Interdisciplinary Journal of Information, Knowledge, and Management

An Official Publication of the Informing Science Institute InformingScience.org

IJIKM.org

Volume 16, 2021

UNDERSTANDING THE DETERMINANTS OF WEARABLE PAYMENT ADOPTION: AN EMPIRICAL STUDY

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ABSTRACT

Aim/Purpose	The aim of this study is to determine the variables which affect the intention to use Near Field Communication (NFC)-enabled smart wearables (e.g., smartwatches, rings, wristbands) payments.
Background	Despite the enormous potential of wearable payments, studies investigating the adoption of this technology are scarce.
Methodology	This study extends the Technology Acceptance Model (TAM) with four additional variables (Perceived Security, Trust, Perceived Cost, and Attractiveness of Alternatives) to investigate behavioral intentions to adopt wearable payments. The moderating role of gender was also examined. Data collected from 311 Kuwaiti respondents were analyzed using Structural Equation Modeling (SEM) and multi-group analysis (MGA).
Contribution	The research model provided in this study may be useful for academics and scholars conducting further research into m-payments adoption, specifically in the case of wearable payments where studies are scarce and still in the nascent stage; hence, addressing the gap in existing literature. Further, this study is the first to have specifically investigated wearable payments in the State of Kuwait; therefore, enriching Kuwaiti context literature.
Findings	This study empirically demonstrated that behavioral intention to adopt wearable payments is mainly predicted by attractiveness of alternatives, perceived usefulness, perceived ease of use, perceived security and trust, while the role of perceived cost was found to be insignificant.

Accepting Editor Dale Trott │ Received: February 22, 2021│ Revised: April 4, April 14, 2021 │ Accepted: April 15, 2021.

Cite as: Rabaa'i, A. A., & Zhu, X. (2021). Understanding the determinants of wearable payment adoption: An empirical study. *Interdisciplinary Journal of Information, Knowledge, and Management*, *16,* 173-211. https://doi.org/10.28945/4746

Recommendations for Practitioners	This study draws attention to the importance of cognitive factors, such as perceived usefulness and ease of use, in inducing users' behavioral intention to adopt wearable payments. As such, in the case of perceived usefulness, smart wearable devices manufacturers and banks enhance the functionalities and features of these devices, expand on the financial services provided through them, and maintain the availability, performance, effectiveness, and efficiency of these tools. In relation to ease of use, smart wearable devices should be designed with an easy to use, high quality and customizable user interface. The findings of this study demonstrated the influence of trust and perceived security in motivating users to adopt wearable payments, Hence, banks are advised to focus on a relationship based on trust, especially during the early stages of acceptance and adoption of wearable payments.
Recommendations for Researchers	The current study validated the role of attractiveness of alternatives, which was never examined in the context of wearable payments. This, in turn, provides a new dimension about a determinant factor considered by customers in predicting their behavioral intention to adopt wearable payments.
Impact on Society	This study could be used in other countries to compare and verify the results. Additionally, the research model of this study could also be used to investigate other m-payments methods, such as m-wallets and P2P payments.
Future Research	Future studies should investigate the proposed model in a cross-country and cross-cultural perspective with additional economic, environmental, and technological factors. Also, future research may conduct a longitudinal study to explain how temporal changes and usage experience affect users' behavioral intentions to adopt wearable payments. Finally, while this study included both influencing factors and inhibiting factors, other factors such as social influence, perceived compatibility, personal innovativeness, mobility, and customization could be considered in future research.

Keywords	gender, mobile payment, near field communication, smart wearables, wearable payment, Kuwait

INTRODUCTION

The current revolution of financial technology, known as FinTech, and the wide penetration of mobile devices, such as smartphones, tablets, and smart wearable devices (e.g., smartwatches, rings, wristbands, etc.) (Lee et al., 2020), have transformed traditional payment methods from simply cash or credit card transactions into mobile payments (e.g., Choi et al., 2020; Lee et al., 2020; Liébana-Cabanillas et al., 2019; Patil et al., 2020). A mobile payment (m-payment) can be defined as any payment service carried out through a mobile device using wireless communication technologies (Singh et al., 2020). M-payment represents a type of payment for products and services, where mobile devices are used to complete exchange transactions between multiple stakeholders such as customers, merchants, or banks (Choi et al., 2020; Oliveira et al., 2016). M-payments are considered to be the next-generation payment methods (Choi et al., 2020), as they allow users to conduct and confirm electronic transactions in an efficient, effective, convenient, and fast way (e.g., Leong et al., 2020). The adoption of m-payments is increasing worldwide and is driving the growth in cashless payment transactions (Singh et al., 2020). It is estimated that there will be 1.31 billion m-payment transactions worldwide in 2023, up from 950 million users in 2019 (Statista, 2020), and it is forecasted that the transaction volume of m-payments will reach about 14 trillion US dollars in 2022, compared to 3.1 trillion US dollars in 2017 (Statista, 2021a). Given the spread of COVID-19, one can imagine that many more m-payment transactions have been conducted due to the health and hygiene requirements mandated to avoid the handling of cash money.

The use of smart wearable devices, such as smartwatches, wristbands, health and fitness trackers, has been growing rapidly in the last five years (e.g. Ali & Li, 2019; Beh et al., 2019; Hew, 2017), and it is estimated that the market for smart wearable devices will continue to grow globally (Niknejad et al., 2020). Smart wearable devices "are making technology personal and effortless to use with the integration of wireless connectivity, advanced circuitry, and independent processing ability embedded into designs that are worn on a user's body" (Lee et al., 2020, p. 3). Similar to smartphones, smart wearable devices have interactive interfaces, touch screens, built-in NFC-enabled communication functions, and other functions (Park, 2020). Recently, the wide market penetration of smart wearable devices and the technological advancements of the Internet of Things (IoT) have enabled users to pay for products and services anywhere and anytime, introducing an emergent payment method known as wearable payment (Lee et al., 2020; Niknejad et al., 2020), which is considered as a form of m-payment (Lee et al., 2020). A wearable payment is defined as a form of contactless m-payment using a near field communication (NFC) technology enabled wearable device (Gerpott & Meinert, 2017). Lee et al. (2020) argued that "wearable payment serves as the next generation of mobile payment, [and it is] predicted to open up doors to more business opportunities in several different product categories" (p. 1). Yet, the market penetration rate for wearable payments is low, and research regarding the adoption of such payment methods is still in its infancy (Lee et al., 2020; Niknejad et al., 2020).

While the literature offers several research studies investigating the factors that influence users' behavioral intention to adopt m-payments (e.g., Liébana-Cabanillas, Marinkovic, et al., 2018; Ramos de Luna et al., 2019; Singh et al., 2020), smart wearable devices in healthcare (e.g., Ali & Li, 2019; Sun & Rau, 2015; Tison et al., 2018) and fitness (e.g., Beh et al., 2019; Dehghani, 2018), studies investigating the adoption of wearable payments are scarce (Lee et al., 2020). Additionally, the majority of m-payment studies are focusing on countries such as UK, India, China, Malaysia, and USA (e.g., Lee et al., 2020; Patil et al., 2020). However, successful scenarios of m-payment adoption in general, and wearable payments in particular, cannot be directly used in different countries, due to the varying market constraints in terms of economic, infrastructural, social, and cultural aspects (Patil et al., 2020; Slade, Dwivedi, et al., 2014; Slade, Williams, et al., 2014). Hence, given the immense potential of wearable payments in both the financial and mobile sectors, this study aims at investigating the adoption of wearable payments in the State of Kuwait, a Middle Eastern developing country, by examining the factors that influence users' behavioral intention to adopt such payment method.

This study is relevant to Kuwaiti academic literature, financial services, and the mobile industry for the following reasons. First, wearable payment is still in its infancy, where many Kuwaiti banks are spending large sums of money to encourage customers to use such technology (National Bank of Kuwait [NBK], 2020). Second, despite being a small market, "Kuwait has amongst the highest adoption rates of new technology and highest revenue per user for tech companies in the Middle East and North Africa region" (Global Finance, 2020). Third, in Kuwait, the penetration of mobile broadband in Kuwait is healthy at 66.8%, and mobile penetration stands at 146.6%, relatively higher than most developed countries and the world average of 64.5%. Furthermore, ownership of smartphones is also high at 99.7% of households, mobile network infrastructure is well developed, and 100% of land area and population is covered (Kuwait Foundation for the Advancement of Sciences [KFAS], 2019). Finally, during the Coronavirus (COVID-19) pandemic, the Kuwaiti government and banks promote the use of contactless m-payment and limit the use of cash to contain this outbreak and minimize its impact on the population at large. As such, the Kuwait population used wearable payments more frequently because of the real risk of getting infected and the paranoia of the situation.

The significance of this study is fivefold. First, this study aims to investigate users' behavioral intention to adopt wearable payments in the State of Kuwait by using the Technology Acceptance Model (TAM) as its theory base; hence, addressing the gap that exists in wearable payments literature by offering empirical evidence and theoretical supports on the main determinant factors and analyzing their influence on adoption. Second, examining the adoption of wearable payments in the State of Kuwait, where to date no similar research study has been conducted, is an important contribution. Third, while previous studies primarily investigated positive factors that influence users' behavioral intention to adopt m-payments (e.g., Bailey et al., 2017; Chawla & Joshi, 2019; Hampshire, 2017; Lee et al., 2020; Zhao et al., 2019), inhibiting factors received little attention (e.g., Leong et al., 2020; Liu et al., 2019). However, inhibiting factors can play a vital role in preventing users from adopting a new technology (Hoehle et al., 2012). Consequently, Leong et al. (2020) and Liu et al. (2019) argued that researchers should pay more attention to these inhibiting factors. Consequently, this study includes both influencing factors (perceived usefulness, perceived ease of use, perceived security, and trust) and inhibiting factors (perceived cost and attractiveness of alternatives) in order to investigate users' behavioral intention to adopt wearable payments. Fourth, while several m-payment studies investigated the moderating role of gender on behavioral intentions and reported contradicting as well as inconsistent results (e.g., Liébana-Cabanillas, Marinkovic, et al., 2018; Shao et al., 2019), to date, no study has investigated to what extent gender affects wearable payments adoption. Finally, this study aims at forming theoretical and practical guidance and recommendations for scholars and practitioners who are interested in wearable payments.

The remainder of this paper is organized as follows. The literature review is presented in the next section, followed by a discussion on the theoretical background, the conceptual model, and hypotheses development. The research methodology section presents the methods and data used in this study, followed by a section discussing the results and in-depth data analysis. Discussions and implications are explained in a following section. The last section presents the study conclusion, limitations, and future research.

LITERATURE REVIEW

MOBILE PAYMENTS

Mobile payments can be broadly classified into three main categories. The first category is person-to-person payment (P2P) uses a dedicated mobile device (Lara-Rubio et al., 2020). The second category is remote payments and in-store technologies such as mobile wallets (m-wallet) and quick response (QR) code (Liébana-Cabanillas et al., 2015; Singh et al., 2020). M-wallets (remote mobile payments) are technologies, such as an app, website or software, that need to be installed in a smart device (i.e., mobile phone, tablet, etc.) allowing customers to store money and conduct online transactions directly from their m-wallet without the need to be physically in a store. On the other hand, QR code (in-store) works through a few banking apps and store apps to integrate debit/credit card details (Singh et al., 2020). The third category is in-person m-payment or contactless payment (Slade, Dwivedi, et al., 2014). This type of m-payment works on near field communication (NFC) technology in which a transaction is done by establishing a connection between a mobile device and point of sale (POS) through radio waves (Sharma et al., 2019).

NFC technology enables transactions to be conducted merely by holding a mobile device within the range of the NFC terminal at a POS (e.g., Chen & Chang, 2013; Gerpott & Meinert, 2017). NFC can transfer data either in active or passive modes (Zhu & Chen, 2011) via a short-range high frequency wireless communication technology (Gerpott & Meinert, 2017). The operational distance under passive mode is 10 cm (Gerpott & Meinert, 2017), while the inactive mode is 20 cm (Chen & Chang, 2013). Given the short distance requirements, NFC is often referred to as 'mere touch', 'proximity wave', or 'tap' method of transfer and has become a popular method of exchange between mobile devices and POS (Ooi & Tan, 2016). According to Gerpott and Meinert (2017), there are three different methods in which NFC technology stores a customer's banking information, including: (1) on the microchip of bank-issued NFC (credit or debit) cards or NFC labels; (2) on the customer's identity module (SIM) or secure digital (SD) memory card; or (3) on a mobile device (e.g. tablet or smartphone) (Ramos de Luna et al., 2019), or a smart wearable device (e.g. smartwatches, rings, wristbands) (Lee et al., 2020), the focus of this study, which stores this information in a so-called secure element (Gerpott & Meinert, 2017).

MOBILE PAYMENT ADOPTION RESEARCH

The extant m-payments literature confirmed that various research studies have been conducted in different countries; for example, USA (e.g. Zhang & Mao, 2020), UK (Slade, Williams, et al., 2014), Germany (Gerpott & Meinert, 2017), Japan (Amoroso & Magnier-Watanabe, 2012), France (De Kerviler et al., 2016), China (Su et al., 2018; Zhou, 2014), Indonesia (Widodo et al., 2019), Malaysia (Lee et al., 2020; Leong et al., 2020; Tang et al., 2014), Oman (Sharma et al., 2018), India (e.g. Singh et al., 2020), Brazil (Ramos de Luna et al., 2016), South-Africa (Matemba & Li, 2018), and South Korea (Choi et al., 2020). However, in a recent systematic review about digital payments and banking adoption research, Alkhowaiter (2020) reported that researchers have not examined the adoption of m-payments in the State of Kuwait, a Middle Eastern country.

While information systems (IS) researchers have used various models and theoretical frameworks to investigate determinant factors that influence users' behavioral intention to adopt a new technology, such as the Theory of Reasoned Action (TRA) by Ajzen and Fishbein (1977), Theory of Planned Behavior (TPB) by Ajzen (1991), Innovation Diffusion Theory (IDT) by Moore and Benbasat (1991), Social Cognitive Theory (SCT) by Compeau et al. (1999), Diffusion of Innovation Theory (DOI) by Rogers (2003), the Technology Acceptance Model (TAM) by Davis (1989), the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extension (UTAUT2) by Venkatesh et al. (2003, 2012), in the context of mobile technologies, TAM and UTAUT/UTAUT2 are the most utilized models to assess individuals' behavioral intentions (Chhonker et al., 2018; Patil et al., 2020).

In the m-payment context, researchers (e.g., Alaeddin et al., 2018; Kalinic et al., 2019a; Liébana-Cabanillas et al., 2014b, 2017; Matemba & Li, 2018; Ramos de Luna et al., 2016; Su et al., 2018; Zhao et al., 2019) have used TAM. UTAUT/UTAUT2 were used by other researchers (e.g., Gupta & Arora, 2019; Madan & Yadav, 2016; Oliveira et al., 2016; Shaw, 2015; Slade, Dwivedi, et al., 2014; Wang & Yi, 2012; Widodo et al., 2019). Though other studies (e.g., Chawla & Joshi, 2019; Khalilzadeh et al., 2017; Koenig-Lewis et al., 2015; Singh & Sinha, 2020) have combined TAM and UTAUT to investigate individuals' behavioral intention to adopt m-payments.

In NFC-enabled m-payment context, Leong et al. (2013) developed a model, by extending TAM with constructs from psychological science, trust-based and behavioral control theories, to investigate the factors influencing the adoption of NFC-enabled m-payments. Their results confirmed that there is a significant and direct relationship between both perceived ease of use and perceived usefulness on the intention to use such a technology, while other variables such as trust and personal innovativeness in information technology (PIIT) have significant indirect effects on the intention to use. The authors also reported that variables such as trust and PIIT have a significant direct effect on perceived ease of use and perceived usefulness. Slade, Dwivedi, et al. (2014) extended the UTAUT2 with trust and risk constructs to determine the factors affecting the adoption of NFC mobile payments and compared the original UTAUT model with the extended model. The findings revealed that the extended model explains more variance in behavioral intentions among UK consumers, but performance expectancy was the strongest predictor in both models. Tan et al. (2014) combined TAM, psychological science constructs and financial related risk to study the intention to adopt the NFC mobile credit card. Their empirical study confirmed the applicability of the combined model and concluded that finance-related risk is insignificant.

Taking into consideration the theoretical backgrounds of innovation diffusion and specific characteristics of NFC m-payments, Pham and Ho (2015) proposed a research framework to provide an understanding of factors facilitating or impeding the adoption of NFC-based m-payments among Taiwanese consumers. The results revealed that intention to adopt NFC m-payments is affected by product-related factors (perceived usefulness, compatibility, perceived risk, and trialability), personal-related factors (personal innovativeness and absorptive capacity), and attractiveness of alternatives. However, perceived cost, perceived ease of use and trust were found insignificant. Balachandran and Tan (2015) studied NFC m-payment based on a modified DOI theory. The authors integrated amount of information, financial resources, and variety of services with relative advantage, complexity and compatibility from DOI. The study results found that only relative advantage is insignificant.

Morosan and DeFranco (2016) extended the UTAUT2 model to examine factors that motivate consumers to use NFC mobile payment systems in hotels. The authors added four constructs to the UTAUT2 model, namely, perceived security, system-related privacy, and general privacy. Their results found that performance expectancy was the highest predictor of intentions, while hedonic motivations, habit, and social influences have relatively lower effects. Additionally, the results confirmed that effort expectancy, general privacy and perceived security were not significant in predicting intention to use NFC payment systems. Cocosila and Trabelsi (2016) investigated consumer adoption views on credit card contactless NFC payments with smartphones. The study findings indicated that the integrated value-risk perception is a significant factor of adoption with smartphones having utilitarian and enjoyment values as the main user motivators, and psychological and privacy risks as the most important deterrents. On the other hand, Ooi and Tan (2016) proposed a new mobile technology acceptance model (MTAM) to investigate users' behavioral intention to adopt NFC-enabled smartphones credit card. The model consists of mobile usefulness (MU) and mobile ease of use (MEU). In anticipating the complexity that exists in the mobile environment, additional mobile constructs, namely, mobile perceived security risk (MPSR), mobile perceived trust (MPT), mobile perceived compatibility (MPC) and mobile perceived financial resources (MPFR), were incorporated into the MTAM. While the model confirms the role of MU in MTAM, MEU was found to be insignificant. Additionally, the results from the extended model showed that MPT and MPC were significant in influencing users' behavioral intention to adopt smartphones credit card, while MPFR and MPSR were insignificant.

Ramos de Luna et al. (2017) investigated the acceptance of NFC technology for payment through mobile. The results show that attitude, personal innovation in IT, and perceived usefulness, are determinants of future intention to use the NFC technology for payments in Brazil. Liébana-Cabanillas et al. (2017) integrated variables of TAM (i.e., perceived usefulness, perceived ease of use, and attitude) with subjective norms and perceived security to investigate consumers' behavioral intention to adopt SMS and NFC mobile payment systems. The findings showed that perceived usefulness, perceived ease of use, subjective norms, and perceived security are key factors in influencing behavioral intention; however, attitude was the most important determinate factor that influenced users' intention to adopt these payment methods. Khalilzadeh et al. (2017) combined TAM and UTAUT to examine the determinants of NFC based m-payment acceptance in the restaurant industry. The study results indicated strong evidence of the effects of risk, security, and trust on customers' intentions to use NFC-enabled m-payment. In addition, considering the total effect, attitude, security, and risk have the most substantial impact on customers' behavioral intentions. The study results also demonstrated that risk, security, and trust are also important determinants with direct and indirect impacts of other critical constructs (i.e., effort expectancy, hedonic and utilitarian performance expectancy, attitude, and intention). Liébana-Cabanillas et al. (2019) analyzed the status of NFC m-payments in public transportation as well as the factors that affect users' intentions to continue using such a technology. The results showed that satisfaction, service quality, effort expectancy, and perceived risk are determining factors of the continued intention to use this payment method. However, perceived trust, social value, and convenience were insignificant in influencing users' satisfaction.

Zhao et al. (2019) extended TAM with financial incentives and perceived risk to investigate the factors which identified consumers' intention to adopt NFC m-payments. Their study found that the availability of financial incentives did not have a direct effect on intention to adopt NFC m-payment; however, financial incentives indirectly affected consumers' intention through perceived risk.

Esfahani and Ozturk (2019) studied the relationship between individual differences of customers and their intentions to use NFC-based m-payment in restaurants. The findings indicated that there are significant differences in customers' intention to use NFC m-payment in restaurants for past experience, age and gender. However, education and income did not play a significant role in predicting behavioral intentions. Building upon the theory of reasoned action (TRA) and TAM, Zhang and Mao (2020) investigated the effects of consumer factors on behavioral intention to adopt NFC m-payment. The results showed that relative advantage, attitude, and subjective norms significantly affected individual behavioral intentions. Finally, Lee et al. (2020) integrated the Mobile Technology Acceptance Model (MTAM) (Ooi & Tan, 2016) with Fashion Theory (i.e., perceived aesthetics) and Technology Readiness Theory to examine the roles of perceived aesthetics, technology readiness, mobile usefulness and mobile ease of use on behavioral intention to adopt wearable payments. The study findings revealed that all variables were significant in determining users' behavioral intention to adopt this payment method.

THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

While different IS models and theoretical frameworks have been employed to explore an individual's acceptance and adoption of a new technology, TAM is the most commonly employed model to explain an individual's use and adoption of a particular technology (Driediger & Bhatiasevi, 2019), due to its robust characteristics.

THE CONCEPTUAL MODEL AND HYPOTHESES DEVELOPMENT

TAM is derived from the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1977). The theory investigates the individual's perceived usefulness (PU) and perceived ease of use (PEOU) toward a technology, which then determines the attitude (ATT) toward use, behavioral intention to use, and finally, the actual use of the technology (Davis, 1989; Venkatesh et al., 2003; Venkatesh & Davis, 2000). In other words, TAM states that PU and PEOU by users are the main factors that determine the attitude towards the adoption of a technology, and consequently determine intention to use resulting in the adoption of the technology (Davis et al., 1989). However, in their proposed extension of the model, Venkatesh and Davis (2000) removed attitude towards a given technology from the TAM, because of its weak prediction of both behavioral intention and actual system use (Driediger & Bhatiasevi, 2019). The decision to remove attitude was confirmed and supported by several other studies (e.g., Driediger & Bhatiasevi, 2019; Liébana-Cabanillas et al., 2019; Wu & Wang, 2005).

TAM was also criticized for not having sufficient explanatory and predictive ability in the use of technology (e.g., Chuttur, 2009; Legris et al., 2003; Wu et al., 2016). The model lacks necessary use and adoption aspects such as task-environment specific and social factors which are needed during the adoption phase of a technology (e.g., Benbasat & Barki, 2007). In fact, while TAM considers PU and PEOU as the most important factors in explaining system use and adoption (Driediger & Bhatiasevi, 2019; Legris et al., 2003), many researchers have expressed the need for additional factors to provide an even stronger model and to increase its predictive power (e.g., Driediger & Bhatiasevi, 2019; Kalinic et al., 2019b; Legris et al., 2003; Liébana-Cabanillas et al., 2019; Liébana-Cabanillas, Marinkovic, et al., 2018).

After reviewing existing technology adoption literature, the Technology Acceptance Model (TAM) was selected as the theory-base for this study, given: (1) it has been widely used as the primary theoretical model for understanding and investigating individuals' adoption behavior of different new technologies (e.g. Chakraborty, 2020; Driediger & Bhatiasevi, 2019; Rabaai et al., 2015; Rabaa'i, 2016; Ramos de Luna et al., 2017; Zogheib et al., 2015a); (2) it focuses on the early adoption stage rather than the acceptance or rejection stages (e.g. Davis, 1989; Pham & Ho, 2015); and (3) it allows for augmentation to incorporate additional variables to capture aspects of adoption and increase its predictive power (e.g. Kalinic et al., 2019a; Liébana-Cabanillas et al., 2019; Phonthanukitithaworn et al., 2016a). Consequently, this study employed the modified version of TAM, as suggested by Venkatesh and Davis (2000), and further extended the model with four additional variables, namely, trust, perceived cost, perceived security, and attractiveness of alternatives. The research model is depicted in Figure 1.

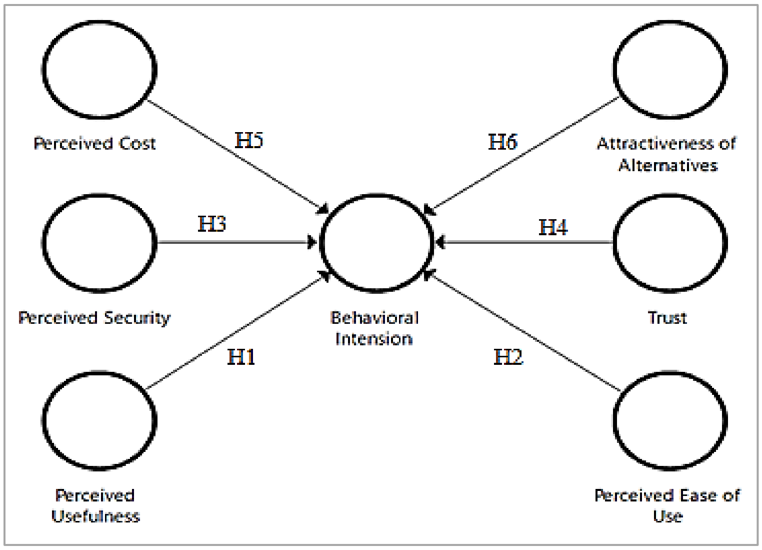

Figure 1. The research model

Perceived usefulness (PU)

Perceived usefulness, similar to performance expectancy in the UTAUT (Huang, 2019; Venkatesh et al., 2003), is defined as "the extent to which a person believes that using the system will enhance his or her job performance" (Venkatesh & Davis, 2000, p. 187). According to Phonthanukitithaworn et al. (2016a), perceived usefulness does not only assess the extrinsic characteristics of a technology, it also shows how such technology can help users to achieve task-related goals, such as being more efficient and effective in performing an activity. In this study, perceived usefulness is defined as the degree to which users believe that wearable payments are useful and convenient in paying for different products or services. Chuah et al. (2016) found that perceived usefulness as one of the most important factors that influence users' behavioral intention to adopt smart wearable devices in Malaysia. Further, smart wearable devices have been developed to fulfill customers' needs through one device in order to improve their performance (Gu et al., 2016; Park, 2020). As such, the advantages of using wearable payments are related to their characteristics, such as mobility, flexibility, efficiency, ubiquity, and personalization, which distinguish them from traditional payment methods (Bölen, 2020; Lee et al., 2020). Hence, the more users believe that wearable payments are useful, the higher their intention to adopt this payment method.

Perceived usefulness was found to be an important predictor of behavioral intentions in different research settings, including artificial intelligence in FinTech (Belanche et al., 2019), mobile food ordering applications (Alalwan, 2020), mobile banking (Alalwan et al., 2017), e-learning systems (Rabaa'i, 2016; Zogheib et al., 2015a), mobile shopping (Madan & Yadav, 2018), e-government (Rabaa'i et al., 2015; Rabaa'i, 2015; Rabaa'i, 2017b), m-payments (Gupta & Arora, 2019; Liébana-Cabanillas, Muñoz-Leiva, & Sánchez-Fernández, 2018; Ramos de Luna et al., 2019), m-wallets (Sharma et al., 2018; Singh et al., 2020; Singh & Sinha, 2020; Rabaa'i, in press), peer-to-peer m-payment (Kalinic et al., 2019a), NFC m-payments (Zhao et al., 2019), and wearable payments (Lee et al., 2020). Therefore, the study proposes the following hypothesis:

H1: Perceived usefulness will have a positive effect on the intention to use wearable payments.

Perceived ease of use (PEOU)

Perceived ease of use, similar to effort expectancy in the UTAUT (Huang, 2019; Venkatesh et al., 2003), is defined as "the extent to which a person believes that using the system will be free of effort" (Venkatesh & Davis, 2000, p. 187). In general, customers are concerned about the extent to which using a new technology is easy and requires less effort (Alalwan et al., 2017; Okumus et al., 2018). Thus, perceived ease of use was found to be vital predictor in the early stages of new technology adoption (Alalwan, 2020; Chopdar et al., 2018; Okumus & Bilgihan, 2014). Perceived ease of use was found to be an important variable that shapes users' behavioral intention to adopt smart wearable devices (Chuah et al., 2016). In this study, perceived ease of use is defined as the degree to which users believe that the effort required to learn and use wearable payments would be minimal. Wearable payments require users to follow certain procedures, such as activating the payment applications in the smart wearable device and holding their devices to the terminal as instructed to complete a payment (Lee et al., 2020). Further, the ease of use of smart wearable devices' features will facilitate acquiring informative skills to use such a technology to make payments. As such, the easier the users believe wearable payments are to use, the higher their intention to adopt this payment method. While Lee et al. (2020) reported insignificant effect of ease of use on behavioral intention to adopt wearable payments, various studies confirmed the significant positive relationship between perceived ease of use and users' behavioral intention in different technology contexts, such as in mobile grocery shopping (Chakraborty, 2020), mobile food ordering applications (Alalwan, 2020), mobile shopping (Tan & Ooi, 2018), fashion mobile applications (Soni et al., 2019), e-government (Rabaa'i et al., 2015; Rabaa'i, 2015; Rabaa'i, 2017b), m-payments (Gupta & Arora, 2019; Morosan & DeFranco, 2016; Slade, Williams, et al., 2014), smart wearable devices (Park, 2020), smartphone credit card adoption (Ooi & Tan, 2016), and NFC credit card payments (Tan et al., 2014). Consequently, the following hypothesis is proposed:

H2: Perceived ease of use will have a positive effect on the intention to use wearable payments.

Perceived security (PS)

Perceived security is defined as "a consumer's feeling that his/her personal credentials will not be viewed, stored, or manipulated by unauthorized users when undertaking online transactions" (Chawla & Joshi, 2019, p. 1596). In m-payment contexts, perceived security refers to "the degree to which a customer believes that using a particular m-payment procedure will be secure" (Shin, 2009, p. 1346). Heinze et al. (2017, p. 368) argued that users' payment concerns, when using mobile channels, were ultimately associated with perceived security, which refers to the "value to secure one's own property". M-payments, in general, raise greater security concerns than traditional payment methods (e.g., cash), as they involve storage and transfers of personal and financial information over a wireless communication environment (Chawla & Joshi, 2019; Ooi & Tan, 2016).

While Zupanovic (2015) asserted that that NFC-enabled devices allow users to experience safer transaction exchanges due to its better encryption of transacted data, data can be intercepted or stolen during any NFC transactions (Ooi & Tan, 2016). Thus, Hoy (2013) argued that NFC technology must be configured properly to avoid any misuse or attacks, and safety must be a priority in order for NFC applications to be successfully adopted (Grassie, 2007). In turn, perceived security became an important additional variable in the context of m-payments, as it can play a vital role in determining the decision of consumers whether to adopt a new innovative payment method such as wearable payment (e.g., Khalilzadeh et al., 2017; Ooi & Tan, 2016; Shin, 2009). In their study, Hoehle et al. (2012), found 63 studies out of 247 peer-reviewed articles stating that security was a major factor influencing consumers' intention to use the electronic banking systems. For instance, security breaches were considered to significantly prevent consumers from providing sensitive information online (Merhi et al., 2019). Hence, perceived security is expected to affect behavioral intentions directly. As such, it was added to the proposed research model. Prior studies found perceived security as a significant factor in mobile shopping (Huseynov & Özkan Yıldırım, 2019), m-banking adoption

(Changchit et al., 2020), and m-payments (e.g., Chawla & Joshi, 2019; Oliveira et al., 2016; Sharma et al., 2019). Accordingly, the following hypothesis is posited:

H3: Perceived security will have a positive effect on the intention to use wearable payments.

Trust (TR)

Due to the high degree of uncertainty associated with m-payments in general, trust becomes an important factor for a person to obtain confidence in an exchange partner (Zhou, 2012), and represents a catalyst for exchange relationships between buyers and sellers (Malaquias & Hwang, 2016; Wang et al., 2015). In fact, when customers perceive a technological platform as a trustworthy system, their intentions to use such platform will be enhanced (Shao et al., 2019). Shareef et al. (2018) stated that numerous studies have identified that trust has a more important role in transaction behavior, like accepting and adopting wearable payments, than traditional behavior, like traditional banking transactions. According to Choudrie et al. (2018), trust often includes three beliefs: ability, integrity and benevolence. Ability is defined as service providers having the knowledge and ability necessary to fulfil their tasks. Integrity means that service providers keep their promises and do not deceive users. Benevolence means that service providers are concerned with users' interests, not just their own benefits. Similarly, Shareef et al. (2018) defined trust as the degree to which users have attitudinal confidence for reliability, credibility, safety, and integrity of m-payment service providers from the technical, organizational, and social standpoints.

Trust can also be segmented into initial trust and experiential trust (Kim et al., 2009) and these two aspects of trust are influenced by different factors (Hampshire, 2017). However, a consumer's initial trust plays a critical role in accepting and adopting a new technology, such as wearable payments (Hampshire, 2017; Kim & Prabhakar, 2004). In a dynamic online environment, where wearable payments exist, if trust is not present, there is no adoption and no use of such services (Zhou, 2012, 2013). Therefore, wearable payments service providers are advised to focus on a relationship based on trust during the early stages of acceptance and adoption of such technology in order to facilitate users' behavioral intention (e.g., Shareef et al., 2018; Sharma & Sharma, 2019; Singh et al., 2020). Furthermore, while users always prefer to have their privacy matters (e.g., phone numbers, passwords, shopping records and financial transactions) protected against any potential privacy risk, they are willing to disclose their personal data on digital platforms (like wearable payments) depending on the trust and confidence they have regarding the reliability and integrity of the service providers (Matemba & Li, 2018). In fact, the perceived levels of risk diminished and neutralized when trust exists between the parties involved in a technological transaction (Hampshire, 2017; Rouibah et al., 2016).

Yan et al. (2009) reported that trust in service providers has a direct impact on consumer intentions to use m-payment services associated with the purchase of music downloads in Malaysia. In Kuwait, the context of this study, Rouibah et al. (2016) reported that customers' trust is the most important factor affecting customers' intention to use electronic online payments among Kuwaiti citizens. Thereby, trust stands as an important factor in order to enhance users' behavioral intention to use wearable payments. Prior studies confirmed the significant effect of trust on behavioral intention in m-payments (Liébana-Cabanillas, Marinkovic, et al., 2018), m-wallets (Chawla & Joshi, 2019; Singh & Sinha, 2020), peer-to-peer m-payment (Kalinic et al., 2019b), and mobile banking (Alalwan et al., 2017; Hanafizadeh et al., 2014). Consequently, the following hypothesis is proposed:

H4: Trust will have a positive effect on the intention to use wearable payments.

Perceived cost (PC)

In this study, perceived cost is defined as the extent to which an individual believes that using a wearable payment will cost money (Luarn & Lin, 2005). Using a wearable payment may lead customers to pay for additional resources, such as the cost of acquiring a smart wearable device (e.g., smartwatch, wristband, ring, etc.), the cost to maintain and upgrade it, and the transactional fees to use such a payment method (Liu et al., 2019; Phonthanukitithaworn et al., 2016b). Therefore, users are expected to compare the cost of using a wearable payment with traditional payment methods such as cash or credit/debit cards. If the cost of using a wearable payment exceeds their expectations, they may consider such payment method as not cost-effective (Choi et al., 2020; Liu et al., 2019).

According to Tan et al. (2014), the high usage costs associated with using m-payment services, including communication and transaction fees, can potentially result in the underutilization of such services. Luarn and Lin (2005) and Hanafizadeh et al. (2014) confirmed that perceived cost is a significant factor influencing the adoption of mobile banking in Taiwan and Iran respectively. Zhou (2011) argued that perceived cost is an important variable that can negatively influence users' behavioral intention to adopt m-payments. In the context of smart wearable devices, Park (2020) found that perceived cost negatively affects users' behavioral intention. For instance, various studies suggested that perceived cost could be a major barrier to the adoption of new mobile technologies (e.g., Alalwan, 2020; Sobti, 2019). In m-payments context, while Tan et al. (2014) and Oliveira et al. (2016) found no significant relationship between perceived cost and behavioral intention to use NFC credit card payments and m-payments respectively, Slade, Dwivedi, et al. (2014) reported a significant effect of perceived cost on behavioral intention to adopt proximity m-payments. The effect of perceived cost on behavioral intention has been confirmed in different IS contexts, for example in interbank mobile payment services (Kapoor et al., 2015), m-payments (e.g., Balachandran & Tan, 2015; Phonthanukitithaworn et al., 2016b; Singh & Sinha, 2020), m-banking (Alalwan et al., 2017), and m-Government as well as e-Government adoption (Ahmad & Khalid, 2017; Dwivedi et al., 2017). As such, the more expensive users believe wearable payments are, the less willing they would be to use them. Thus, the following hypothesis is proposed:

H5: Perceived cost will have a negative effect on the intention to use wearable payments.

Attractiveness of alternatives (AoA)

Alternative attractiveness is conceptualized as the user's estimate of the likely satisfaction available in an alternative relationship (Ping, 1993). Individuals' commitment to a relationship should increase when they are satisfied with the relationship and/or when there are no good alternatives available (Ghazali et al., 2016). In other words, when a user perceives that alternatives are not different from their existing provider or does not perceive them as 'any more attractive' than their existing relationship, they tend to remain loyal to their existing provider (Patterson & Smith, 2003). Attractiveness of alternatives refers to "customer perceptions regarding the extent to which viable competing alternatives are available in the marketplace" (Jones et al., 2000, p. 262). In m-payments, behavioral intentions are affected by the presence of alternative technologies (Amoroso & Magnier-Watanabe, 2012; Pham & Ho, 2015). Given that wearable payments are still in their infancy, few alternatives may exist (e.g., cash and credit/debit cards). Thus, in the context of this study, attractiveness of alternatives refers to a user's perception regarding the extent to which alternative payment methods are more attractive than wearable payments.

Jones et al. (2000) argued that when users perceive few viable alternatives, the perceived net benefit of defecting should be relatively low, and this in turn will result in higher levels of retention. However, users may decide to terminate the current relationship and look for a new provider if they perceive the alternative to be attractive due to the availability and satisfaction of better services, the availability of a full range of services, or lower cost and fees (Pham & Ho, 2015; Sharma & Patterson, 2000). Therefore, users are expected to compare wearable payments with alternative payment methods. If alternatives have a higher net benefit in making a payment compared to wearable payments, users are likely to choose and stay in the attractive alternatives. On the contrary, if alterative payment methods lack necessary appeal to attract and keep users' loyalty, their behavioral intention to adopt wearable payments will be enhanced (Pham & Ho, 2015). Prior studies have confirmed the effect of attractiveness of alternatives on behavioral intention (e.g., Amoroso & Magnier-Watanabe, 2012; Kim et al., 2011; Pham & Ho, 2015). Based on the above discussion, the following hypothesis is posited:

H6: Attractiveness of alternatives will have a negative effect on the intention to use wearable payments.

The Moderating Role of Gender in Technology Adoption

Findings of a recent meta-analysis confirmed that males hold more favorable attitudes towards technology than females do (Cai et al., 2017), suggesting gender differences in technology perceptions. Gender refers to the "social paradigm of getting to know men and women with specific physical characteristics such as individual values, attitudes, roles and behavior" (Hossain, 2019, p. 182). Researchers have explained gender differences in behavioral intentions to adopt a particular technology using the social role theory (Deng et al., 2010; Eagly et al., 2000), cognitive abilities (Stoet et al., 2013), and the gender role theory (Zhang et al., 2017). Wang (2010) argued that both males and females experience various roles experience, role conflict and role overload that guide their behavior. Sobieraj and Krämer (2020) attributed gender differences, regarding technology, to their gender roles and how they should behave. Males are inspired to be brave and independent while females follow the behavior to be more social, emotional, and caring of others (Zhang et al., 2017). Building on social cognitive theories, Kalinić et al. (2019a) asserted that the decision-making process differs among gender, as men are more outcome-oriented and focus on usefulness whereas women are more process-oriented and focus on security and privacy. In referencing the social role theory, Gentina and Rowe (2020) argued that females are more socially oriented when they use their smartphones, compared to males, who are not responsive to social relationship motives. In line with this reflection, Lim and Kumar (2019) found that females' Internet use and behavior are primarily influenced by relationship maintenance and social connections, whereas males use the Internet mainly for task-oriented activities, such as information gathering. With respect to gender role, Selwyn (2007) suggested that certain technologies such as Email, e-learning and graphics are perceived as feminine technologies, while digital cameras, online banking, laptops, and digital music are perceived as masculine technologies.

The moderating role of gender has gained research attention as a factor that influences technology adoption in different contexts, such as food delivery applications (Okumus et al., 2018), mobile banking (Glavee-Geo et al., 2017), computer usage (Sobieraj & Krämer, 2020), mobile tourism applications (Tan & Ooi, 2018), web-based services (Arif et al., 2018), multimedia for e-learning (Park et al., 2019), smartphones (Baishya & Samalia, 2020; Gentina & Rowe, 2020), mobile health services (Alam et al., 2020), e-learning (Alghamdi et al., 2020; Zogheib et al., 2015b), and m-payments (e.g. Esfahani & Ozturk, 2019; Kalinić et al., 2019; Liu et al., 2019; Ramos de Luna et al., 2019). Nevertheless, compared to other factors, such as usage experience and age, the role of gender as a moderating variable has received less consideration in past technology adoption studies (Alam et al., 2020), has generally been avoided in behavioral research in the technology field (Gefen & Straub, 1997), and has been generally missing from most of the TAM-related research (Tan et al., 2014).

In reference to the original TAM, Gefen and Straub (1997) investigated the role of gender on the perception and on the adoption of email services. Their study results revealed that women are more influenced by the perceived usefulness and the perceived ease of use of email higher than men, and women's adoption of e-mail is greater than men. Venkatesh and Morris (2000) found that men are driven by perceived usefulness, whereas women are more influenced by perceived ease of use and subjective norms. In the UTAUT, Venkatesh et al. (2003) argued that the effect of perceived usefulness on behavioral intention to use and accept a technology is moderated by gender where its effect is greater for men. Furthermore, in the UTAUT2, Venkatesh et al. (2012) reported a significant moderating of gender on behavioral intention to adopt mobile internet technology. In Kuwait, Rouibah (2007) studied motivational factors that influence users to adopt a new m-payment system known as M-net. The study results revealed that gender is an important factor affecting M-net adoption. It was found that males are influenced by perceived usefulness and enjoyment, while females are driven by enjoyment. Using quasi-experiments, Rouibah (2009) also investigated the factors that affect the adoption of M-net in Kuwait and found that gender and enjoyment have a moderation role on the adoption decision. The results found that while enjoyment and perceived usefulness are strong predictors for males and females, the effect is stronger for males.

The moderating role of gender in the context of m-payments adoption is contradicting and inconsistent. While, for example, Liébana-Cabanillas et al. (2014a) reported a greater significant influence of perceived usefulness on behavioral intention to use mobile payments among men than among women, the influence of gender on the relationship between perceived usefulness and behavioral intention to use NFC-enabled mobile credit card was reported as insignificant (Leong et al., 2013; Tan et al., 2014). In another example, Shao et al. (2019) reported a significant moderating role of gender on trust and behavioral intention to adopt m-payments, yet Khalilzadeh et al. (2017) found gender to be insignificant in moderating the relationship between trust and behavioral intention to adopt NFC based m-payment in the restaurant industry. Similarly, Sobti (2019) and Tan et al. (2014) reported insignificant moderating effect of gender on the relationship between perceived cost and perceived risk and behavioral intention to adopt m-payment services and NFC mobile credit card respectively.

Given the contradicting as well as inconsistent findings in the literature, and the fact that the moderating role of gender in the context of wearable payments was never assessed in prior research, there is not enough empirical evidence to clearly state hypotheses regarding gender differences. Therefore, this study will assess the moderating effect of gender in all the hypotheses of the proposed model.

RESEARCH METHODOLOGY

An empirical study was conducted with an objective to test the relationships between the constructs of the conceptual model depicted in Figure 1. To achieve this objective and to test the research hypotheses, a survey-based study was employed to collect the needed empirical data. This section describes the measurement items, pretesting, survey design and data collection, the study sample, and the demographic statistics.

MEASUREMENT ITEMS

To ensure the content validity and reliability of the measurement scales, all items selected for the constructs were adapted from previous studies and modified to fit the context of this study. As seen in Table 1, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) constructs were adapted from Davis (1989) and Venkatesh et al. (2012). Measurement scale for Trust (TR) was adapted from Slade, Dwivedi, et al. (2014). Perceived Security (PS) construct was adapted from Khalilzadeh et al. (2017). The items for Perceived Cost (PC) were adapted from Wei et al. (2009) and Phonthanukitithaworn et al. (2016b). Attractiveness of Alternatives (AoA) and Behavioral Intention (BI) were taken from Pham and Ho (2015) and Venkatesh et al. (2012) respectively. All measurement items were measured with a seven-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7).

Table 1. Constructs, measurement items and sources

Constructs	Items		Sources
Perceived Usefulness (PU)	PU1	Using a wearable payment can improve my efficiency in paying for different products/services	Davis (1989) and Venkatesh et al. (2012)
	PU2	Using a wearable payment can save me a lot of time	
	PU3	Overall, I would find a wearable payment useful.	
Perceived Ease of Use (PEOU)	PEOU1	A wearable payment is/might be easy to use.	Davis (1989) and Venkatesh et al. (2012)
	PEOU2	It is/might be easy to become skillful at using a wearable payment	

Constructs	Items		Sources
	PEOU3	It is/might be easy for me to follow the procedures when using a wearable payment	
	PEOU4	Overall, I believe that a wearable payment is/might be easy to use	
Trust (TR)	TR1	I believe wearable payment service providers are trustworthy	Slade, Dwivedi, et al. (2014)
	TR2	I believe wearable payment service providers keep customers' interests in mind	
	TR3	I believe wearable payment service providers will do everything to secure the transactions for users	
Perceived Security (PS)	PS1	I would feel totally safe providing sensitive information about myself when using a wearable payment.	Khalilzadeh et al. (2017)
	PS2	Wearable payments are secure means through which to send/use sensitive information	
	PS3	Overall, wearable payments are safe to transmit sensitive information.	
Perceived Cost (PC)	PC1	I believe that the transaction and communication fees for using a wearable payment will be high	Wei et al. (2009) and Phonthanukitithaworn et al. (2016b)
	PC2	I believe that the cost of acquiring, maintaining, and upgrading a smart wearable device, to be used for wearable payments, will be high	
	PC3	Overall, I believe that using a wearable payment will cost me a lot of money.	
Attractiveness of Alternatives (AoA)	AoA1	If I need to change payment services, there are other good services to choose from.	Pham and Ho (2015)
	AoA2	I would probably be happy with other payment methods than wearable payments	
	AoA3	Compared to wearable payments, there are other payment methods with which I would probably be equally or more satisfied.	
	AoA4	Compared to wearable payments, there are not very many other payment methods with which I would probably be equally or more satisfied.	
Behavioral Intention (BI)	BI1	I intend to use a wearable payment in the future.	Venkatesh et al. (2012)
	BI2	I will always try to use a wearable payment in my daily life.	
	BI3	I plan to use a wearable payment.	

Pretesting

Before proceeding with the data collection for this study, a pre-test and a pilot test were employed. In the pre-test, four expert academics were involved to verify the measurement scales, assess the suitability, relevance, readability of the questionnaire, and discuss possible changes to be implemented in the questions to clarify any ambiguity. Then, to ensure the adequacy as well as reliability of the measures and to avoid any confusion or misinterpretations of the survey questions, a pilot study was conducted before the main study. Twenty-two questionnaires were used for the pilot study. The questionnaires were given to senior students at an American University in the State of Kuwait, who were asked to fill the given questionnaire and provide any comments or concerns. Noticeably, the vast majority of the respondents indicated that the questionnaire is easy, the language used was very clear and understandable, and did not require much time to be filled in. Cronbach's alpha was used to check the reliability of the constructs' scale used. Values for all constructs were higher than 0.70 as suggested by Nunnally and Bernstein (1994).

SURVEY DESIGN AND DATA COLLECTION

The data collection took place in the State of Kuwait, a Middle Eastern developing country. A web-based survey, using Google Docs, was administered. The questionnaire was written in English (no Arabic to English back-translation was required) and designed to allow flexible time to be filled in to avoid the overclaim usage of the respondents (Alam et al., 2020). The questionnaire included three sections. In the first section, the motivation and purpose of the study were explained. To avoid potential biases, participants were: (1) informed that the participation in this study was voluntary and no rewards or incentives were offered (Alam et al., 2020; Podsakoff et al., 2003); (2) ensured that the confidentiality of the responses was maintained (Podsakoff et al., 2003), as no names or private personal details were collected and only aggregated results would be used and reported; and (3) they were also notified of their rights to withdraw from this study at any time (Alam et al., 2020). The second section contained demographic questions. Finally, the last section was devoted to the main constructs' measurement items.

Data for this study were collected by sending WhatsApp and Instagram messages with a link to the online questionnaire to the first researcher contacts who was residing in Kuwait at that time, an email invitation with a link to the online questionnaire to students, alumni, faculty members and staff, at a private American university in the State of Kuwait, and all potential respondents were also asked to forward the invitation to their friends and relatives who reside in Kuwait. Also, people were invited randomly, outside university and academic context, to take part of this study.

THE STUDY SAMPLE AND DEMOGRAPHIC STATISTICS

Since the population size is unknown for this study, a convenience sampling method was used. The convenience sampling method is cost effective and has been widely accepted in Information System research (e.g., Alalwan, 2020; Alam et al., 2020) and m-payment context, in particular, (e.g., Alam et al., 2020; Sharma et al., 2019; Singh et al., 2020). A total of 311 questionnaires were collected. The demographic profiles of the respondents are provided in Table 2.

Table 2. Demographic characteristics of respondents

Demographic variables		Frequency	Percentage
Gender	Male	171	55.0%
	Female	140	45.0%
	Total	311	100.0%
Age	< 18 years	40	12.9%
	18-25 years	80	25.7%
	26-35 years	139	44.7%
	> 40 years	52	16.7%
	Total	311	100.0%
Education level	High school	22	7.1%
	University student	98	31.5%
	Bachelor	118	37.9%
	Postgraduate	52	16.7%
	Other	21	6.8%
	Total	311	100.0%

Demographic variables		Frequency	Percentage
Monthly income (KD)	< 500	67	21.5%
	500-1000	119	38.3%
	1001-2000	81	26.0%
	> 2000	44	14.1%
	Total	311	100.0%
Experience in using smart wearable devices	Never used	19	6.1%
	< 1 year	51	16.4%
	1 - 2 years	154	49.5%
	> 2 years	87	28.0%
	Total	311	100.0%
Experience in using smart wearable devices to make payments	Never used	35	11.3%
	< 1 year	139	44.7%
	1 - 2 years	98	31.5%
	> 2 years	39	12.5%
	Total	311	100.0%
Frequency of using smart wearable devices in making payments	Never used	35	11.3%
	Once a year	39	12.5%
	Several times a year	116	37.3%
	Once a month	67	21.5%
	Several times a month	36	11.6%
	Several times a week	18	5.8%
	Total	311	100.0%

More than half (55%) the participants were male; accordingly, females accounted for 45% of participants. As for the age categories, the vast majority (44.7%) of respondents were within the age group of 26-35, with 25.7% in the age group of 18-25, and the smallest percentage (12.9%) in the group of those aged less than 18 years. In terms of educational level, holders of bachelor's degrees constituted the largest group in the current sample size, accounting for 37.9% of the total sample size, followed by those who are still university students (31.5%).

Regarding the monthly income, the largest part (38.3%) of the current sample was for those who have a monthly income level ranging from 500 to 1,000 KD; about 14.1% of current study participants reported having an income level higher than 2,000 KD. In relation to the experience in using smart wearable devices, most participants (49.5%) in the current study had 1-2 years' experience with smart wearable devices, yet 44.7% of respondents had less than 1 year experience in using smart wearable devices to make payments. Finally, 37.3% of current study participants reported using smart wearable devices in making payments several times a year.

DATA ANALYSIS AND RESULTS

The research model of this study was analyzed using Partial Least Squares Structure Equation Modeling (PLS-SEM). PLS-SEM was used to assess and validate the contents of the proposed model and the hypothesized relationships among the constructs (e.g., Alam et al., 2020; Götz et al., 2010; Hair, Hollingsworth, et al., 2017; Rabaa'i, Tate, Gable, 2015; Rabaa'i & AlMaati, in press). In this section, model specification and evaluations, using SmartPLS 3.2.9 software (Ringle et al., 2015), is discussed, and partial least squares multi-group analysis (PLS-MGA), based on gender, is presented in a following section.

MODEL SPECIFICATION

Hair, Hollingsworth, et al. (2017) recommended that the first phase in PLS-SEM is to specify a path model that connects the measurement items with the constructs. The model specification is concerned with setting up the outer (i.e., measurement) model and the inner (i.e., structural) model. The outer model presents the relationships between the measurement items and constructs, while the inner model presents the relationships between the constructs. Figure 2 presents the model specification (measurement and structural models) of this study.

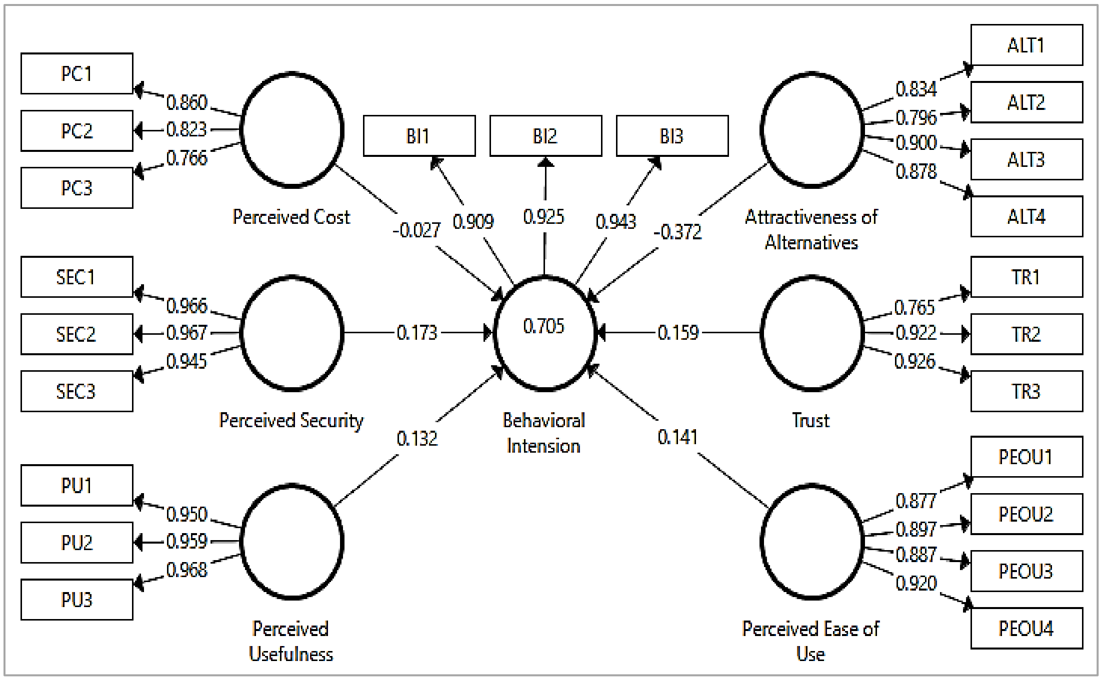

Figure 2. The measurement and structural models

After specifying the research model, Anderson and Gerbing (1988) recommended a two-step approach to validate the model by: (1) assessing the outer (i.e. measurement) model, then (2) assessing the inner (i.e. structural) model. The two-step approach aims at establishing the reliability and the validity of the constructs before assessing the structural relationship of the research model (Alam et al., 2020; Hair, Hollingsworth, et al. 2017).

Measurement model assessment

Measurement model reliability is measured by utilizing both Cronbach's alpha (CA) and composite reliability (CR) (Hair, Hollingsworth, et al., 2017). Table 3 shows that the CA and CR values for all the latent variables are above the threshold measurement of 0.7 and 0.85 respectively (Fornell & Larcker, 1981; Henseler et al., 2009, 2015). Hence, it is confirmed that all factors in the measurement model have adequate reliability.

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

Items	Loading	p-value	Cronbach's alpha	Composite reliability	AVE
Perceived Ease of Use (PEOU)			0.918	0.942	0.802
PEOU1	0.877	0.000			
PEOU2	0.897	0.000			
PEOU3	0.887	0.000			
PEOU4	0.920	0.000			

Items	Loading	p-value	Cronbach's alpha	Composite reliability	AVE
Trust (TR)			0.842	0.906	0.765
TR1	0.765	0.000			
TR2	0.922	0.000			
TR3	0.926	0.000			
Perceived Usefulness (PU)			0.956	0.972	0.919
PU1	0.950	0.000			
PU2	0.959	0.000			
PU3	0.968	0.000			
Perceived Security (PS)			0.957	0.972	0.921
PS1	0.966	0.000			
PS2	0.967	0.000			
PS3	0.945	0.000			
Perceived Cost (PC)			0.751	0.858	0.668
PC1	0.860	0.000			
PC2	0.823	0.000			
PC3	0.766	0.000			
Attractiveness of Alternatives (AoA)			0.875	0.914	0.727
AoA1	0.834	0.000			
AoA2	0.796	0.000			
AoA3	0.900	0.000			
AoA4	0.878	0.000			
Behavioral Intention (BI)			0.917	0.948	0.858
CI1	0.909	0.000			
CI2	0.925	0.000			
CI3	0.943	0.000			

Measurement model validity is evaluated by assessing convergent validity and discriminant validity. Henseler et al. (2009, p. 299) argued that convergent validity is established when "a set of indicators represents one and the same underlying construct". The convergent validity was assessed using the average variance extracted (AVE) and factor loadings. The AVE should be at least 0.50 and above (Hair, Hult, et al., 2017; Henseler et al., 2015). Additionally, the loadings of all measurement items (i.e. indicators) should be 0.50 or above on their hypothesized construct and they should be significant ($p < 0.05$) (Hair, Hollingsworth, et al., 2017). These two criteria have been fulfilled as shown in Table 3.

Discriminant validity refers to "the extent to which a construct is empirically distinct from other constructs in the path model" (Sarstedt et al., 2014, p. 108), and can be assessed by the Heterotrait-Monotrait (HTMT) criterion as recommended by Henseler et al. (2015). Using a Monte Carlo simulation study, Henseler et al. (2015) found that HTMT is able to achieve higher specificity and sensitivity rates (97% to 99%) compared to Fornell-Lacker (20.82%) criterion, the most commonly used method to assess discriminant validity. The results shown in Table 4 demonstrate that all the HTMT values were lower than the recommended threshold 0.90 (e.g. Alam et al., 2020; Hair, Hollingsworth, et al. 2017; Teo et al., 2008; Voorhees et al., 2016). Hence, the criterion for discriminant validity was achieved.

Table 4. Hetrotrait-Monotrait ratio (HTMT) test

	AoA	BI	PC	PEOU	PS	PU	TR
AoA							
BI	0.857						
PC	0.836	0.735					
PEOU	0.653	0.682	0.696				
PS	0.686	0.729	0.592	0.614			
PU	0.669	0.685	0.617	0.526	0.699		
TR	0.820	0.780	0.755	0.650	0.663	0.567	

Structural model assessment

After ensuring the reliability and validity of the measurement model, the structure model is then assessed (Hair, Hollingsworth, et al., 2017; Henseler et al., 2009, 2015). As suggested in SEM literature (e.g., Chin, 2010; Hair, Hollingsworth, et al., 2017; Hair, Hult, et al., 2017; Henseler et al., 2009, 2015; Rabaa'i, 2017a), the assessment of the structural model entails: estimates for path coefficients (β), determination of coefficient (R2), predictive relevance (Q2) and estimates for total effects (f2) and (q2).

The first step in assessing the structural model, using PLS, should be based on the path coefficient's ("β") direction algebraic sign, magnitude and significance (e.g., Chin, 2010; Hair, Hult, et al., 2017; Henseler et al., 2009). In PLS, the individual path coefficients of the structural model can be interpreted as standardized beta coefficients of ordinary least squares regressions (Henseler et al., 2009). Path coefficients should exceed 0.100 to account for a certain impact within the structural model (Urbach and Ahlemann, 2010). Furthermore, path coefficients should be significant at least at the 0.050 level (Henseler et al., 2009; Urbach and Ahlemann, 2010). A bootstrapping method with 5,000 samples was employed to examine the significance levels of path coefficients (Hair, Hollingsworth, et al., 2017; Hair, Hult, et al., 2017). Table 5 presents the path coefficient, t-statistics and p-values for the proposed hypothesis. The path coefficient provides the significance of the hypothesized relations connecting the constructs. Table 5 reveals that hypotheses H1, H2, H3, H4, and H6 were supported, whereas H5 was not.

Table 5. Hypotheses' path coefficients, t-statistics, and p-values

	Hypothesis No.	Path coefficient	t-statistics	p-values	Supported
PU → BI	H1	0.132	2.092	0.036	Yes
PEOU → BI	H2	0.141	2.737	0.006	Yes
PS → BI	H3	0.173	3.090	0.002	Yes
TR → BI	H4	0.159	2.527	0.012	Yes
PC → BI	H5	-0.027	0.477	0.633	No
AoA → BI	H6	-0.372	5.227	0.000	Yes

In PLS, R^2 values represent "the amount of variance in the construct in question that is explained by the model" (Chin, 2010, p. 674). As seen in Figure 3, the research model was also able to predict a large portion of variance in the behavioral intention with a R^2 value of 0.705.

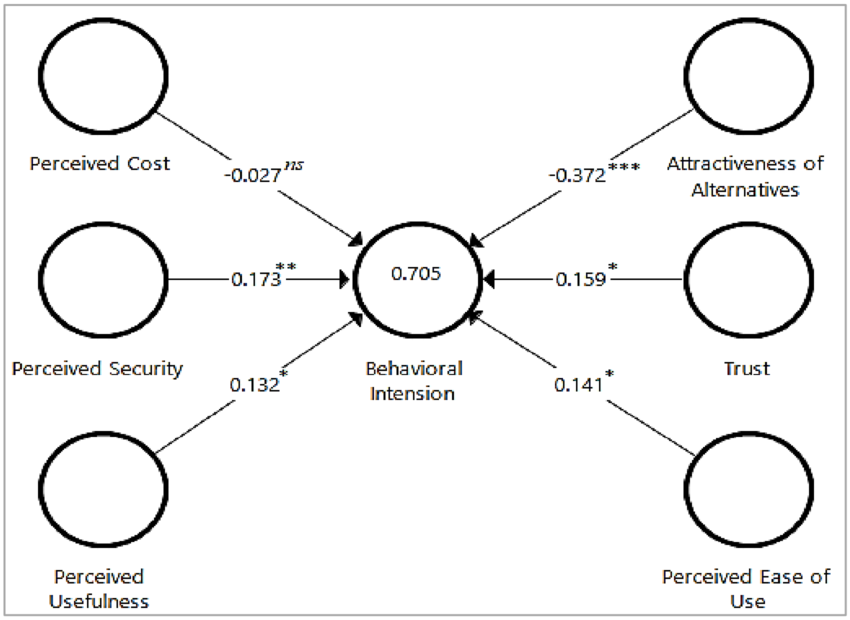

Figure 3: The structural model

Predictive relevance (Q^2) values were also assessed by running a blindfolding procedure and calculated using the cross-validated redundancy approach. The findings show that the predictive relevance (Q^2) for the behavioral intention to adopt smartwatch m-payment (0.591) is larger than zero as suggested by Chin (2010), Fornell and Cha (1994) and Hair et al. (2014). This indicates that the model has a significant predictive relevance.

As described by Hair et al. (2012), effect size f^2 "considers the relative impact of a particular exogenous latent variable on an endogenous latent variable by means of changes in the R^2". Similar to the effect size f^2, effect size q^2 shows an exogenous variable's contribution to an endogenous variable's Q^2 value (Hair et al., 2012). Cohen (1988) suggested that f^2 effect sizes of 0.02, 0.15, and 0.35 are termed small, medium, and large, respectively. However, Aguinis et al. (2005), based on a 30 year review, has shown that the average effect size in tests of moderation is only 0.009. As such, Kenny (2018) argued that a more realistic standard for effect sizes might be 0.005, 0.01, and 0.025 for small, medium, and large, respectively. The author stated that these values are "optimistic" given Aguinis et al.'s (2005) review. Table 6 shows the effect sizes' results. While, for example, the effect size f^2 of perceived usefulness (PU) on behavioral intention is large (0.028), its effect size q^2 (i.e. contribution on behavioral intention) (0.010) is considered medium, according to Kenny's (2018) standard effect size.

Table 6. Effect sizes

	f^2	q^2
	BI	BI
AoA	0.161	0.098
PC	0.001	-0.002
PEOU	0.035	0.017
PU	0.028	0.010
SEC	0.044	0.022
TR	0.037	0.020

The study extends the standard reporting of PLS-SEM by running the Importance-Performance Map Analysis (IPMA). The PLS-IPMA tests the total effect of an exogenous variable on a specific target endogenous variable (i.e. importance) with the averaged latent variable score of the exogenous construct (i.e. performance) (Hair, Hult, et al., 2017). This test aims at detecting an exogenous variable that more effectively improved the value of the target endogenous variable (i.e. behavioral intention in this case) with its relatively high importance and low performance (Hock et al., 2010). As noted in Table 7, to predict users' behavioral intentions to adopt smartwatch m-payment, attractiveness of alternatives has the highest importance (0.472), followed by trust (0.189), perceived ease of use (0.181), perceived security (0.157), perceived usefulness (0.114), and perceived cost (0.037). Yet, in terms of the performance of these constructs to predict users' behavioral intentions to adopt smartwatch m-payment, attractiveness of alternatives tops the list (86.204), followed by trust (84.792), perceived ease of use (84.513), perceived cost (78.246), perceived security (75.563), and perceived usefulness (72.032). These results imply that attractiveness of alternatives is the most important predictor of users' behavioral intentions to adopt smartwatch m-payment and should be the highest priority.

Table 7. PLS-IPMA analysis for behavioral intention to adopt smartwatch m-payment

	Total effect (importance)	**Index value (performance)**
Attractiveness of alternatives	-0.472	86.204
Perceived cost	-0.037	78.426
Perceived ease of use	0.181	84.513
Perceived security	0.157	75.563
Perceived usefulness	0.114	72.032
Trust	0.189	84.792

Unlike covariance-based CB-SEM, such as AMOS, PLS does not provide the overall model-goodness-of-fit statistics. To address this issue, Hair, Hult, et al. (2017) and Henseler et al. (2015) suggested using the Standardized Root Mean Square Residual (SRMR) fit index. For the structural model, the SRMR fit index is 0.055 which is lower than the proposed threshold value of 0.08 (Hair, Hult, et al., 2017; Henseler et al., 2015). Additionally, as suggested by Hair, Hult, et al. (2017), the structural model was also assessed through the following measures: average path coefficient (APC), average R-squared (ARS), and average variance inflation factor (AVIF). Hair, Hult, et al. (2017) recommended that the values for both the APC and ARS be significant at least at the 0.05 level, whereas the AVIF should be lower than 5. Table 8 reveals that the model meets the recommended threshold values, suggesting that the data is a good fit with the proposed model.

Table 8. Inner model evaluation indices

Average path coefficient (APC)	**Average R-squared (ARS)**	**Average variance inflation factor (AVIF)**	**SRMR fit index**
0.167**	0.705***	3.75	0.055

Note: *** $p<0.01$, *** $p<0.001$*

Gender Based PLS Multi Group Analysis (PLS-MGA)

Prior to conducting multigroup analysis (MGA), the measurement invariance of composite models (MICOM) should be considered (Henseler et al., 2016). The MICOM procedure contains three steps: Step 1, configural invariance; Step 2, compositional invariance; and Step 3, equality of means and variances (Henseler et al., 2016). Configural invariance requires that identical measurement items for all constructs in the model are specified across the groups of the population (King et al., 2017). Compositional invariance tests if each construct's scores are created equally across the groups in the population (Henseler et al., 2016), implying that the scores of a given construct calculated in one group, with weights estimated in that group, correlate perfectly with the scores of the construct calculated in the other group (King et al., 2017). Step 3 evaluates the equality of the constructs' means and variances across all specified groups (Matthews, 2017). In this study, the MICOM process was performed with SmartPLS 3.2.9 software (Ringle et al., 2015), generated 5,000 permutations for each group: males and females.

The SmartPLS 3.2.9 software automatically established the configural invariance (Step 1) (Garson, 2016). As shown in Table 9, the compositional invariance (Step 2) has been fulfilled for all the constructs. This is evident based on the original correlations being greater than the 5% quantile correlations (shown in the 5% column) (Henseler et al., 2016; Matthews, 2017). That is, in all instances, the actual observed correlation between the construct scores in the compared groups was very high; as such, it was determined that compositional invariance was effectively established.

Table 9. MICOM Step 2 results

	Original correlation	**Correlation permutation mean**	**5%**	**Permutation p-values**
Attractiveness of Alternatives	0.999	0.999	0.998	0.349
Behavioral Intention	1	1	1	0.110
Perceived Cost	1	0.996	0.989	0.980
Perceived Ease of Use	0.999	0.999	0.999	0.222
Perceived Security	1	1	1	0.192
Perceived Usefulness	1	1	1	0.160
Trust	1	0.999	0.997	0.628

In Step 3, the composites' (i.e., constructs) equality of mean values and variances across the groups were assessed. For invariance to be established, the first column (mean original difference) must be a number that falls within the 95% confidence interval (Matthews, 2017). This is evaluated by comparing the mean original difference to the lower (2.5%) and upper (97.5%) boundaries shown in columns three and four (Matthews, 2017). Table 10 shows that all constructs pass this part of the test, thus providing initial evidence of invariance (i.e., the first part of Step 3).

Table 10. MICOM Step 3 results - Part 1

	Mean - Original cifference (female - male)	**Mean - Permutation mean difference (female - male)**	**2.5%**	**97.5%**	**Permutation p-Values**
Attractiveness of Alternatives	0.010	0.003	-0.234	0.218	0.925
Behavioral Intention	-0.067	0.000	-0.212	0.227	0.554
Perceived Cost	0.004	0.001	-0.216	0.235	0.970
Perceived Ease of Use	-0.209	-0.002	-0.213	0.227	0.067
Perceived Security	-0.185	-0.002	-0.218	0.224	0.096
Perceived Usefulness	-0.116	0.001	-0.220	0.213	0.318
Trust	-0.035	-0.001	-0.224	0.237	0.735

The second part of the results for the MICOM Step 3 is presented in Table 11. Similar to Step 3 (part 1), the data in column one (variance original difference) must be a number that falls within the 95% confidence interval. Thus, the first column is again compared to the lower (2.5%) and upper (97.5%) confidence interval (Matthews, 2017). Table 11 shows that all constructs pass this part of the test, thus providing evidence of full measurement invariance (Henseler et al., 2016).

Table 11. MICOM Step 3 results - Part 2

	Variance - Original Difference (female - male)	Variance - Permutation Mean Difference (female - male)	2.5%	97.5%	Permutation p-Values
Attractiveness of Alternatives	-0.088	-0.008	-0.536	0.527	0.747
Behavioral Intention	0.044	-0.005	-0.479	0.432	0.835
Perceived Cost	0.229	-0.008	-0.529	0.486	0.432
Perceived Ease of Use	0.547	-0.002	-0.637	0.601	0.093
Perceived Security	0.260	-0.005	-0.368	0.360	0.160
Perceived Usefulness	0.341	-0.014	-0.378	0.347	0.059
Trust	0.060	-0.010	-0.653	0.568	0.846

Since the results obtained in the MICOM procedure supported the "full measurement invariance" for the two groups of data, showing the pertinence of the MGA tests in this study, the MGA analysis was then performed to test the moderating role of gender on the hypotheses of the research model of this study, as gender is considered as a categorical variable (Hair et al., 2014). MGA tests whether predefined data groups have statistically significant differences in their group-specific parameter estimates (Alzahrani et al., 2018).

To ensure the solidity of the MGA results and given that the parametric approach fails to fit the distribution-free characteristics of the PLS-SEM method (Henseler, 2012; Henseler et al., 2009; Sarstedt et al., 2011), partial least squares multi-group analysis (PLS-MGA) was employed in this study. PLS-MGA is the most conventional method of testing significant differences (Sarstedt et al., 2011), uses a nonparametric significance test for the difference of group-specific results that builds on PLS-SEM bootstrapping results (Alam et al., 2020), and is implemented in SmartPLS as an extension of the original Henseler's MGA method (Alzahrani et al., 2018). Consequently, following Hair et al.'s (2014) and Matthews' (2017) recommendations, the model for each group was run separately using 5,000 bootstrapping samples. As can be seen in Table 12, the relationships between perceived ease of use and behavioral intention (PEOU → BI) as well as trust and behavioral intention (TR → BI) are significant for males and are not for females. The other relationships do not indicate a major difference between males and females.

Table 12. Bootstrapping results for males and females separately

	Female				Male			
	Path coefficients	t-Value	p-Value	supported	Path Coefficients	t-Value	p-Value	supported
AoA → BI	-0.461	4.478	0.000	Yes	-0.313	3.067	0.002	Yes
PC → BI	0.025	0.273	0.785	No	-0.055	0.731	0.465	No
PEOU → BI	0.133	1.785	0.074	No	0.144	2.159	0.031	Yes
PS → BI	0.187	2.212	0.027	Yes	0.200	2.755	0.006	Yes
PU → PE	0.079	0.831	0.406	No	0.146	1.860	0.063	No
TR → BI	0.151	1.308	0.191	No	0.155	2.093	0.036	Yes

PLS-MGA was then employed to investigate if the differences in the relationships between the two groups are significant. The results are depicted in Table 13.

Table 13. PLS-MGA results

	Path coefficients diff (male vs. female)	p-value original (male vs. female)	p-value new (male vs. female)	Probability of error level < 0.05
AoA → BI	-0.148	0.845	0.309	No
PC → BI	0.080	0.241	0.482	No
PEOU → BI	-0.011	0.552	0.896	No
PS → BI	-0.013	0.548	0.905	No
PU → BI	-0.067	0.707	0.586	No
TR → BI	-0.004	0.509	0.941	No

A result is significant at the 5% probability of error level if the p-value is smaller than 0.05 for a certain difference of group-specific path coefficients (Alam et al., 2020). Hence, based on the PLS-MGA results, it can be concluded that there are no statistically significant differences between males and females in their behavioral intentions to adopt wearable payments.

Discussions, Theoretical and Practical Contributions

Discussions of Results

The results of the hypotheses testing are displayed in Table 5. Based on the hypothesis test, the following relationships are supported: H1: PU → BI ($\beta = 0.132$, $p < 0.05$), H2: PEOU → BI ($\beta = 0.141$, $p < 0.01$), H3: PS → BI ($\beta = 0.173$, $p < 0.01$), H4: TR → BI ($\beta = 0.159$, $p < 0.05$), and H6: AoA → BI ($\beta = -0.372$, $p < 0.001$). However, H5: PC → BI ($\beta = -0.027$, $p = 0.633$) is not supported.

Perceived usefulness posed as a significant factor in this study, affecting users' behavioral intention to adopt wearable payments. Several studies have found similar results in relation to this role of perceived usefulness in the context of smart wearable devices (Chuah et al., 2016), m-payments (e.g., Kalinić et al., 2019; Singh et al., 2020; Zhao et al., 2019) and wearable payments (Lee et al., 2020). This result highlights the significance of the cognitive and functional benefits of wearable payments from the customers' perspective. Smart wearable devices have been developed to fulfill customers' needs through one device in order to improve their performance (Gu et al., 2016; Park, 2020). Further, smart wearable devices have several attractive characteristics, such as mobility, flexibility, efficiency, ubiquity, convenience, and personalization, which distinguish them from traditional payment methods (Bölen, 2020; Lee et al., 2020). Hence, customers are more able to save time and effort in paying for different products or services. Additionally, this study's findings demonstrate that users will have positive intentions to adopt wearable payments if they are perceived as easy to use. While this result contradicts the finding of Lee et al. (2020), in the context of wearable payments, it is consistent with several previous m-payments and smart wearable devices studies (e.g., Gupta & Arora, 2019; Park, 2020). This implies that users who perceive the effort required to learn and use wearable payment as low are more likely to adopt this payment method.

The empirical results of the current study confirm the significant role of perceived security in promoting users' behavioral intention to adopt wearable payments. This finding is consistent with prior m-payment studies (e.g., Chawla & Joshi, 2019; Khalilzadeh et al., 2017; Liu et al., 2019; Sharma et al., 2019). This result implies that when users have high confidence toward the security features of wearable payments, they will be motivated to use this payment method. That is, since wearable payments' transactions involve critical financial information, it is important to assure users that it is secure to conduct an electronic exchange using such technology. Hence, it is crucial to assure users of the security measures taken by wearable payments' service providers. These assurances will influence users' behavioral intention to use such a payment method (e.g., Hanafizadeh et al., 2014; Khalilzadeh et al., 2017).

The statistical analysis of this study demonstrates that user's behavioral intention is significantly and positively influenced by trust. This finding confirmed the argument of Shao et al. (2019), who suggested that in an emerging country, like Kuwait, with relatively weaker institutional and legal environments, trust plays a salient role in shaping users' behaviors. The result implies that our study's respondents are influenced by trust due to the immature stage of the wearable payments in Kuwait and the high degree of uncertainty in such a payment method. As such, trust becomes an important factor for users to obtain confidence in an exchange partner (Zhou, 2012) and induce their behavioral intention (Hampshire, 2017) to adopt wearable payments. Similar finding is reported in prior m-payment studies (e.g., Hampshire, 2017; Kalinic et al., 2019a; Singh & Sinha, 2020).

Interestingly, the findings demonstrate that attractiveness of alternatives is the most important variable in predicting users' behavioral intention to adopt wearable payments. This significant relationship between attractiveness of alternatives and behavioral intention was reported in previous studies (e.g., Amoroso & Magnier-Watanabe, 2012; Kim et al., 2011) including NFC-enabled m-payment (Pham & Ho, 2015). This implies that, when making decisions, customers do not only assess the value of the target service, but also its relative advantage in comparison with other alternatives (Thaler, 1985). In line with Pham and Ho's (2015) argument, when making a payment decision, users will compare different payment methods and will not only consider cognitive factors as well as product-related factors (e.g., perceived usefulness, ease of use, trust, and perceived security) in making their choice. In fact, the vast majority of Kuwait population already has credit/debit cards, and cash is the most used payment methods in developing countries (Verkijika, 2020). Hence, established payments' substitutes (e.g., cash and credit/debit cards) with strong network externalities may be an obstacle to wearable payments adoption (Pham & Ho, 2015).

The empirical results of this study failed to confirm the role of perceived cost in predicting behavioral intention to adopt wearable payments, contradicting this study's hypothesis (H5) and prior existing m-payment studies (e.g., Phonthanukitithaworn et al., 2016b; Singh & Sinha, 2020; Sobti, 2019). Similar findings of a non-significant relationship between perceived cost and behavioral intention were reported by Tan et al. (2014) and Oliveira et al. (2016) in the use of NFC credit card payments and m-payments respectively. This implied that users' behavioral intention to adopt wearable payments is largely predicted by the role of trust, perceived security, attractiveness of alternatives, and cognitive factors, such as perceived usefulness and ease of use, and is not shaped by financial and cost issues. These results can be interpreted by two perspectives. Firstly, as discussed in the study's sample section, the vast majority of the current study participants are actual owners of smart wearable devices (i.e., they were able to afford buying such technology). Secondly, the use of wearable payments in Kuwait is free and banks do not charge any service fees to use this payment method. This implies that customers will not incur additional financial cost in using wearable payments in Kuwait.

Finally, the moderating role of gender was found to be insignificant in this study. This implies that behavioral intentions to adopt wearable payments of both genders followed the same patterns equally (Tan et al., 2014). As m-payment studies reported contradicting and inconsistent results (e.g., Khalilzadeh et al., 2017; Liébana-Cabanillas, Marinkovic, et al., 2018; Shao et al., 2019; Sobti, 2019), the moderating role of gender requires further investigation.

IMPLICATIONS

In terms of theoretical implications, the research model provided in this study may be useful for academics and scholars conducting further research into m-payments adoption, specifically in the context of wearable payments, where studies are scarce and still in the nascent stage; hence, addressing the gap in existing literature. This study investigated influencing as well as inhibiting factors that influence users' behavioral intention to adopt wearable payments and empirically demonstrated that behavioral intentions is mainly predicted by attractiveness of alternatives, perceived usefulness, perceived ease of use, perceived security, and trust, while the role of perceived cost was found to be insignificant. The current study also contributes to existing knowledge by validating the roles of attractiveness of alternatives, which in the context of m-payments was only examined in the context of NFC-based m-payments among Taiwanese consumers (Pham & Ho, 2015), and was never examined in the wearable payment context. This, in turn, provides a new dimension about a determinant factor considered by customers in predicting their behavioral intention to adopt wearable payments. Further, this study is the first to have specifically investigated wearable payments in the State of Kuwait; therefore, enriching Kuwaiti context literature. Scholars could use this study to compare and verify the results in other countries. Additionally, the research model of this study could also be used to investigate other m-payments methods, such as m-wallets and P2P. Finally, this study contributed to the existing knowledge by investigating the moderating role of gender.

There are four main practical implications of the current study. First, this study investigated different important factors, including perceived usefulness, perceived ease of use, perceived security, trust, and attractiveness of alternatives, which significantly influence users' behavioral intention to adopt wearable payments. Therefore, smart wearable devices manufacturers and banks should focus their attention to any aspect relating to these factors to motivate customers to use these devices for payment purposes. Second, the study findings demonstrated that attractiveness of alternatives is the main inhibitors of wearable payments adoption. Hence, unless banks emphasized the main characteristics and uniqueness of wearable payments, users are unlikely to adopt them (Pham & Ho, 2015). Awareness and marketing campaigns should highlight the benefits of using wearable payments and what they can uniquely offer better than established substitutes (Pham & Ho, 2015). Additionally, banks can offer financial incentives, loyalty programs and discounts when using wearable payments.

Third, this study draws attention to the importance of cognitive factors, such as perceived usefulness and ease of use, in inducing users' behavioral intention to adopt wearable payments. As such, in the case of perceived usefulness, smart wearable devices manufacturers and banks should enhance the functionalities and features of these devices, expand on the financial services provided through them, and maintain the availability, performance, effectiveness, and efficiency of these tools 24/7. In relation to ease of use, smart wearable devices should be designed with an easy to use, high quality and customizable user interface (Alalwan, 2020). Further, attractive commercial videos that explain how to use smart wearable devices for payment purposes and increase users' familiarity with different features of these devices would be of significance to promote users' perceived ease of use of wearable payments. Also, online brochures and promotional campaigns, through television, newspapers and social media platforms (e.g., Facebook, Instagram, YouTube) must also promote the ease of use and usefulness of wearable payments by emphasizing the main benefits of using such payment method; like improved performance, efficiency, convenience, faster shopping, secured transactions, and easy to use, may capture consumers' attention, and enhance their behavioral intentions to adopt such a payment method (Liébana-Cabanillas, Marinkovic, et al., 2018).

Finally, the findings of this study demonstrated the influence of trust and perceived security in motivating users to adopt wearable payments. Hence, banks are advised to focus on a relationship based on trust, especially during the early stages of acceptance and adoption of wearable payments. Banks must assure users that wearable payments are reliable and that "promises and commitments are kept" (Shin, 2009, p. 1353). Banks must also ensure data protection, the availability of the services, the security of the platforms used for wearable payments and assure users that they can conduct different financial transactions effectively, efficiently, and securely using smart wearable devices. Further, certain type of trust certification, such as VeriSign or TRUSTe, could be implemented indicating that wearable payments have been verified by trusted organizations (Liébana-Cabanillas, Marinkovic, et al., 2018). As security concerns can become an inhibitor to the adoption of wearable payments (Oliveira et al., 2016), manufacturers of smart wearable devices must ensure that these devices are free of errors, software bugs, and use advanced encryption as well as authentication methods, like fingerprint or biometrics identifications. Also, banks should emphasize that security measures are a priority in wearable payments and ensure that users are aware of such measures through marketing campaigns. These measures will enhance the security perceptions of wearable payments and users will perceive the service providers as trustworthy.

CONCLUSIONS, LIMITATIONS AND FUTURE RESEARCH

CONCLUSIONS

Studies on wearable payments are scarce. The current study is the first empirical study that investigates users' behavioral intention to adopt wearable payments in Kuwait. The modified TAM was found to be a suitable theoretical foundation for the proposed conceptual model. The study extended TAM with important variables relevant to the wearable payment context, such as trust, security, perceived cost, and attractiveness of alternatives. Data was then analyzed using PLS-SEM and all of the research model variables were able to fulfill the main criteria of constructs reliability and validity. The findings revealed that attractiveness of alternatives is the most important factor influencing users' behavioral intention to adopt wearable payments, and only perceived cost and the moderating effect of gender are the non-significant factors in this study. Further, the research model of this study was able to explain about 70.5% of the variance in behavioral intention. An in-depth discussion was presented regarding the adoption of wearable payments in Kuwait. Finally, theoretical as well as practical contributions of this study were discussed.

LIMITATIONS AND FUTURE RESEARCH

While the present research contributes to the literature on wearable payments, a number of limitations should be noted. Since the current study used a convenience sampling technique, the generalizability of the results is uncertain. Therefore, future research could apply random sampling techniques by extracting wearable payment users from banks' databases. This study was conducted in Kuwait, a Middle Eastern rich country with well-advanced technology infrastructure. Kuwaiti citizens are well-educated and technology savvy (Rabaa'i et al., 2015; Statista, 2021b, 2021c) compared to the citizens in many other developing countries and enjoy one of the highest Internet and mobile penetration levels in the world (KFAS, 2019; NBK, 2018). Future studies should investigate the proposed model in a cross-country and cross-cultural perspective with additional economic, environmental, and technological factors. Moreover, this study is cross-sectional, which captures users' responses at one point in time and cannot explain how users' perception could change over time. Hence, future research may conduct a longitudinal study to explain how temporal changes and usage experience affect users' behavioral intentions to adopt wearable payments. While this study investigated the moderating role of gender and found no statistical differences between males and females, the study did not consider other moderating factors such as age, monthly income, and usage experience. Future studies could investigate these factors to enhance the current understanding of the main moderating variables that support or inhibit the use of wearable payments. Finally, while this study included both influencing factors (perceived usefulness, perceived ease of use, perceived security, and trust) and inhibiting factors (perceived cost and attractiveness of alternatives) in the research model, other factors such as social influence, perceived compatibility, personal innovativeness, mobility, and customization could be considered in future research.

REFERENCES

Aguinis, H., Beaty, J. C., Boik, R. J., & Pierce, C. A. (2005). Effect size and power in assessing moderating effects of categorical variables using multiple regression: A 30-year review. *Journal of Applied Psychology, 90*(1), 94-107. https://doi.org/10.1037/0021-9010.90.1.94

Ahmad, S. Z., & Khalid, K. (2017). The adoption of m-government services from the user's perspectives: Empirical evidence from the United Arab Emirates. *International Journal of Information Management, 37*(5), 367-379. https://doi.org/10.1016/j.ijinfomgt.2017.03.008

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

Ajzen, I., & Fishbein, M. (1977). Attitude-behavior relations: A theoretical analysis and review of empirical research. *Psychological Bulletin, 84*(5), 888-918. https://doi.org/10.1037/0033-2909.84.5.888

Alaeddin, O., Altounjy, R., Zainudin, Z., & Kamarudin, F. (2018). From physical to digital: Investigating consumer behaviour of switching to mobile wallet. *Polish Journal of Management Studies, 17*(2)*,* 18-30. https://doi.org/10.17512/pjms.2018.17.2.02

Alalwan, A. A. (2020). Mobile food ordering apps: An empirical study of the factors affecting customer e-satisfaction and continued intention to reuse. *International Journal of Information Management, 50*, 28-44. https://doi.org/10.1016/j.ijinfomgt.2019.04.008

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management, 37*(3), 99-110. https://doi.org/10.1016/j.ijinfomgt.2017.01.002

Alam, M. Z., Hoque, Md. R., Hu, W., & Barua, Z. (2020). Factors influencing the adoption of mHealth services in a developing country: A patient-centric study. *International Journal of Information Management, 50*, 128-143. https://doi.org/10.1016/j.ijinfomgt.2019.04.016

Alghamdi, A., Karpinski, A. C., Lepp, A., & Barkley, J. (2020). Online and face-to-face classroom multitasking and academic performance: Moderated mediation with self-efficacy for self-regulated learning and gender. *Computers in Human Behavior, 102*, 214-222. https://doi.org/10.1016/j.chb.2019.08.018

Ali, H., & Li, H. (2019). Evaluating a smartwatch notification system in a simulated nursing home. *International Journal of Older People Nursing, 14*(3), e12241. https://doi.org/10.1111/opn.12241

Alkhowaiter, W. A. (2020). Digital payment and banking adoption research in Gulf countries: A systematic literature review. *International Journal of Information Management, 53*, 102102. https://doi.org/10.1016/j.ijinfomgt.2020.102102

Alzahrani, L., Al-Karaghouli, W., & Weerakkody, V. (2018). Investigating the impact of citizens' trust toward the successful adoption of e-government: A multigroup analysis of gender, age, and internet experience. *Information Systems Management, 35*(2)*,* 124-146. https://doi.org/10.1080/10580530.2018.1440730

Amoroso, D. L., & Magnier-Watanabe, R. (2012). Building a research model for mobile wallet consumer adoption: The case of Mobile Suica in Japan. *Journal of Theoretical and Applied Electronic Commerce Research, 7*(1)*,* 13-14. https://doi.org/10.4067/S0718-18762012000100008

Anderson, J., & Gerbing, D. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin, 103*(3), 411-423. https://doi.org/10.1037/0033-2909.103.3.411

Arif, M., Ameen, K., & Rafiq, M. (2018). Factors affecting student use of Web-based services: Application of UTAUT in the Pakistani context. *The Electronic Library, 36*(3), 518-534. https://doi.org/10.1108/EL-06-2016-0129

Bailey, A. A., Pentina, I., Mishra, A. S., & Ben Mimoun, M. S. (2017). Mobile payments adoption by US consumers: An extended TAM. *International Journal of Retail & Distribution Management, 45*(6)*,* 626-640. https://doi.org/10.1108/IJRDM-08-2016-0144

Baishya, K., & Samalia, H. V. (2020). Extending unified theory of acceptance and use of technology with perceived monetary value for smartphone adoption at the bottom of the pyramid. *International Journal of Information Management, 51*, 102036. https://doi.org/10.1016/j.ijinfomgt.2019.11.004

Balachandran, D., & Tan, G. W. H. (2015). Regression modelling of predicting NFC mobile payment adoption in Malaysia. *International Journal of Modelling in Operations Management, 5*(2)*,* 100-115. https://doi.org/10.1504/IJMOM.2015.072671

Beh, P. K., Ganesan, Y., Iranmanesh, M., & Foroughi, B. (2019). Using smartwatches for fitness and health monitoring: The UTAUT2 combined with threat appraisal as moderators. *Behaviour & Information Technology, 40*(3)*,* 282-299. https://doi.org/10.1080/0144929X.2019.1685597

Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial intelligence in FinTech: Understanding robo-advisors adoption among customers. *Industrial Management & Data Systems, 119*(7)*,* 1411-1430. https://doi.org/10.1108/IMDS-08-2018-0368

Benbasat, I., & Barki, H. (2007). Quo vadis TAM? *Journal of the Association for Information Systems, 8*(4). https://doi.org/10.17705/1jais.00126

Bölen, M. C. (2020). Exploring the determinants of users' continuance intention in smartwatches. *Technology in Society, 60*, 101209. https://doi.org/10.1016/j.techsoc.2019.101209

Cai, Z., Fan, X., & Du, J. (2017). Gender and attitudes toward technology use: A meta-analysis. *Computers & Education, 105*, 1-13. https://doi.org/10.1016/j.compedu.2016.11.003

Chakraborty, D. (2020). Indian shoppers' attitude towards grocery shopping apps: A survey conducted on smartphone users. *Metamorphosis: A Journal of Management Research, 18*(2)*,* 83-91. https://doi.org/10.1177/0972622519885502

Changchit, C., Klaus, T., Lonkani, R., & Sampet, J. (2020). A cultural comparative study of mobile banking adoption factors. *Journal of Computer Information Systems, 60*(5), 484-494. https://doi.org/10.1080/08874417.2018.1541724

Chawla, D., & Joshi, H. (2019). Consumer attitude and intention to adopt mobile wallet in India: An empirical study. *International Journal of Bank Marketing, 37*(7)*,* 1590-1618. https://doi.org/10.1108/IJBM-09-2018-0256

Chen, K.-Y., & Chang, M.-L. (2013). User acceptance of 'near field communication' mobile phone service: An investigation based on the 'unified theory of acceptance and use of technology' model. *The Service Industries Journal, 33(6),* 609-623. https://doi.org/10.1080/02642069.2011.622369

Chhonker, M. S., Verma, D., Kar, A. K., & Grover, P. (2018). m-Commerce technology adoption: Thematic and citation analysis of scholarly research during (2008-2017). *The Bottom Line, 31*(3/4)*,* 208-233. https://doi.org/10.1108/BL-04-2018-0020

Chin, W. W. (2010). Bootstrap cross-validation indices for PLS Path Model Assessment. In V. Esposito Vinzi, W. Chin, J. Henseler, & H. Wang (Eds), *Handbook of partial least squares*. Springer Handbooks of Computational Statistics. https://doi.org/10.1007/978-3-540-32827-8_4

Choi, H., Park, J., Kim, J., & Jung, Y. (2020). Consumer preferences of attributes of mobile payment services in South Korea. *Telematics and Informatics, 51*. https://doi.org/10.1016/j.tele.2020.101397

Chopdar, P. Kr., Korfiatis, N., Sivakumar, V. J., & Lytras, M. D. (2018). Mobile shopping apps adoption and perceived risks: A cross-country perspective utilizing the Unified Theory of Acceptance and Use of Technology. *Computers in Human Behavior, 86*, 109-128. https://doi.org/10.1016/j.chb.2018.04.017

Choudrie, J., Jr, C.-O., McKenna, B., & Richter, S. (2018). Understanding and conceptualising the adoption, use and diffusion of mobile banking in older adults: A research agenda and conceptual framework. *Journal of Business Research, 88*, 449-465. https://doi.org/10.1016/j.jbusres.2017.11.029

Chuah, S. H.-W., Rauschnabel, P. A., 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. https://doi.org/10.1016/j.chb.2016.07.047

Chuttur, M. Y. (2009). Overview of the technology acceptance model: Origins, developments and future directions. *Working Papers on Information Systems, 9*(37), 9-37.

Cocosila, M., & Trabelsi, H. (2016). An integrated value-risk investigation of contactless mobile payments adoption. *Electronic Commerce Research and Applications, 20*, 159-170. https://doi.org/10.1016/j.elerap.2016.10.006

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Lawrence Erlbaum Associates Publishers.

Compeau, D., Higgins, C., & Huff, S. (1999). Social cognitive theory and individual reactions to computing technology: A longitudinal study. *MIS Quarterly, 23*(2)*,* 145-158. https://doi.org/10.2307/249749

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3)*,* 319-340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8)*,* 982-1003. https://doi.org/10.1287/mnsc.35.8.982

De Kerviler, G., Demoulin, N. T. M., & Zidda, P. (2016). Adoption of in-store mobile payment: Are perceived risk and convenience the only drivers? *Journal of Retailing and Consumer Services, 31*, 334-344. https://doi.org/10.1016/j.jretconser.2016.04.011

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

Deng, L., Turner, D. E., Gehling, R., & Prince, B. (2010). User experience, satisfaction, and continual usage intention of IT. *European Journal of Information Systems, 19*(1), 60-75. https://doi.org/10.1057/ejis.2009.50

Driediger, F., & Bhatiasevi, V. (2019). Online grocery shopping in Thailand: Consumer acceptance and usage behavior. *Journal of Retailing and Consumer Services, 48*, 224-237. https://doi.org/10.1016/j.jretconser.2019.02.005

Dwivedi, Y. K., Rana, N. P., Janssen, M., Lal, B., Williams, M. D., & Clement, M. (2017). An empirical validation of a unified model of electronic government adoption (UMEGA). *Government Information Quarterly, 34*(2), 211-230. https://doi.org/10.1016/j.giq.2017.03.001

Eagly, A., Wood, W., & Diekman, A. (2000). Social role theory of sex differences and similarities: A current appraisal. In T. Eckes & H. M. Trautner (Eds.), *The developmental social psychology of gender* (pp. 123-174). Lawrence Erlbaum Associates Publishers.

Esfahani, S. S., & Ozturk, A. B. (2019). The influence of individual differences on NFC-based mobile payment adoption in the restaurant industry. *Journal of Hospitality and Tourism Technology, 10*(2)*,* 219-232. https://doi.org/10.1108/JHTT-01-2018-0009

Fornell, C., & Cha, J. (1994). Partial least squares. *Advanced Methods of Marketing Research*, *407*, 52-78. https://ci.nii.ac.jp/naid/10017428683/

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research, 18*(3), 382-388. https://doi.org/10.1177/002224378101800313

Garson, G. D. (2016). *Partial least squares: Regression and structural equation models*. Statistical Associates Publishers.

Gefen, D., & Straub, D. W. (1997). Gender differences in the perception and use of e-mail: An extension to the technology acceptance model. *MIS Quarterly, 21*(4), 389. https://doi.org/10.2307/249720

Gentina, E., & Rowe, F. (2020). Effects of materialism on problematic smartphone dependency among adolescents: The role of gender and gratifications. *International Journal of Information Management, 54*, 102134. https://doi.org/10.1016/j.ijinfomgt.2020.102134

Gerpott, T. J., & Meinert, P. (2017). Who signs up for NFC mobile payment services? Mobile network operator subscribers in Germany. *Electronic Commerce Research and Applications, 23*, 1-13. https://doi.org/10.1016/j.elerap.2017.03.002

Ghazali, E., Nguyen, B., Mutum, D. S., & Mohd-Any, A. A. (2016). Constructing online switching barriers: Examining the effects of switching costs and alternative attractiveness on e-store loyalty in online pure-play retailers. *Electronic Markets, 26*(2), 157-171. https://doi.org/10.1007/s12525-016-0218-1

Glavee-Geo, R., Shaikh, A. A., & Karjaluoto, H. (2017). Mobile banking services adoption in Pakistan: Are there gender differences? *International Journal of Bank Marketing, 35*(7), 1090-1114. https://doi.org/10.1108/IJBM-09-2015-0142

Global Finance. (2020, January 6). Kuwait startups: Seeding tomorrow's giants. *Global Finance.* https://www.gfmag.com/magazine/january-2020/kuwait-startups-seeding-tomorrows-giants

Götz, O., Liehr-Gobbers, K., & Krafft, M. (2010). Evaluation of structural equation models using the partial least Squares (PLS) approach. In V. Esposito Vinzi, W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of partial least squares*. Springer Handbooks of Computational Statistics. https://doi.org/10.1007/978-3-540-32827-8_30

Grassie, K. (2007). Easy handling and security make NFC a success. *Card Technology Today, 19*(10), 12-13. https://doi.org/10.1016/S0965-2590(08)70134-8

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. https://doi.org/10.1080/08874417.2015.11645804

Gupta, K., & Arora, N. (2019). Investigating consumer intention to accept mobile payment systems through unified theory of acceptance model: An Indian perspective. *South Asian Journal of Business Studies, 9*(1)*,* 88-114. https://doi.org/10.1108/SAJBS-03-2019-0037

Hair, J. F., Hollingsworth, C., Randolph, A., & Chong, A. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems, 117*(3), 442-458. https://doi.org/10.1108/IMDS-04-2016-0130

Hair, J. F., Hult, T., Ringle, C., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM).* SAGE Publications. https://doi.org/10.15358/9783800653614

Hair, J. F., Sarstedt, M., Hopkins, L., & G. Kuppelwieser, V. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review, 26*(2), 106-121. https://doi.org/10.1108/EBR-10-2013-0128

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science, 40*(3), 414-433. https://doi.org/10.1007/s11747-011-0261-6

Hampshire, C. (2017). A mixed methods empirical exploration of UK consumer perceptions of trust, risk and usefulness of mobile payments. *International Journal of Bank Marketing, 35*(3), 354-369. https://doi.org/10.1108/IJBM-08-2016-0105

Hanafizadeh, P., Behboudi, M., Abedini Koshksaray, A., & Jalilvand Shirkhani Tabar, M. (2014). Mobile-banking adoption by Iranian bank clients. *Telematics and Informatics, 31*(1)*,* 62-78. https://doi.org/10.1016/j.tele.2012.11.001

Heinze, J., Thomann, M., & Fischer, P. (2017). Ladders to m-commerce resistance: A qualitative means-end approach. *Computers in Human Behavior, 73*, 362-374. https://doi.org/10.1016/j.chb.2017.03.059

Henseler, J. (2012). PLS-MGA: A non-parametric approach to partial least squares-based multi-group analysis. In W. Gaul, A. Geyer-Schulz, L. Schmidt-Thieme, & J. Kunze (Eds.), *Challenges at the interface of data analysis, computer science, and optimization. Studies in classification, data analysis, and knowledge organization*. Springer. https://doi.org/10.1007/978-3-642-24466-7_50

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. https://doi.org/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. https://doi.org/10.1007/s11747-014-0403-8

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009), The use of partial least squares path modeling in international marketing. In R. R. Sinkovics. & P. N. Ghauri (Eds.) *New challenges to international marketing (Advances in international marketing, Vol. 20)* (pp. 277-319). Emerald Group Publishing Limited. https://doi.org/10.1108/S1474-7979(2009)0000020014

Hew, J.-J. (2017). Hall of fame for mobile commerce and its applications: A bibliometric evaluation of a decade and a half (2000-2015). *Telematics and Informatics, 34*(1), 43-66. https://doi.org/10.1016/j.tele.2016.04.003

Hock, C., Ringle, C. M., & Sarstedt, M. (2010). Management of multi-purpose stadiums: Importance and performance measurement of service interfaces. *International Journal of Services Technology and Management, 14*(2-3), 188. https://doi.org/10.1504/IJSTM.2010.034327

Hoehle, H., Scornavacca, E., & Huff, S. (2012). Three decades of research on consumer adoption and utilization of electronic banking channels: A literature analysis. *Decision Support Systems, 54*(1), 122-132. https://doi.org/10.1016/j.dss.2012.04.010

Hossain, Md. A. (2019). Security perception in the adoption of mobile payment and the moderating effect of gender. *PSU Research Review, 3*(3), 179-190. https://doi.org/10.1108/PRR-03-2019-0006

Hoy, M. B. (2013). Near field communication: Getting in touch with mobile users. *Medical Reference Services Quarterly, 32*(3), 351-357. https://doi.org/10.1080/02763869.2013.807083

Huang, Y.-M. (2019). Examining students' continued use of desktop services: Perspectives from expectation-confirmation and social influence. *Computers in Human Behavior, 96*, 23-31. https://doi.org/10.1016/j.chb.2019.02.010

Huseynov, F., & Özkan Yıldırım, S. (2019). Online consumer typologies and their shopping behaviors in B2C e-commerce platforms. *SAGE Open, 9*(2). https://doi.org/10.1177/2158244019854639

Jones, M. A., Mothersbaugh, D. L., & Beatty, S. E. (2000). Switching barriers and repurchase intentions in services. *Journal of Retailing, 76*(2), 259-274. https://doi.org/10.1016/S0022-4359(00)00024-5

Kalinic, Z., Liébana-Cabanillas, F. J., Muñoz-Leiva, F., & Marinković, V. (2019a). The moderating impact of gender on the acceptance of peer-to-peer mobile payment systems. *International Journal of Bank Marketing, 38*(1), 138-158. https://doi.org/10.1108/IJBM-01-2019-0012

Kalinic, Z., Marinkovic, V., Molinillo, S., & Liébana-Cabanillas, F. (2019b). A multi-analytical approach to peer-to-peer mobile payment acceptance prediction. *Journal of Retailing and Consumer Services, 49*, 143-153. https://doi.org/10.1016/j.jretconser.2019.03.016

Kapoor, K. K., Dwivedi, Y. K., & Williams, M. D. (2015). Examining the role of three sets of innovation attributes for determining adoption of the interbank mobile payment service. *Information Systems Frontiers, 17*(5), 1039-1056. https://doi.org/10.1007/s10796-014-9484-7

Kenny, D. (2018). *Moderator variables*. http://davidakenny.net/cm/moderation.htm

Khalilzadeh, J., Ozturk, A. B., & Bilgihan, A. (2017). Security-related factors in extended UTAUT model for NFC based mobile payment in the restaurant industry. *Computers in Human Behavior, 70*, 460-474. https://doi.org/10.1016/j.chb.2017.01.001

Kim, G., Shin, B., & Lee, H. (2009). Understanding dynamics between initial trust and usage intentions of mobile banking. *Information Systems Journal, 19*(3), 283-311. https://doi.org/10.1111/j.1365-2575.2007.00269.x

Kim, H.-W., Jeon, Y. S., & Choi, S. (2011, July). Attractiveness of alternatives in information systems continuance: A case of WiMAX. *The 11th International DSI and the 16th APDSI Joint Meeting, Taipei, Taiwan.*

Kim, K., & Prabhakar, B. (2004). Initial trust and the adoption of B2C e-commerce: The case of internet banking. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems, 35*(2), 50-64. https://doi.org/10.1145/1007965.1007970

King, C., Murillo, E., & Lee, H. (2017). The effects of generational work values on employee brand attitude and behavior: A multi-group analysis. *International Journal of Hospitality Management, 66*, 92-105. https://doi.org/10.1016/j.ijhm.2017.07.006

Koenig-Lewis, N., Marquet, M., Palmer, A., & Zhao, A. L. (2015). Enjoyment and social influence: Predicting mobile payment adoption. *The Service Industries Journal, 35*(10), 537-554. https://doi.org/10.1080/02642069.2015.1043278

Kuwait Foundation for the Advancement of Sciences (KFAS). (2019, September 22). *FinTech: Future of financial services.* https://www.kfas.org/media-publications/research-studies-whitepaper/fintech-future-of-financial-services

Lara-Rubio, J., Ramos de Luna, I., & Liébana-Cabanillas, F. (2020). Explanatory and predictive model of the adoption of P2P payment systems. *Behaviour & Information Technology*, 1-14. https://doi.org/10.1080/0144929X.2019.1706637

Lee, V. H., Hew, J. J., Leong, L. Y., Tan, G. W. H., & Ooi, K. B. (2020). Wearable payment: A deep learning-based dual-stage SEM-ANN analysis. *Expert Systems with Applications, 157*, 1-15. https://doi.org/10.1016/j.eswa.2020.113477

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management, 40*(3), 191-204. https://doi.org/10.1016/S0378-7206(01)00143-4

Leong, L. Y., Hew, T. S., Ooi, K. B., & Wei, J. (2020). Predicting mobile wallet resistance: A two-staged structural equation modeling-artificial neural network approach. *International Journal of Information Management, 51*, 102047. https://doi.org/10.1016/j.ijinfomgt.2019.102047

Leong, L.-Y., Hew, T.-S., Tan, G. W.-H., & Ooi, K.-B. (2013). Predicting the determinants of the NFC-enabled mobile credit card acceptance: A neural networks approach. *Expert Systems with Applications*, *40*(14), 5604-5620. https://doi.org/10.1016/j.eswa.2013.04.018

Liébana-Cabanillas, F., Marinkovic, V., Ramos de Luna, I., & Kalinic, Z. (2018). Predicting the determinants of mobile payment acceptance: A hybrid SEM-neural network approach. *Technological Forecasting and Social Change, 129,* 117-130. https://doi.org/10.1016/j.techfore.2017.12.015

Liébana-Cabanillas, F., Molinillo, S., & Ruiz-Montañez, M. (2019). To use or not to use, that is the question: Analysis of the determining factors for using NFC mobile payment systems in public transportation. *Technological Forecasting and Social Change, 139*, 266-276. https://doi.org/10.1016/j.techfore.2018.11.012

Liébana-Cabanillas, F., Muñoz-Leiva, F., & Sánchez-Fernández, J. (2018). A global approach to the analysis of user behavior in mobile payment systems in the new electronic environment. *Service Business, 12*(1), 25-64. https://doi.org/10.1007/s11628-017-0336-7

Liébana-Cabanillas, F., Ramos de Luna, I., & Montoro-Ríos, F. (2017). Intention to use new mobile payment systems: A comparative analysis of SMS and NFC payments. *Economic Research - Ekonomska Istraživanja, 30*(1), 892-910. https://doi.org/10.1080/1331677X.2017.1305784

Liébana-Cabanillas, F., Ramos de Luna, I., & Montoro-Ríos, F. J. (2015). User behaviour in QR mobile payment system: The QR payment acceptance model. *Technology Analysis & Strategic Management, 27*(9), 1031-1049. https://doi.org/10.1080/09537325.2015.1047757

Liébana-Cabanillas, F., Sánchez-Fernández, J., & Muñoz-Leiva, F. (2014a). Role of gender on acceptance of mobile payment. *Industrial Management & Data Systems, 114*(2), 220-240. https://doi.org/10.1108/IMDS-03-2013-0137

Liébana-Cabanillas, F., Sánchez-Fernández, J., & Muñoz-Leiva, F. (2014b). Antecedents of the adoption of the new mobile payment systems: The moderating effect of age. *Computers in Human Behavior, 35*, 464-478. https://doi.org/10.1016/j.chb.2014.03.022

Lim, H., & Kumar, A. (2019). Variations in consumers' use of brand online social networking: A uses and gratifications approach. *Journal of Retailing and Consumer Services, 51*, 450-457. https://doi.org/10.1016/j.jretconser.2017.10.015

Liu, Y., Wang, M., Huang, D., Huang, Q., Yang, H., & Li, Z. (2019). The impact of mobility, risk, and cost on the users' intention to adopt mobile payments. *Information Systems and E-Business Management, 17*(2), 319-342. https://doi.org/10.1007/s10257-019-00449-0

Luarn, P., & Lin, H.-H. (2005). Toward an understanding of the behavioral intention to use mobile banking. *Computers in Human Behavior, 21*(6), 873-891. https://doi.org/10.1016/j.chb.2004.03.003

Madan, K., & Yadav, R. (2016). Behavioural intention to adopt mobile wallet: A developing country perspective. *Journal of Indian Business Research, 8*(3), 227-244. https://doi.org/10.1108/JIBR-10-2015-0112

Madan, K., & Yadav, R. (2018). Understanding and predicting antecedents of mobile shopping adoption: A developing country perspective. *Asia Pacific Journal of Marketing and Logistics, 30*(1), 139-162. https://doi.org/10.1108/APJML-02-2017-0023

Malaquias, R. F., & Hwang, Y. (2016). An empirical study on trust in mobile banking: A developing country perspective. *Computers in Human Behavior, 54*, 453-461. https://doi.org/10.1016/j.chb.2015.08.039

Matemba, E. D., & Li, G. (2018). Consumers' willingness to adopt and use WeChat wallet: An empirical study in South Africa. *Technology in Society, 53*, 55-68. https://doi.org/10.1016/j.techsoc.2017.12.001

Matthews, L. (2017) Applying multigroup analysis in PLS-SEM: A step-by-step process. In H. Latan & R. Noonan (Eds.), *Partial least squares path modeling*. Springer. https://doi.org/10.1007/978-3-319-64069-3_10

Merhi, M., Hone, K., & Tarhini, A. (2019). A cross-cultural study of the intention to use mobile banking between Lebanese and British consumers: Extending UTUAT2 with security, privacy and trust. *Technology in Society, 59*, 101151. https://doi.org/10.1016/j.techsoc.2019.101151

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research, 2*(3), 192-222. https://doi.org/10.1287/isre.2.3.192

Morosan, C., & DeFranco, A. (2016). It's about time: Revisiting UTAUT2 to examine consumers' intentions to use NFC mobile payments in hotels. *International Journal of Hospitality Management, 53*, 17-29. https://doi.org/10.1016/j.ijhm.2015.11.003

National Bank of Kuwait [NBK]. (2018, December 31). *2018 annual report and financial statements: Diversifying for the future.* https://www.nbk.com/dam/jcr:8f570451-466b-421d-ac10-1764dab374ae/Annual-Report-2018-English.pdf

National Bank of Kuwait [NBK]. (2020, January 30). *First bank locally in Kuwait launches Fitbit Pay.* https://www.nbk.com/kuwait/news-and-insights/media-relations/news.html?news=nbk--first-bank-locally--in-kuwait-launches-fitbit-pay-

Niknejad, N., Ismail, W. B., Mardani, A., Liao, H., & Ghani, I. (2020). A comprehensive overview of smart wearables: The state of the art literature, recent advances, and future challenges. *Engineering Applications of Artificial Intelligence, 90*, 103529. https://doi.org/10.1016/j.engappai.2020.103529

Nunnally, C., & Bernstein, H. (1994). *Psychometric theory* (3rd ed.). McGraw Hill.

Okumus, B., Ali, F., Bilgihan, A., & Ozturk, A. B. (2018). Psychological factors influencing customers' acceptance of smartphone diet apps when ordering food at restaurants. *International Journal of Hospitality Management, 72*, 67-77. https://doi.org/10.1016/j.ijhm.2018.01.001

Okumus, B., & Bilgihan, A. (2014). Proposing a model to test smartphone users' intention to use smart applications when ordering food in restaurants. *Journal of Hospitality and Tourism Technology, 5*(1), 31-49. https://doi.org/10.1108/JHTT-01-2013-0003

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. https://doi.org/10.1016/j.chb.2016.03.030

Ooi, K.-B., & Tan, G. W.-H. (2016). Mobile technology acceptance model: An investigation using mobile users to explore smartphone credit card. *Expert Systems with Applications, 59*, 33-46. https://doi.org/10.1016/j.eswa.2016.04.015

Park, C., Kim, D., Cho, S., & Han, H.-J. (2019). Adoption of multimedia technology for learning and gender difference. *Computers in Human Behavior, 92*, 288-296. https://doi.org/10.1016/j.chb.2018.11.029

Park, E. (2020). User acceptance of smart wearable devices: An expectation-confirmation model approach. *Telematics and Informatics, 47*, 101318. https://doi.org/10.1016/j.tele.2019.101318

Patil, P., Tamilmani, K., Rana, N. P., & Raghavan, V. (2020). Understanding consumer adoption of mobile payment in India: Extending Meta-UTAUT model with personal innovativeness, anxiety, trust, and grievance redressal. *International Journal of Information Management*, *54*, 102144. https://doi.org/10.1016/j.ijinfomgt.2020.102144

Patterson, P. G., & Smith, T. (2003). A cross-cultural study of switching barriers and propensity to stay with service providers. *Journal of Retailing, 79*(2), 107-120. https://doi.org/10.1016/S0022-4359(03)00009-5

Pham, T.-T. T., & Ho, J. C. (2015). The effects of product-related, personal-related factors and attractiveness of alternatives on consumer adoption of NFC-based mobile payments. *Technology in Society, 43*, 159-172. https://doi.org/10.1016/j.techsoc.2015.05.004

Phonthanukitithaworn, C., Sellitto, C., & Fong, M. W. L. (2016a). An investigation of mobile payment (m-payment) services in Thailand. *Asia-Pacific Journal of Business Administration, 8*(1)*,* 37-54. https://doi.org/10.1108/APJBA-10-2014-0119

Phonthanukitithaworn, C., Sellitto, C., & Fong, M. W. L. (2016b). A comparative study of current and potential users of mobile payment services. *SAGE Open, 6*(4). https://doi.org/10.1177/2158244016675397

Ping, R. A. (1993). The effects of satisfaction and structural constraints on retailer exiting, voice, loyalty, opportunism, and neglect. *Journal of Retailing, 69*(3), 320-352. https://doi.org/10.1016/0022-4359(93)90010-G

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879-903. https://doi.org/10.1037/0021-9010.88.5.879

Rabaa'i, A. A. (2015). An empirical investigation on the adoption of e-government in developing countries: The case of Jordan. *Computer and Information Science, 8*(3), 83. https://doi.org/10.5539/cis.v8n3p83

Rabaa'i, A. A. (2016). Extending the technology acceptance model (TAM) to assess students' behavioural intentions to adopt an e-learning system: The case of Moodle as a learning tool. *Journal of Emerging Trends in Engineering and Applied Sciences, 7*(1)*,* 13-30.

Rabaa'i, A. A. (2017a). Holistic procedures for contemporary formative construct validation using PLS: A comprehensive example. *International Journal of Business Information Systems, 25*(3), 279-318. https://doi.org/10.1504/IJBIS.2017.084436

Rabaa'i, A. A. (2017b). The use of UTAUT to investigate the adoption of e-government in Jordan: A cultural perspective. *International Journal of Business Information Systems, 24*(3), 285-315. https://doi.org/10.1504/IJBIS.2017.082037

Rabaa'i, A. A., Tate, M., & Gable, G. (2015). Can't see the trees for the forest? Why IS-ServQual Items Matter. Asia Pacific Journal of Information Systems, *25*(2), 211-238. http://dx.doi.org/10.14329/apjis.2015.25.2.211

Rabaa'i, A. A., Zogheib, B., AlShatti, A., & AlJamal, E. M. (2015). Adoption of e-government in developing countries: The case of the State of Kuwait. *Journal of Global Research in Computer Science, 6*(10)*,* 6-21.

Rabaa'i, A. A. (in press). An investigation into the acceptance of mobile wallets in the FinTech era: An empirical study from Kuwait, *International Journal of Business Information Systems*.

Rabaa'i, A. A. & AlMaati, S. (in press). Exploring the determinants of users' continuance intention to use mobile banking services in Kuwait: Extending the expectation-confirmation model, *Asia Pacific Journal of Information Systems.*

Ramos de Luna, I., Liébana-Cabanillas, F., Sánchez-Fernández, J., & Muñoz-Leiva, F. (2019). Mobile payment is not all the same: The adoption of mobile payment systems depending on the technology applied. *Technological Forecasting and Social Change, 146*, 931-944. https://doi.org/10.1016/j.techfore.2018.09.018

Ramos de Luna, I., Montoro-Ríos, F., & Liébana-Cabanillas, F. (2016). Determinants of the intention to use NFC technology as a payment system: An acceptance model approach. *Information Systems and E-Business Management, 14*(2), 293-314. https://doi.org/10.1007/s10257-015-0284-5

Ramos de Luna, I., Montoro-Ríos, F., Liébana-Cabanillas, F., & de Luna, J. G. (2017). NFC technology acceptance for mobile payments: A Brazilian perspective. *Review of Business Management, 19*(63), 82-103. https://doi.org/10.7819/rbgn.v0i0.2315

Ringle, C., Wende, S., & Becker, J. (2015). *SmartPLS 3. Boenningstedt: SmartPLS GmbH*. http://www.smartpls.com

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

Rouibah, K. (2007). Does mobile payment technology M-net attract potential consumers? The case of Kuwait. *The 18th Australasian Conference on Information Systems*, 199-211.

Rouibah, K. (2009). The failure of mobile payment: Evidence from quasi-experimentations. *EATIS'09: Proceedings of the 2009 Euro American Conference on Telematics and Information Systems: New Opportunities to Increase Digital Citizenship*, 1-7. https://doi.org/10.1145/1551722.1551751

Rouibah, K., Lowry, P. B., & Hwang, Y. (2016). The effects of perceived enjoyment and perceived risks on trust formation and intentions to use online payment systems: New perspectives from an Arab country. *Electronic Commerce Research and Applications, 19*, 33-43. https://doi.org/10.1016/j.elerap.2016.07.001

Sarstedt, M., Henseler, J., & Ringle, C. M. (2011). Multigroup analysis in partial least squares (PLS) path modeling: Alternative methods and empirical results. In M. Sarstedt, M. Schwaiger, & C.R. Taylor (Eds.), *Measurement and research methods in international marketing (Advances in international marketing, Vol. 22)* (pp. 195-218). Emerald Group Publishing Limited. https://doi.org/10.1108/S1474-7979(2011)0000022012

Sarstedt, M., Ringle, C. M., Smith, D., Reams, R., & Hair, J. F. (2014). Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers. *Journal of Family Business Strategy, 5*(1), 105-115. https://doi.org/10.1016/j.jfbs.2014.01.002

Selwyn, N. (2007). Hi-tech = guy-tech? An exploration of undergraduate students' gendered perceptions of information and communication technologies. *Sex Roles*, *56*(7-8), 525-536. https://doi.org/10.1007/s11199-007-9191-7

Shao, Z., Zhang, L., Li, X., & Guo, Y. (2019). Antecedents of trust and continuance intention in mobile payment platforms: The moderating effect of gender. *Electronic Commerce Research and Applications, 33*. https://doi.org/10.1016/j.elerap.2018.100823

Shareef, M. A., Baabdullah, A., Dutta, S., Kumar, V., & Dwivedi, Y. K. (2018). Consumer adoption of mobile banking services: An empirical examination of factors according to adoption stages. *Journal of Retailing and Consumer Services, 43*, 54-67. https://doi.org/10.1016/j.jretconser.2018.03.003

Sharma, N., & Patterson, P. G. (2000). Switching costs, alternative attractiveness and experience as moderators of relationship commitment in professional, consumer services. *International Journal of Service Industry Management, 11*(5), 470-490. https://doi.org/10.1108/09564230010360182

Sharma, S. K., Mangla, S. K., Luthra, S., & Al-Salti, Z. (2018). Mobile wallet inhibitors: Developing a comprehensive theory using an integrated model. *Journal of Retailing and Consumer Services, 45*, 52-63. https://doi.org/10.1016/j.jretconser.2018.08.008

Sharma, S. K., Sharma, H., & Dwivedi, Y. K. (2019). A hybrid SEM-neural network model for predicting determinants of mobile payment services. *Information Systems Management*, *36*(3), 243-261. https://doi.org/10.1080/10580530.2019.1620504

Sharma, S. K., & Sharma, M. (2019). Examining the role of trust and quality dimensions in the actual usage of mobile banking services: An empirical investigation. *International Journal of Information Management, 44*, 65-75. https://doi.org/10.1016/j.ijinfomgt.2018.09.013

Shaw, N. (2015). Younger persons are more likely to adopt the mobile wallet than older persons, or are they? The moderating role of age. *The 21st Americas Conference on Information Systems* (*AMCIS 2015*). https://aisel.aisnet.org/amcis2015/AdoptionofIT/GeneralPresentations/28

Shin, D.-H. (2009). Towards an understanding of the consumer acceptance of mobile wallet. *Computers in Human Behavior, 25*(6), 1343-1354. https://doi.org/10.1016/j.chb.2009.06.001

Singh, N., & Sinha, N. (2020). How perceived trust mediates merchant's intention to use a mobile wallet technology. *Journal of Retailing and Consumer Services, 52*, 101894. https://doi.org/10.1016/j.jretconser.2019.101894

Singh, N., Sinha, N., & Liébana-Cabanillas, F. J. (2020). Determining factors in the adoption and recommendation of mobile wallet services in India: Analysis of the effect of innovativeness, stress to use and social influence. *International Journal of Information Management, 50*, 191-205. https://doi.org/10.1016/j.ijinfomgt.2019.05.022

Slade, E., Dwivedi, Y. K., Piercy, N. C., & Williams, M. D. (2014). Modeling consumers' adoption intentions of remote mobile payments in the United Kingdom: Extending UTAUT with innovativeness, risk, and trust: Consumers' adoption intentions of remote mobile payments. *Psychology & Marketing, 32*(8), 860-873. https://doi.org/10.1002/mar.20823

Slade, E., Williams, M., Dwivedi, Y., & Piercy, N. (2014). Exploring consumer adoption of proximity mobile payments. *Journal of Strategic Marketing, 23*(3), 209-223. https://doi.org/10.1080/0965254X.2014.914075

Sobieraj, S., & Krämer, N. C. (2020). Similarities and differences between genders in the usage of computer with different levels of technological complexity. *Computers in Human Behavior, 104*, 106145. https://doi.org/10.1016/j.chb.2019.09.021

Sobti, N. (2019). Impact of demonetization on diffusion of mobile payment service in India: Antecedents of behavioral intention and adoption using extended UTAUT model. *Journal of Advances in Management Research, 16*(4), 472-497. https://doi.org/10.1108/JAMR-09-2018-0086

Soni, M., Jain, K., & Kumar, B. (2019). Factors affecting the adoption of fashion mobile shopping applications. *Journal of Global Fashion Marketing, 10*(4), 358-376. https://doi.org/10.1080/20932685.2019.1649165

Statista. (2020). *Mobile payments worldwide – Statistics & Facts*. https://www.statista.com/topics/4872/mobile-payments-worldwide/

Statista. (2021a). *Annual transaction value of the next-generation payment technology market worldwide from 2015 to 2022*. https://www.statista.com/statistics/788318/worldwide-payment-technology-transaction-value-market-size/

Statista. (2021b). *Kuwait: Gross Domestic Product (GDP) in current prices from 1984 to 2024*. https://www.statista.com/statistics/438858/gross-domestic-product-gdp-in-kuwait/

Statista. (2021c). *Kuwait – Statistics & facts*. https://www.statista.com/topics/4650/kuwait/

Stoet, G., O'Connor, D. B., Conner, M., & Laws, K. R. (2013). Are women better than men at multi-tasking? *BMC Psychology, 1*(1), 18. https://doi.org/10.1186/2050-7283-1-18

Su, P., Wang, L., & Yan, J. (2018). How users' Internet experience affects the adoption of mobile payment: A mediation model. *Technology Analysis & Strategic Management, 30*(2), 186-197. https://doi.org/10.1080/09537325.2017.1297788

Sun, N., & Rau, P.-L. P. (2015). The acceptance of personal health devices among patients with chronic conditions. *International Journal of Medical Informatics, 84*(4), 288-297. https://doi.org/10.1016/j.ijmedinf.2015.01.002

Tan, G. W.-H., & Ooi, K.-B. (2018). Gender and age: Do they really moderate mobile tourism shopping behavior? *Telematics and Informatics, 35*(6), 1617-1642. https://doi.org/10.1016/j.tele.2018.04.009

Tan, G. W.-H., Ooi, K.-B., Chong, S.-C., & Hew, T.-S. (2014). NFC mobile credit card: The next frontier of mobile payment? *Telematics and Informatics, 31*(2), 292-307. https://doi.org/10.1016/j.tele.2013.06.002

Tang, C. Y., Lai, C. C., Law, C. W., Liew, M. C., & Phua, V. V. (2014). Examining key determinants of mobile wallet adoption intention in Malaysia: An empirical study using the unified theory of acceptance and use of technology 2 model. *International Journal of Modelling in Operations Management, 4*(3/4), 248. https://doi.org/10.1504/IJMOM.2014.067383

Teo, T. S. H., Srivastava, S. C., & Jiang, L. (2008). Trust and electronic government success: An empirical study. *Journal of Management Information Systems, 25*(3), 99-132. https://doi.org/10.2753/MIS0742-1222250303

Thaler, R. (1985). Mental accounting and consumer choice. *Marketing Science, 4*(3), 199-214. https://doi.org/10.1287/mksc.4.3.199

Tison, G. H., Sanchez, J. M., Ballinger, B., Singh, A., Olgin, J. E., Pletcher, M. J., Vittinghoff, E., Lee, E. S., Fan, S. M., Gladstone, R. A., Mikell, C., Sohoni, N., Hsieh, J., & Marcus, G. M. (2018). Passive detection of atrial fibrillation using a commercially available smartwatch. *JAMA Cardiology, 3*(5)*,* 409. https://doi.org/10.1001/jamacardio.2018.0136

Urbach, N., & Ahlemann, F. (2010). Structural equation modeling in information systems research using partial least squares. *Journal of Information Technology Theory and Application*, *11*(2), 5-40.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2)*,* 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly, 24*(1), 115-139. https://doi.org/10.2307/3250981

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3)*,* 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1)*,* 157-178. https://doi.org/10.2307/41410412

Verkijika, S. F. (2020). An affective response model for understanding the acceptance of mobile payment systems. *Electronic Commerce Research and Applications, 39*. https://doi.org/10.1016/j.elerap.2019.100905

Voorhees, C. M., Brady, M. K., Calantone, R., & Ramirez, E. (2016). Discriminant validity testing in marketing: An analysis, causes for concern, and proposed remedies. *Journal of the Academy of Marketing Science, 44*(1)*,* 119-134. https://doi.org/10.1007/s11747-015-0455-4

Wang, E. S.-T. (2010). The effects of browsing frequency and gender on the relationship between perceived control and patronage intentions in E-tail. *International Journal of Electronic Commerce, 14*(3)*,* 129-144. https://doi.org/10.2753/JEC1086-4415140306

Wang, L. & Yi, Y. (2012) The impact of use context on mobile payment acceptance: An empirical study in China. In A. Xie & X. Huang (Eds.), *Advances in computer science and education (Advances in intelligent and soft computing, Vol. 140)* (pp. 293-299). Springer. https://doi.org/10.1007/978-3-642-27945-4_47

Wang, S., Ngamsiriudom, W., & Hsieh, C.-H. (2015). Trust disposition, trust antecedents, trust, and behavioral intention. *The Service Industries Journal, 35*(10)*,* 555-572. https://doi.org/10.1080/02642069.2015.1047827

Wei, T. T., Marthandan, G., Chong, A. Y. L., Ooi, K., & Arumugam, S. (2009). What drives Malaysian m-commerce adoption? An empirical analysis. *Industrial Management & Data Systems, 109*(3), 370-388. https://doi.org/10.1108/02635570910939399

Widodo, M., Irawan, M. I., & Ambarwati Sukmono, R. (2019). Extending UTAUT2 to explore digital wallet adoption in Indonesia. *The 2019 International Conference on Information and Communications Technology (ICOIACT)* (pp. 878-883). https://doi.org/10.1109/ICOIACT46704.2019.8938415

Wu, J.-H., & Wang, S.-C. (2005). What drives mobile commerce? An empirical evaluation of the revised technology acceptance model. *Information & Management, 42*(5)*,* 719-729. https://doi.org/10.1016/j.im.2004.07.001

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

Yan, A. W., Md-Nor, K., Abu-Shanab, E., & Sutanonpaiboon, J. (2009). Factors that affect mobile telephone users to use mobile payment solution. *International Journal of Economics and Management, 3*(1), 37-49.

Zhang, J., & Mao, E. (2020). Cash, credit, or phone? An empirical study on the adoption of mobile payments in the United States. *Psychology & Marketing, 37*(1), 87-98. https://doi.org/10.1002/mar.21282

Zhang, Y., Dang, Y., Brown, S. A., & Chen, H. (2017). Investigating the impacts of avatar gender, avatar age, and region theme on avatar physical activity in the virtual world. *Computers in Human Behavior, 68*, 378-387. https://doi.org/10.1016/j.chb.2016.11.052

Zhao, H., Anong, S. T., & Zhang, L. (2019). Understanding the impact of financial incentives on NFC mobile payment adoption: An experimental analysis. *International Journal of Bank Marketing, 37*(5)*,* 1296-1312. https://doi.org/10.1108/IJBM-08-2018-0229

Zhou, T. (2011). The effect of initial trust on user adoption of mobile payment. *Information Development, 27*(4), 290-300. https://doi.org/10.1177/0266666911424075

Zhou, T. (2012). Understanding users' initial trust in mobile banking: An elaboration likelihood perspective. *Computers in Human Behavior, 28*(4), 1518-1525. https://doi.org/10.1016/j.chb.2012.03.021

Zhou, T. (2013). An empirical examination of continuance intention of mobile payment services. *Decision Support Systems, 54*(2), 1085-1091. https://doi.org/10.1016/j.dss.2012.10.034

Zhou, T. (2014). An empirical examination of initial trust in mobile payment. *Wireless Personal Communications, 77*(2)*,* 1519-1531. https://doi.org/10.1007/s11277-013-1596-8

Zhu, Y.-Q., & Chen, H.-G. (2011). An integrative model of consumer's adoption of RFID credit card service. Presented in the *44th Hawaii International Conference on System Sciences*, 1-9. https://doi.org/10.1109/HICSS.2011.57

Zogheib, B., Rabaa'i, A., Zogheib, S., & Elsaheli, A. (2015a). University student perceptions of technology use in mathematics learning. *Journal of Information Technology Education: Research, 14*, 417-438. https://doi.org/10.28945/2315

Zogheib, S., Rabaa'I, A., Zogheib, B., & Saheli, A. E. (2015b). University students' acceptance of technology in math classes: Does gender matter? *Journal of Emerging Trends in Engineering and Applied Sciences*, *6*(4), 273-287.

Zupanovic, D. (2015). Implementation model for near field communication in Croatian ferry ticketing system. *Procedia Engineering, 100*(2015), 1396-1404.

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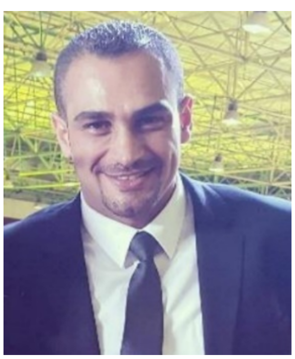

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