b) found that users' satisfaction was impacted by confirmation of expectations and performance expectancy. Past studies (e.g., Dai et al., 2020; Dehghani et al., 2018; Ding, 2019; Ifinedo, 2018; Pal et al., 2020; Rabaa'i et al., 2021; Rabaa'i & Abu ALMaati, 2021; Tam et al., 2018) found significant positive influence of PE on both satisfaction and continuous usage. Therefore, it is proposed that the more users believe that smartwatches are useful, handy, and advantageous, the greater: (1) they are satisfied with them, (2) the likelihood that they will continue using them. Accordingly, the study hypothesizes that:

H3: *Performance expectancy has a positive effect on individuals' satisfaction with smartwatches.*

H4: *Performance expectancy has a positive effect on individuals' continuous usage of smartwatches.*

Satisfaction (SAT)

Satisfaction is defined as "an ex-post appraisal of consumers' initial (trial) experience with the service, expressed as a pleasant feeling (satisfaction), apathy, or negative feeling (dissatisfaction)" (Bhattacherjee, 2001a, p. 354). According to the ECM, user satisfaction is the most critical factor in determining a user's intention to use a technology in the future (Bhattacherjee, 2001a, 2001b). Foroughi et al., (2019) stated that customers' satisfaction, with a product or service, is the key factor for making a repurchase decision, which is the same notion as continuance intention towards using a technology in the future (Tran et al., 2019). In fact, it is argued that users who are satisfied with a technology are more likely to want to use it again in the future (e.g., Alraimi et al., 2015; Cheng, 2014; Rabaa'i et al., 2021; Rabaa'i & Abu ALMaati, 2021). Previous studies have shown the significant positive effect of satisfaction on continuance intention to use a technology, for example in: mobile apps (Tam et al., 2018; Hammouri et al., 2021); social networking (Rabaa'i et al., 2018); desktop services (Huang, 2019), food delivery apps (Alalwan, 2020), smartwatches (Pal et al., 2020), e-learning systems (Rabaa'i et al., 2021), and mobile banking services (Rabaa'i & Abu ALMaati, 2021). Adapted to this study, if smartwatches' users are satisfied with them, they will continue using them in the future. Therefore, the following hypothesis is proposed:

H₅: *Satisfaction has a positive effect on individuals' continuous usage of smartwatches*.

Healthology (HT)

Individuals who embrace a healthy lifestyle are more likely to be motivated to engage in restrictive health practices (e.g., exercising regularly, eating well, and sleeping sufficiently) than those who are unconcerned about their health (Claussen et al., 2015). Health motivations are defined by Dehghani et al., (2018, p. 484) as "the extent to which a person's health is incorporated into his or her daily activities". Through personal data insights, wearable technology gadgets, such as smartwatches, can provide people with direct motivations to move toward their goals (Asimakopoulos et al., 2017). Furthermore, the features of such gadgets might enable people to define and achieve personal health objectives (Nelson et al., 2016). In fact, the precision of personal data insights, supplied by smartwatches (e.g., calories burnt, pulse monitoring, steps tracker), can enable users to be more proactive in tracking their health and well-being (Canhoto & Arp, 2017). This will result in improving individuals' physical health, emotions, as well as their experienced meaning and accomplishment (Stiglbauer et al., 2019). As a result, Dehghani et al., (2018, p. 484) developed the "healthtology" construct, which is defined as "an interaction of health concerns, informatics, and technology aimed at providing creative approaches to meet distinct healthcare demands". This new construct "not only include technology attributes but also continuous multi-parameter health monitoring" (Dehghani et al., 2018, p. 488). Dehghani et al., (2018) verified the association between healthology and actual usage, however their findings failed to show that healthology had an impact on smartwatch continuous usage. Nevertheless, this study argues that health-related data, offered by smartwatches, will not only stimulate users to exercise frequently and monitor their own health, but will also encourage them to use the device in the future. Consequently, a hypothesis is presented as follows:

H₆: *Healthtology has a positive effect on individuals' continuous usage of smartwatches*.

Perceived Aesthetics (PA)

Aesthetics is defined as "the flow of philosophical exploration of style, color, fashion, and beauty" (Bloch, 1982; Nam et al., 2007), and it includes "psychological responses to certain shapes and styles of a product design" (Lee, 2020). The aesthetics of a product's look are referred to as design aesthetics (Hsiao & Chen, 2018). Aesthetics in design has been studied from various perspectives, including "beauty, psychological response, and emotional appeal" (Baskerville et al., 2018). According to Lee (2020), the subjective judgment of a product is influenced by design aesthetics. In fact, consumers' decisions concerning product consumption are heavily influenced by design aesthetics (Dehghani et al., 2018). According to Reimann et al., (2010), good design aesthetics result in a better user experience. Sonderegger and Sauer (2010) confirmed that good design aesthetics influenced the usage of smartphones. Jeong et al., (2017) posited that perceived beauty is a key feature of wearable devices in general and smartwatches in particular. Furthermore, because smartwatches are considered as fashion products, Choi and Kim (2016) claimed that buyers seeking distinctiveness will be more interested in them. This claim was then backed up by Yang et al., (2016), who proposed that having a wearable gadget with good design aesthetics could allow people to stand out. While previous research (e.g., Cyr et al., 2006; Nanda et al., 2008, 2008; Sabbir et al., 2020; Yang et al., 2016) found a significant relationship between perceived aesthetics and perceived usefulness, perceived ease of use, perceived enjoyment, attitudes, and behavioral intention, only Dehghani et al.'s, (2018) study found a positive significant effect of perceived aesthetics on continuous smartwatch usage. Therefore, this study argues that users will be intrinsically driven to continue using smartwatches if they believe that they have strong design aesthetics. Consequently, the study hypothesizes that:

H₇: *Perceived Aesthetics has a positive effect on individuals' continuous usage of smartwatches*.

Habilt (HB)

Habit was described by Limayem et al., (2007, p. 709) as "the amount to which persons tend to conduct behaviors (use IS) automatically as a result of learning". Alalwan (2020, p. 33) indicated that "habit formation could occur organically as a result of the user's prior learning experience". The author further argued that as a result of this accumulated learning experience and the establishment of habitual behavior, users' attitudes and beliefs can be influenced, which predicts their continued intention

to behave in the same way as before. Barnes (2011) and Tam et al., (2018) stated that the amount to which a behavior has become automatic, as a result of earlier learning, can influence the continuous usage of a technology. Amoroso and Lim (2017) observed that users who are satisfied with their previous experience with mobile applications are more likely to acquire habitual behavior toward such apps, and hence will be more eager to use these apps in the future. Habit has been found to be a strong predictor of continuous usage intentions in a variety of studies, including mobile food delivery apps (Alalwan, 2020), incumbent mobile technologies (Amoroso & Lim, 2017), virtual world systems (Barnes, 2011), mobile apps (Tam et al., 2018), and world wide web continuous usage (Limayem et al., 2007). As such, it is hypothesized that users who develop a habit of using smartwatches will be more likely to do so in the future. Accordingly, a hypothesis is presented as follows:

H₈: *Habit has a positive effect on individuals' continuous usage of smartwatches*.

Social Influence (SI)

Social influence is defined as "the degree to which consumers perceive that important others (e.g., family and friends) believe they should utilize a specific technology" (Venkatesh et al., 2012, p. 195). Venkatesh et al., (2003) suggested that, whether positive or negative, SI is an influential factor in many parts of people's life and is likely to have a significant impact. In fact, consumer adoption studies have proven SI to be one of the most important adoption factors (Dahlberg et al., 2015). SI around individuals could have a vital influence in molding their intentions toward a technology (Alalwan et al., 2017). Previous IS research has found a significant relationship between SI and continuance usage intention in a variety of technological contexts, including e-learning (Rabaa'i et al., 2021), social networking services (Yoon & Rolland, 2015), mobile telecommunication services (Hsu et al., 2019), massive open online courses (MOOCs) (Shao, 2018), and mobile apps (Tam et al., 2018). As a result, it is reasonable to argue that people are more likely to weigh the opinions of others while deciding whether or not to continue using smartwatches in the future. Therefore, the study hypothesizes that:

H₉: *Social influence has a positive effect on individuals' continuous usage of smartwatches*.

4. Research methodology

A survey-based instrument, with items for all constructs in the model, was used to collect the empirical data needed to evaluate the hypotheses stated in the conceptual model (Figure 1). The measuring items, the study sample, and the data collection technique are all described in this section.

4.1 Measurement Instrument

The survey instrument comprised 24 items and assessed 8 research constructs: confirmation, performance expectancy, satisfaction, healthology, perceived aesthetics, habit, social influence, and continuous intention. Questionnaire items were adopted from relevant past studies with slight wording changes to suit the smartwatches context. Confirmation (CON), satisfaction (SAT), and continuous intention (CI) were assessed using three items obtained from Bhattacherjee (2001a). For measuring performance expectancy (PE), social influence (SI), and habit (HB), all items were taken from Venkatesh et al., (2012). The items for the healthology (HT) construct were adapted from Dehghani et al., (2018). Finally, for assessing perceived aesthetics (PA), all items were adapted from Yang et al. (2016).

Table 1
The constructs, measurement items and sources

Constructs	Items		Sources
Confirmation (CON)	CON1	My experience with using my smartwatch was better than what I had expected.	Bhattacherjee (2001a)
	CON2	The expectations that I have about my smartwatch were correct.	
	CON3	Overall, most of my expectations from using my smartwatch were confirmed.	
Performance expectancy (PE)	PE1	I found that using my smartwatch is useful in my daily life.	Venkatesh et al. (2012)
	PE2	My smartwatch could increase my productivity.	
	PE3	I found that using my smartwatch is useful for completing tasks.	
Satisfaction (SAT)	SAT1	frustrated/contented.	Bhattacherjee (2001a)
	SAT2	displeased/pleased.	
	SAT3	dissatisfied/satisfied.	
Healthology (HT)	HT1	My smartwatch motivates me to exercise.	Dehghani et al., (2018)
	HT2	My smartwatch helps me to have a well-balanced diet.	
	HT3	I have better control over my daily calorie intake with my smartwatch.	
Perceived aesthetics (PA)	PA1	I find that my smartwatch looks attractive.	Yang et al. (2016)
	PA2	The smartwatch is aesthetically appealing.	
	PA3	My smartwatch has a professional design.	
Social influence (SI)	SI1	People whose opinions that I value prefer that I use my smartwatch.	Venkatesh et al. (2012)
	SI2	People who are important to me think that I should use my smartwatch.	
	SI3	People who influence my behavior think that I should use my smartwatch.	
Habit (HB)	HB1	The use of my smartwatch has become a habit for me.	Venkatesh et al. (2012)
	HB2	Using my smartwatch has become natural to me.	
	HB3	I must use my smartwatch.	
Continuous intention (CI)	CI1	I plan to continue using my smartwatch frequently.	Bhattacherjee (2001a)
	CI2	I will keep using my smartwatch as regularly as I do now	
	CI3	I will always try to use my smartwatch in my daily life.	

All items, except for the Satisfaction construct measurement items, were measured with a seven-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7). The Satisfaction construct is based on Spreng et al.'s (1996) dimensions, which has been validated in the IS context (e.g., Bhattacherjee, 2001a; Rabaa'i, 2012, 2017a; Rabaa'i et al., 2021). This construct measures respondents' satisfaction in terms of intensity and direction, using seven-point scales anchored by four semantic differential adjective pairs: "frustrated/contented," "displeased/pleased," and "dissatisfied/satisfied" (Oliver, 1997). The complete list of measurement items used in this study is reported in Table 1.

We ran a convenience sample pilot survey with 21 participants to further assess the quality of the measures and the questionnaire's reliability and validity. The participants confirmed that the questionnaire was simple, clear, and took little time to be completed. Cronbach's alpha was utilized to test the reliability of the constructs' scale. All constructs had values more than 0.70, as suggested by Nunnally and Bernstein (1994). As a result, the questionnaire was then utilized for data collection. The results of the pilot survey were excluded from the final data analysis.

4.2 Sample and Data Collection

The data was collected in the State of Kuwait. The data was gathered through an online questionnaire that was distributed to the participants. Students, alumni, faculty members, and staff at a private American institution were sent an email invitation with a link to the online questionnaire for this research study, and they were also invited to extend the invitation to their friends and relatives. Random persons from outside of the institution and academic context were also invited to participate in this research. Finally, in order to reach as many respondents as possible, the online questionnaire was sent to the first researcher's contacts, who live in Kuwait, via various social media platforms (e.g., WhatsApp, Instagram, LinkedIn, and Facebook).

A convenient sampling approach was used, as the size of the study's population is unknown (e.g., Liébana-Cabanillas et al., 2018; Rabaa'i et al., 2021; Sharma et al., 2019). To assure the study's legitimacy, all of the individuals who were chosen for the survey were actual smartwatch users. The question "Do you use a smartwatch?" was utilized to screen and eradicate the respondents who do not use smartwatches. Respondents who answered "no" were filtered out of the study and were not included.

A total of 423 surveys were gathered. The screening question eliminated 136 of the submitted questionnaires, leaving 287 viable survey responses. The descriptive statistical analysis was carried out using SPSS 23. 54% of respondents were males, and most of the respondents were bachelor's degree holders (52%). Only 12% of respondents were between the ages of 17 and 20, with the majority (39%) being between the ages of 26 and 30. Students and working professionals were represented in the sample, with roughly (28%) students and (59%) working professionals. In total, (63%) of respondents owned smartwatches for 1 to 3 years, with Apple and Samsung smartwatches accounting for 76% of the total. Table 2 summarizes the descriptive statistics.

Table 2
Demographic characteristics of respondents

Demographic variables			Frequency	Percentage
Gender	Male		156	54%
	Female		131	46%
		Total	287	100%
Age	17-20 years		35	12%
	21-25 years		54	19%
	26-30 years		112	39%
	> 30 years		86	30%
		Total	287	100%
Education level	High school		11	4%
	University student		68	24%
	Bachelor		148	52%
	Postgraduate		43	15%
	Others		17	5%
	Total		287	100%
Employment	Student		79	28%
	Working professionals		170	59%
	Unemployed		38	13%
	Total		287	100%
Smartwatch brand	Apple		117	41%
	Samsung		99	35%
	Huawei		33	12%
	Others		38	13%
	Total		287	100%
Smartwatch ownership	< 1 year		27	9%
	1 – 2 years		94	33%
	2 – 3 years		87	30%
	> 3 years		79	28%
	Total		287	100%

4.3 Controlling Common Method Bias

This study used two approaches to control common method bias (CMB), as suggested by Podsakoff et al. (2003). First, a distinct measurement scale for the satisfaction construct was utilized as a way to limit the risk of CMB (Leong et al., 2020). Second, a common latent factor (CLF) was employed, with all construct indicators included in the model. The CLF came up with a result of 0.6154. The common method variance was calculated by squaring 0.6154, yielding a result of 0.379 (i.e., 37.9%). This value is lower than the required threshold of 50% (McLean et al., 2020), implying that CMB is unlikely in this study.

5. Data analysis and results

Partial least squares of structural equation modeling (PLS-SEM) was employed to examine the research model in this study using SmartPLS 3.2.9 software (Ringle et al., 2015). The PLS-SEM method can be used to investigate complex cause–effect interactions (e.g., Hair et al., 2014; Henseler et al., 2009; Sarstedt et al., 2014). As a result, PLS-SEM was utilized in this study to evaluate and validate the suggested model as well as the hypothesized relationships among the constructs (e.g., Almajali et al., 2021; Hair et al., 2014, 2017; Hammouri, & Abu-Shanab, 2020; Hammouri et al., 2022; Rabaai, 2015; Rabaai et al., 2015; Rabaa'i, 2012, 2016, 2017b; Rabaa'i et al., 2015, 2018, 2021; Rabaa'i & Zhu, 2021; Zogheib et al., 2015). The data was analyzed in two steps, as recommended by Hair et al., (2017): the measurement model and the structural model.

5.1 Measurement Model

Internal reliability, convergent validity, and discriminant validity criteria were investigated in order to validate the measurement model (Hair et al., 2017). Internal reliability is measured using Cronbach's alpha (CA) and composite reliability (CR) (Hair et al., 2017). Table 3 demonstrates that the CA and CR values for all constructs are greater than 0.7 and 0.85, respectively, showing high internal consistency reliability (Fornell & Larcker, 1981; Henseler et al., 2009, 2015). Convergent validity was assessed using factor loadings (FL) and the average variance extracted (AVE). According to Hair et al., (2017), each construct's FL and AVE values should be more than 0.7 and 0.5, respectively. In this study, FL values ranging from 0.754 to 0.971 exceeded the expected threshold of 0.7, as indicated in Table 3. The AVE of all constructs, which ranged from 0.759 to 0.928, met Hair et al., (2017)'s rule of thumb, implying that the constructs in this study explain more than 50% of the variance of their indicators (Henseler et al., 2009).

Table 3
Items loading, p-value, Cronbach's alpha, Composite reliability, and AVE

Items	Loading	p-value	Cronbach's Alpha	Composite Reliability	AVE
Confirmation (CON)			0.945	0.965	0.901
CON1	0.943	0.000			
CON2	0.960	0.000			
CON3	0.944	0.000			
Performance Expectancy (PE)			0.884	0.928	0.811
PE1	0.886	0.000			
PE2	0.911	0.000			
PE3	0.906	0.000			
Satisfaction (SAT)			0.865	0.918	0.788
SAT1	0.862	0.000			
SAT2	0.898	0.000			
SAT3	0.901	0.000			
Healthology (HT)			0.957	0.972	0.920
HT1	0.964	0.000			
HT2	0.967	0.000			
HT3	0.947	0.000			
Perceived Aesthetics (PA)			0.961	0.975	0.928
PA1	0.954	0.000			
PA2	0.971	0.000			
PA3	0.965	0.000			
Habit (HB)			0.837	0.904	0.759
HB1	0.754	0.000			
HB2	0.922	0.000			
HB3	0.926	0.000			
Social Influence (SI)			0.866	0.918	0.790
SI1	0.913	0.000			
SI2	0.924	0.000			
SI3	0.826	0.000			
Continuous intention (CI)			0.916	0.947	0.857
CI1	0.908	0.000			
CI2	0.922	0.000			
CI3	0.947	0.000			

The Heterotrait–Monotrait (HTMT) criterion is used to assess the discriminant validity of the constructs. HTMT represents "the mean value of the measurement item correlations across variables relative to the (geometric) mean of the average correlations for the measurement items measuring the same variable" (Hair et al., 2019, p. 9). Table 4 shows that all of the HTMT

values were less than the suggested threshold of 0.90, indicating the discriminant validity of all constructs in this study (e.g. Hair et al., 2017; Rabaa'i et al., 2021; Rabaa'i & Abu ALMaati, 2021; Rabaa'i & Zhu, 2021).

Table 4
Hetrotrait–Monotrait ratio (HTMT) Test

	CON	CI	HB	HT	PA	PE	SAT	SI
CON								
CI	0.649							
HB	0.577	0.769						
HT	0.68	0.712	0.645					
PA	0.632	0.678	0.565	0.689				
PE	0.66	0.749	0.763	0.672	0.663			
SAT	0.638	0.727	0.672	0.636	0.535	0.732		
SI	0.492	0.613	0.676	0.445	0.492	0.599	0.668	

5.2 Structural Model

This study evaluated the hypotheses using the structural model (e.g., Hair et al., 2017, 2019; Hammouri et a., 2021; Henseler et al., 2009, 2016; Nusairat et al., 2021; Rabaa'i, 2017a; Rabaa'i et al., 2015). The structural model is evaluated by determining the coefficient (R^2), predictive relevance (Q^2), effect size estimates (f^2) and path coefficient estimates (β) (e.g., Chin, 2010; Hair et al., 2017, 2019; Henseler et al., 2016). Figure 2 illustrates the structural model.

This study's research model explained 0.368 of the variance in performance expectancy, 0.468 of the variance in satisfaction, and 0.657 of the variance in continuous intention, indicating that the model can explain 36.8%, 46.8%, and 65.7% of the variance (R^2) in performance expectancy, satisfaction, and continuous intention, respectively. The blindfolding technique was used to evaluate predictive relevance (Q^2) values, which were then determined using the cross-validated redundancy approach. The results demonstrate that the predictive relevance (Q^2) values, for continuous intention to use smartwatches (0.537), performance expectancy (0.284), and satisfaction (0.351), are all larger than zero as suggested by Chin (2010). Effect size estimates (f^2) were also computed to test if a certain independent variable has a significant impact on a dependent variable. The results of the effect sizes are shown in Table 5. According to Kenny (2018), conventional effect sizes for small, medium, and large hypotheses are 0.005, 0.01, and 0.025, respectively. The results demonstrate that the f^2 for the supported hypotheses were adequate.
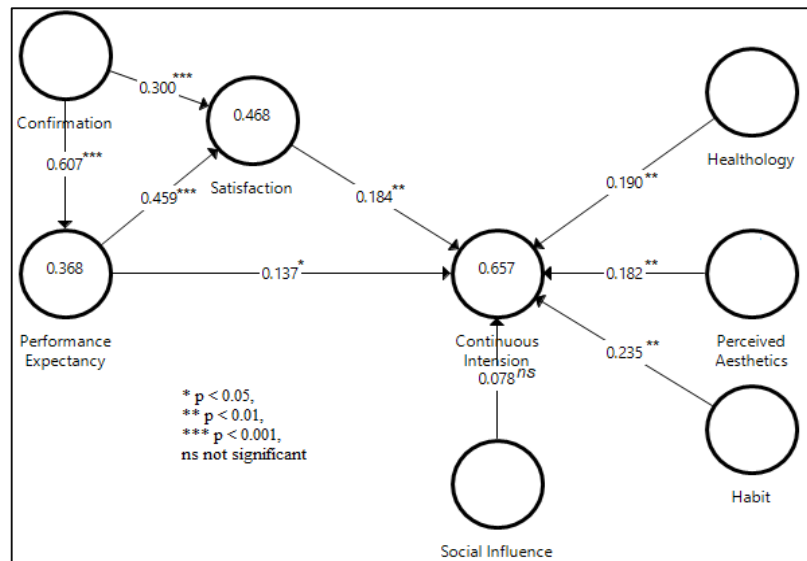

Fig. 2. The structural model

The significance levels of path coefficients were investigated using a nonparametric bootstrapping technique with 5,000 samples (Hair et al., 2017, 2019). The path coefficient, t-statistics, and p-values for the proposed hypotheses are shown in Table 5. The results show a statistically significant associations between confirmation and performance expectancy ($\beta = 0.607$; p 0.001) and satisfaction ($\beta = 0.300$; p 0.001), validating H1 and H2. H3 was corroborated by confirming a substantial link between performance expectancy and satisfaction ($\beta = 0.459$; p 0.001). Finally, performance expectancy ($\beta = 0.137$; p 0.05), satisfaction ($\beta = 0.184$; p 0.01), healthology ($\beta = 0.190$; p 0.01), perceived aesthetics ($\beta = 0.182$; p 0.01), and habit ($\beta = 0.235$; p 0.01) all have significant associations with continuous intention, whereas social influence ($\beta = 0.078$; $p > 0.05$) did not.

Table 5

Hypotheses' path coefficients, t-statistics, and p-values

Relationship	Hypothesis No.	Path coefficient	t-statistics	p-values	f^2	Decision
CON → PE	H1	0.607	12.436	0.000***	0.582	Supported
CON → SAT	H2	0.300	4.711	0.000***	0.107	Supported
PE → SAT	H3	0.459	6.774	0.000***	0.251	Supported
PE → CI	H4	0.137	2.044	0.041*	0.022	Supported
SAT → CI	H5	0.184	3.296	0.001**	0.046	Supported
HT → CI	H6	0.190	3.120	0.002**	0.045	Supported
PA → CI	H7	0.182	2.803	0.005**	0.046	Supported
HB → CI	H8	0.235	3.442	0.001**	0.074	Supported
SI → CI	H9	0.078	1.378	0.168[ns]	0.010	Not supported

Note: *p < 0.05, **p < 0.01, ***p < 0.001, ns → not significant

6. Discussion, theoretical and practical contributions

6.1 Discussions of Results

Unlike most previous studies, which have focused on the behavioral intention to adopt smartwatches, this research investigated the main factors that could influence actual smartwatch users' post-adoption usage intentions. Constructs' reliability and validity and predictive relevance were all obtained, as discussed in the previous section. Furthermore, the statistical findings supported the predictive power of the research model in explaining substantial variance in performance expectancy (R^2=0.368), satisfaction (R^2=0.468) and continuous intentions (R^2=0.657). These R^2 values were within a highly acceptable range, exceeding all recommended levels in this regard, such as: 40% (Straub & Gefen, 2004) and 30% (Kline, 2016). Hypotheses tests are depicted in Table 5. All study hypotheses, except H9 (Social Influence → Continuous Intention), were supported with this study's results.

The ECM was adopted as the theoretical foundation for this study, and it was extended with other constructs that capture the distinctive context of smartwatches continuous use, such as healthology, perceived aesthetics, habit, and social influence. The study's results suggest the following four significant findings. First, as for the ECM constructs, the detailed results demonstrate that performance expectancy and satisfaction are influenced by the confirmation of users' expectations toward smartwatches' advantages, corroborating H1 and H2. These findings resemble those of Tam et al., (2018), Rabaa'i and Abu ALMaati (2021), and Rabaa'i et al., (2021). Furthermore, the empirical findings of this study confirmed both H3 and H4 by demonstrating significant associations between performance expectancy and satisfaction as well as continuous intentions. These results imply that users who believe smartwatches to be a useful and effective technology are more likely to continue using them and to have a higher positive attitude towards them. The original ECM study by Bhattacherjee (2001a) backs up these findings. Finally, satisfaction was verified to have a significant impact on continuous intention to use smartwatches, validating H5. Previous research studies (e.g., Ashfaq et al., 2020; Bhattacherjee, 2001b; Rabaa'i et al., 2021; Rabaa'i & Abu ALMaati, 2021; Sabah, 2020; Tam et al., 2018) have reported similar results.

Second, while Dehghani et al., (2018) reported no significant relationship between healthology and continuous use, this study demonstrates that healthology is an important factor for smartwatches continuous usage, confirming H6. This finding implies that the health-related data, offered by smartwatches, will not only stimulate users to exercise regularly and monitor their own health, but will also encourage them to use the device in the future. Third, the findings confirmed H7 and H8 by demonstrating that perceived aesthetics and habit are major factors and predictors of users' continuous usage of smartwatches. These results are akin to those reported by Dehghani et al., (2018) and Tam et al., (2018). These findings suggest that respondents in this study (1) liked smartwatch design aesthetics and (2) developed habitual behavior toward smartwatches. These have fueled their continuous usage of such a technology.

Finally, social influence was unable to explain any statistical variance in continuous usage of smartwatches in this study, hence H9 was rejected. This finding is similar to those of Tam et al., (2018) and Rabaa'i et al., (2021). This suggests that when determining whether or not to use smartwatches in the future, the respondents in this study are less interested in the advice of their reference groups and people who are important to them. Previous research studies (e.g., Alalwan, 2020; Huang, 2019) suggest that the impact of social influence on technology adoption will be strong in the early stages and will gradually fade as the technology becomes more widely utilized. This could be explained by the fact that 58% of this study's respondents have been using smartwatches for more than two years.

6.2 Theoretical Implications

This research adds to the body of knowledge with a variety of theoretical contributions. First, this study's significant theoretical contribution is the extension of the ECM by including other constructs like healthtology, perceived aesthetics, habit, and social influence that capture the distinctive context of smartwatches continuous usage. Theoretically, the study findings confirmed that the new added constructs significantly increase the predictive power and variance explained in continuous use intention from 41%, in the original ECM study, to 65.7%, providing a rounded view of the variables influencing users' continuous intention toward smartwatches. Second, while this study reiterated the importance of the ECM original constructs (confirmation, performance expectancy, and satisfaction) in predicting smartwatch continuous usage, the study's extension of the original ECM demonstrated how additional constructs, such as healthtology, perceived aesthetics, and habit, have

significant impacts on continuous usage intention. Third, studies examining the context of smartwatches' continuous usage are quite scarce, and the proposed research model of this study was implemented in this context, thereby filling this gap in the literature. Finally, with the high predictive relevance of (Q^2 = 53.7%) and variance explained (R^2= 65.7%) in the continuous intention to use smartwatches, the empirical results of this study provide evidence that the proposed model can be adapted to different types of wearable gadgets such as fitness trackers, smart wristbands, and smart glasses.

6.3 Practical Implications

With the exception of one, this study's hypothesized relationships have all been confirmed, providing empirical evidence of their applicability in a real-world setting. As a result, this research has a variety of practical implications to firms and designers of smartwatches to promote users' continuance intention. First, given the significant effect of performance expectancy and satisfaction on continuous usage of smartwatches, companies and developers should provide additional features and functionalities that clearly highlight the associated benefits with smartwatches, which will positively influence users' sense of satisfaction and willingness to continue using them. Second, the study results confirmed the positive impact of healthtology on continuous usage. Thus, companies and developers should promote smartwatches as "health companions" that can "effectively complement a physician's role" (Pal et al., 2020, p. 278). Further, companies and developers should not only invest in adding/updating smarter and personal health monitoring features in smartwatches (Sabbir et al., 2020), but "they should also improve the current measuring accuracy of the smartwatches, as incorrect measurements can demotivate and discourage the users from their usage" (Pal et al., 2020, p. 278). Companies and developers of smartwatches, for example, could create new features that allow parents to monitor newborns (Dehghani et al., 2018), maintaining health data for several days (Sabbir et al., 2020), or comparing health records with different demographic segments. Third, design aesthetics should be a guiding principle in the development of smartwatches. According to Choi and Kim (2016), smartwatches are viewed as fashion products. As such, companies and developers should concentrate on the design features of smartwatches (e.g., shape, size, and weight) (Dehghani et al., 2018) as an aesthetically pleasant design will encourage the continuous usage of smartwatches. Finally, the findings of this study provided evidence that users' continuous usage is influenced by habit. As a result, companies and developers should create/update smartwatches' features and functions to make sure that they are simple and intuitive to use. This will gradually establish a habitual use pattern for smartwatches, resulting in a continued desire to use them.

7. Limitations and future research

This study has a number of limitations that suggest fruitful opportunities for future research. First, this study was conducted in Kuwait, a Middle Eastern country, with well-advanced technology infrastructure and a technology savvy citizenry, compared to the citizens in many other developing countries (Rabaa'i in press a, c). Thus, future research should look into the proposed model from a cross-national and cross-cultural viewpoint and assess the model in other countries. Second, this study investigated some factors that affected the continuous usage of smartwatches but did not consider all determinant factors. To broaden the scope of the current study, future research should include additional factors such as personal innovativeness, brand attachment, and perceived mobility. Third, the role of moderating factors, such as age, gender, usage experience, and smartwatch type, was not investigated in this study. As a result, future study should look into the moderating effect of these variables on the continued use of smartwatches. Finally, the research model of this study was solely evaluated and validated in the smartwatch's context. Future research can test the model on various wearable devices, such as smart wristbands, smart glasses, fitness trackers, and so on, to improve the model's generalizability.

8. Conclusions

This study investigated several factors that predicted Kuwaiti users' continuous intention to use smartwatches in the post-adoption phase, where studies on this phase of smartwatches are scarce in general, and so far, has not been studied in the State of Kuwait in particular. To close this gap, this research extends the ECM by including additional determinant variables that describe the unique context of smartwatches' continuous usage. A quantitative survey was used to gather the necessary data to evaluate the proposed model. After that, the data was analyzed using the PLS-SEM approach. The findings of this study reconfirm the importance of confirmation, performance expectancy, and satisfaction in promoting continuous usage of smartwatches. The findings also show that healthtology, perceived aesthetics, and habit all have a role in the continuous smartwatches' usage. The primary statistical results of this study confirmed the predictive validity and relevance of the study's model by accounting for 65.7% of variance and 53.7% of predictive relevance of the users' continuous usage intention of smartwatches.

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