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A Dual-Stage SEM-ANN Analysis to Explore Consumer Adoption of Smart Wearable Healthcare Devices

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ABSTRACT

Advances in information technology have included the development of smart wearable healthcare (SWH) devices that have potential benefits for consumer health. The adoption of SWH devices is limited, however, compared with other established digital technologies. This study examines the determinants of consumers' adoption of SWH devices. A conceptual model is proposed that incorporates health (health beliefs and health information accuracy) and technology (compatibility and functional congruence) attributes into the technology acceptance model framework. The proposed model was tested in two steps. Structural equation modelling (SEM) was performed with 473 usable responses to test the hypothesized relationships. The artificial neural network (ANN) approach was then applied to validate the outcomes of Step 1. The SEM analysis indicates that all the hypothesized relationships are supported. The ANN analysis further validates the outcomes of the SEM. The findings of this study and the dual-stage SEM-ANN methodology will have a strong impact on the existing literature regarding SWH devices.

KEYWORDS

Artificial Neural Network, Compatibility, Functional Congruence, Health Information Accuracy, Smart Wearable Healthcare Devices

INTRODUCTION

Advances in information and communication technology (ICT) mean that consumers actively use mobile devices in all areas of human activity. Smart wearable devices (SWDs) have emerged from the popularity of mobile devices (Fang & Chang, 2016). Countless SWDs have been developed, including smartwatches, wristbands, fitness trackers, keychains, rings, jackets and glasses (Jee & Sohn, 2015). SWDs are currently available everywhere, and have become very popular among users (Farivar, Abouzahra, & Ghasemaghaei, 2020). SWDs are used in a variety of sectors, such as communication, management, healthcare and sports (Park, 2020). Deliveries of SWD will reach 9.6 million in 2022, with an 11% compound annual growth rate between 2017 and 2022 (CSS Insight, 2018). It has been forecasted by Gartner (2019) that end-user expenditure on SWDs will reach $52 billion in 2020.

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The SWD refers to smart wearable electronic devices that use seamlessly embedded computers and other electronics and allow ubiquitous interactions between a smart environment and the user (Dehghani & Dangelico, 2017). One of the main applications for SWD is in the medical field and healthcare (Zhang, Luo, Nie, & Zhang, 2017). Presently, m-health has become an integral part of healthcare systems (Nisha, Iqbal, & Rifat, 2019). The Global Observatory for e-Health (GOe) working under the World Health Organization (WHO) has defined m-health as the medical and public health services supported by mobile devices like mobile phones, personal digital assistants, patient monitoring devices, and other wireless devices (Global Observatory for eHealth, 2011). Smart wearable healthcare (SWH) devices play critical role in m-health. SWH devices range from fitness trackers to more sophisticated devices (Casselman, Onopa, & Khansa, 2017; Marakhimov & Joo, 2017). Examples of SWH devices include the Fitbit, Apple Watch, Xiaomi Mi Band wristband and Samsung Gear (Cheung et al., 2019). P&S Market Research has reported that the market for SWH devices is expected to reach $1630.3 million in 2020, following a growth rate of 46.6% during 2015-2020 (He Li, Wu, Gao, & Shi, 2016; Zhang et al., 2017). SWH devices combine healthcare and technology to monitor health activities and provide real-time health information (Zhang et al., 2017). SWH devices provide extensive benefits to consumers in the continual tracking of physical parameters and recording of health information (K. J. Kim & Shin, 2015). SWH device monitoring is helpful in decreasing hospital admissions and mortality rates, sending alerts to physicians, improving physical and mental life, and managing emergencies (S. Y. Lee & Lee, 2018). These devices are helpful in keeping the individuals aware of their health status about the calories consumption and exercise activities. Consequently, such health monitoring is expected to be beneficial in controlling critical disorders due to the higher levels of hypertension, diabetes, and cardiovascular attacks. Thus, hospital emergencies are significantly decreased. SWH devices have the potential to reduce healthcare costs and improve the efficiency of healthcare (He Li et al., 2016). In case of remote patients' monitoring, the physicians are able to monitor remotely the patients' health status. The individuals with chronic diseases, or patients who need continual monitoring, are equipped with SWH devices. These devices can transmit data to medical monitors or smartphones for detailed investigation. If any critical changes relevant to the disease are found, alerts are sent to the physicians. Due to remote patients' monitoring, unnecessary visits to the hospitals are decreased and healthcare cost is reduced (Roman et al., 2015).

Despite the important benefits of using SWH devices, their adoption is limited in comparison with other established digital technologies such as tablets and smartphones (Cheung et al., 2019). This is due to insufficient knowledge about user adoption intentions regarding SWH devices (Chau et al., 2019). Research into the adoption of SWH devices is limited (Cheung et al., 2019). Most studies have investigated the adoption of SWH devices by elderly people (Abouzahra & Ghasemaghaei, 2020; J. Li, Ma, Chan, & Man, 2019; Talukder, Sorwar, Bao, Ahmed, & Palash, 2020). The SWH devices are equally important for younger and older people (Papa, Mital, Pisano, & Del Giudice, 2020). To fill this gap, this study examines the adoption of SWH Devices by individuals from every walk of life, and all ages above 14 years. Some studies have used the technology acceptance model (TAM) or unified theory of acceptance and use of technology (UTAUT) in the context of SWH device adoption (Cheung et al., 2019; J. Li et al., 2019; Papa et al., 2020; Talukder et al., 2020). These studies focused more on technology adoption rather than considering the integration of consumer attributes and health attributes with technology attributes (Zhang et al., 2017). Many researchers have also noted that future studies should explore the drivers of the consumer intentions that influence the adoption of SWH devices (J. Li et al., 2019; Marakhimov & Joo, 2017; Papa et al., 2020). This study uses a dual-stage structural equation modelling-artificial neural network (SEM-ANN) approach to validate the conceptual model of the study. It uses TAM as the base model to investigate user adoption of SWH devices and incorporates the health attributes and technology attributes into the TAM framework. To examine the important factors influencing intentions to use SWH devices, sample data was collected from Saudi Arabia and 473 usable cases were used for data analysis.

This study contributes to research on SWH devices in many ways. It advances the TAM framework to understand and predict consumer adoption of SWH devices. Additional constructs such as health beliefs, health information accuracy, functional congruence and compatibility are required for a thorough understanding of SWH device acceptance. The use of SEM-ANN approach provides deeper insights into linear and non-linear relationships. This is a methodological advance from the SWH device perspective. Such a hybrid approach provides deeper insights into the phenomenon under study, and the shortcomings of one method are balanced by the strengths of the other (Scott & Walczak, 2009). The importance of conventional statistical methods is not disregarded by this research, as prior research has provided a strong base for the predictive interpretation of results. Moreover, future research may broaden the scope of this research to global perspective by using cross-country data.

The remaining sections of the paper are ordered as follows. A review of the literature about the background of the problem is presented, followed by the development of the proposed model and the corresponding hypotheses. Second, the methodology used to test the hypotheses and validate the proposed model is presented. Third, there is a discussion and conclusions based on statistical results. Finally, we present theoretical and practical implications of this research covering limitations and directions for future research.

BACKGROUND AND DEVELOPMENT OF THE FRAMEWORK

Smart Wearable Healthcare (SWH) Devices

In this study, SWH devices are defined as devices worn by the users to monitor their physical activities and vital signs such as distance covered, number of steps, calories, pulse rate, heartbeat and blood pressure (Farivar et al., 2020). SWH devices numerically quantify the conscious and unconscious activities of humans in daily life (J. Lee, Kim, Ryoo, & Shin, 2016). Users are encouraged to be more active through motivational notifications and comparing their statistics with those of their friends and peers (M. S. Patel, Asch, & Volpp, 2015). SWH devices use different sensors to monitor the physiological status and physical activities of users, and to capture data (J. Lee et al., 2016). Wearable sensors carry out monitoring, tracking, and diagnosis through physiological, biochemical and motion sensing (Mostarac et al., 2011; S. Patel, Park, Bonato, Chan, & Rodgers, 2012).

SWH devices can monitor health status and track physical activities at any time and any place. These devices are manufactured to be worn on different body parts, such as the wrist, head, arm, ear, neck, trunk, finger, or foot. Some devices can even be fitted inside the human body (J. Lee et al., 2016). The fast growth of internet of things (IOT), big data and the adoption of small wearable biosensors have provided more e-health and m-health opportunities. The use of SWH devices has numerous advantages for consumers of all ages. Despite the potential benefits of such devices, however, their adoption is still very low and more research is needed to investigate user acceptance of SWH devices (Farivar et al., 2020; Papa et al., 2020).

SWH devices are still in the early stages and research into the adoption of SWH devices is limited. To fill the research gap, this study proposes a model to investigate the antecedents of consumer adoption of SWH devices by extending the TAM framework and combining health attributes (health beliefs and health information accuracy), technology attributes (compatibility and functional congruence) and consumer attributes (perceived usefulness and perceived ease of use) in the same conceptual model.

Technology Acceptance Model (TAM)

TAM was developed by Davis (1989), and it has been used extensively to understand individual and organizational technology adoption. According to TAM, perceived ease of use and perceived usefulness are the two determinants of user attitudes towards system use. Intentions to use the system are influenced by people's attitudes, while the actual use of the system is determined by the users' intentions to use (Davis, 1989).

TAM is considered a pioneering technology adoption model and studies in the context of wearable healthcare technology have used TAM widely to investigate the adoption of wearable technology (Baudier, Ammi, & Lecouteux, 2019; Baudier, Ammi, & Wamba, 2020; Chang, Wang, & Wills, 2020; Cheung et al., 2019; Holden & Karsh, 2010; J. Li et al., 2019; Pai & Huang, 2011; Papa et al., 2020; Zhang et al., 2017). To explore the employee's acceptance of healthcare devices, Baudier et al. (2019) used TAM framework by integrating self-tracking motivations, self-determinations and trusting belief. Their findings confirmed attitude and benevolence as the direct antecedents of behavioral intention while motivations, PEU and PU proved to be indirect influencers of behavioral intention. Baudier et al. (2020) combined perceived connectivity and perceived playfulness to TAM to compare the perceptions of smartwatch users in developing countries. Similarly, TAM was also employed by Chang et al. (2020) to investigate the use and non-use of hearing aids in smart cities. Cheung et al. (2019) used TAM as the base model to examine the adoption of healthcare wearable technology by consumers, combined with other factors such as reference group influence, consumer innovativeness, health beliefs, health information accuracy and privacy protection. Papa et al. (2020) integrated intrusiveness and comfort constructs to TAM to study the e-health monitoring using smart healthcare devices, comfort was found to have a significant impact on perceived ease of use and attitude, but the effects of intrusiveness on perceived ease of use and perceived usefulness were not found to be significant, although its effects on attitude were significant. J. Li et al. (2019) incorporated social influence and facilitating condition variables from the UTAUT model, compatibility, health conditions, perceived social risk, and perceived performance risk factors, with the TAM framework to investigate the health monitoring of older adults through wearable technologies. Their findings validated the TAM framework and confirmed that incorporating other factors in the TAM framework improves its explanatory power in the context of healthcare wearable technology. Pai & Huang (2011) applied the TAM to study the health information systems and incorporated TAM with DeLone and McLean success model. Their results proved the direct significant effects of PU and PEU on intention to use while information quality, service quality and system quality exerted indirect effects on intention to use.

The TAM model is a suitable model to investigate the critical factors in user's acceptance of new information technology (Papa et al., 2020). SWH devices are a relatively new informal digital technology, and therefore this study uses TAM as the base model to study the adoption of SWH devices by users, and incorporates health attributes (health beliefs and health information accuracy) and technology attributes (compatibility and functional congruence) into the TAM framework.

Based on the arguments of DeLone & McLean (2003), the authors of this study believe that the 'Intention to Use' and the 'Actual System Use' variables are alternatives of each other in the adoption of SWH devices. Therefore, the actual use variable has been skipped. Previous research used similar practices in the context healthcare devices adoption (Cheung et al., 2019; Ilie, n.d.; Haitao Li, 2021; J. Li et al., 2019; Papa et al., 2020; Talukder et al., 2020).

Additional Constructs of the Proposed Model

The health belief (HB) refers to an individual's belief about the effectiveness of a particular behavior in improving their health status (Zhang et al., 2017). The user's belief about health related threat and the usefulness of a technology anticipate the possibility of adopting that technology (J. Kim & Park, 2012). Therefore, examining the role of HB in influencing the users' intentions to use SWH devices is important (Chau et al., 2019). Empirical studies have confirmed the key role of health belief in the adoption of healthcare wearable devices (Chau et al., 2019; Cheung et al., 2019; Zhang et al., 2017).

The users' beliefs about the credibility and reliability of the information provided by SWH devices is referred to as Health information accuracy (HIA) (Cheung et al., 2019). The credibility of health related information is crucial for making decisions relevant to health (Owen, Fotheringham, & Marcus, 2002). The SWH devices will lead to mismanagement of health if these devices produce unreliable and inaccurate information (Marakhimov & Joo, 2017). Researchers have confirmed significant positive effects of the accuracy/credibility of health information on a consumer's adoption of health informatics (Kawakami & Parry, 2013; Marakhimov & Joo, 2017; Shin, Lee, & Hwang, 2017; Zhang et al., 2017).

The functional congruence (FUC) refers to the degree of perceptions of the users about the suitability of a product or brand for their product-related and functional needs (Huber, Vollhardt, Matthes, & Vogel, 2010). As SWH devices need some special features such as the battery, function, material and their comfort make them unique from other healthcare technologies and the quality measures of the product, play a vital role in consumer assessments of SWH devices (Chan, Estève, Fourniols, Escriba, & Campo, 2012; He Li et al., 2016). Past research has established the direct or indirect effects of FUC on behavioral intention to use wearable healthcare technology (He Li et al., 2016; Talukder et al., 2020). Cheng (2015) has posited that the users adopt an innovation if they find it compatible with their needs and lifestyle. Vital role of compatibility in the users' adoption of wearable devices has been established by prior research (Jeong, Kim, Park, & Choi, 2017; J. Li et al., 2019; Schmidthuber, Maresch, & Ginner, 2020). Derived from these facts, we chose the health attributes (health beliefs and health information accuracy) and technology attributes (compatibility and functional congruence) to integrate into the TAM framework.

Conceptual Framework and Hypotheses

Perceived Ease of Use (PEU)

Davis (1989) defined PEU as "the degree to which a person believes that using a particular system would be free from effort". In this study, PEU refers to the degree of ease perceived by the user when using SWH devices (Papa et al., 2020). Several studies of SWH device adoption have established the significant effects of PEU on perceived usefulness and/or behavioral intention to use SWH devices (J. Li et al., 2019; Papa et al., 2020). PEU was found to have a significant impact on perceived usefulness and attitudes to use in the context of smartwatch adoption (Chuah et al., 2016; Huang & Ren, 2020; K. J. Kim & Shin, 2015). Significant impacts of effort expectancy (Ease of Use) on intention to use were confirmed by scholars in other contexts of IS also (Abdou & Jasimuddin, 2020; Almuraqab, Jasimuddin, & Mansoor, 2021; Jasimuddin, Mishra, & A. Saif Almuraqab, 2017; Rouibah, Dihani, & Al-Qirim, 2020; Saif, Almuraqab, Jasimuddin, & Mansoor, 2017). Gholami, Singh, Agrawal, Espinosa, & Bamufleh (2021) confirmed indirect effects of PEU on behavioral intention. In this study, we assume that if SWH devices are easy to use, then user perceptions of their usefulness will improve, which will affect their intention to use SWH devices positively. We thus hypothesize:

H1: PEU has significant impacts on (a) perceived usefulness, and (b) behavioral intention to use SWH devices

Perceived Usefulness (PU)

Perceived usefulness (PU) as derived from TAM refers to the degree a user believes that using a specific technology will improve their job performance (Davis, 1989). In this study, PU means the extent of the user's belief that a SWH device would improve their health status. Research into SWH devices has posited that PU has significant effects on behavioral intention to use SWH devices (Cheung et al., 2019; Chuah et al., 2016; Huang & Ren, 2020; Park, 2020; Zhang et al., 2017). Chang, Chen, Xu, & Xiong (2021) have also confirmed significant impacts of PU on behavioral intention in the context of mobile payments. Users critically assess the benefits of SWH devices and will intend to use it if SWH devices are found useful (J. Li et al., 2019). It is thus hypothesized:

H2: PU has significant impacts on behavioral intention to use SWH devices

Functional Congruence (FUC)

The functional congruence (FUC) factor was adapted from self-congruency theory (Sirgy, 1985). FUC refers to the extent that users perceive a product or brand suitable for their product-related and functional needs (Huber et al., 2010). Special features such as sensors and mobility mean that SWH devices are not like other devices (Gao, Li, & Luo, 2015). Users need to wear SWH devices 24 hours a day to provide real-time healthcare monitoring, and some features of SWH devices such as the battery, material and their comfort make them unique from other healthcare technologies (Chan et al., 2012). The quality measures of the product, such as function, comfort, and duration of battery, play a vital role in consumer assessments of SWH devices (He Li et al., 2016). This study therefore expects that users will be more concerned about functional congruence in the adoption of SWH devices. The adoption of healthcare wearable devices by individuals was studied by H. Li et al. (2016), who confirmed that FUC has significant effects on perceived benefits, and that the relationship between FUC and adoption intention is mediated by perceived benefits. In another study, (Talukder et al., 2020) investigated the acceptance of wearable healthcare technology by elderly people, and established the direct significant effects of FUC on behavioral intention to use wearable healthcare technology. In the context of this study, we assume the positive effects of FUC on PU and behavioral intention to use SWH devices. We therefore hypothesize:

H3: Functional congruence has significant impacts on (a) perceived usefulness, and (b) behavioral intention to use SWH devices

Health Belief (HB)

The health belief model (HBM) was developed by social psychologists in the US Public Health Service to investigate the behaviors of people why they do not contribute in early detection and prevention programs (Ariyasriwatana, Buente, Oshiro, & Streveler, 2014). The HBM predicts the behavior of an individual regarding the initial treatment of acute or chronic diseases (Ahadzadeh, Pahlevan Sharif, Ong, & Khong, 2015). The HBM posits that people's health-related behavior is prompted by four main constructs, namely susceptibility, benefits, severity, and barriers (Zhang et al., 2017). Bearing in mind the importance of information technology (IT) in predicting an individual's health-related behavior, Ahadzadeh et al. (2015) incorporated HBM and TAM and posited that individuals who believe that their health is suffering from acute or chronic disease are motivated towards the use of IT to improve their health. In the context of SWH devices, individuals who believe that irregular health behavior can harm their health are motivated to use SWH devices to manage their health activities (Chau et al., 2019).

Health belief (HB) derives from the HBM, and refers to an individual's belief about the effectiveness of a particular behavior in improving their health status (Zhang et al., 2017). The data provided by SWH devices is helpful in activity tracking, evaluating the performance of exercises and planning customized exercises (J. Lee et al., 2016). The main objective of SWH devices is to bring changes to the health behaviors of consumers and improve their health status (Zhang et al., 2017). Empirical studies have used health belief constructs to examine consumer behaviors regarding the adoption of healthcare wearable devices, and have confirmed significant effects of HB on perceived usefulness and behavioral intention to use healthcare wearable devices (Chau et al., 2019; Cheung et al., 2019; Zhang et al., 2017). Consumers with stronger health beliefs constantly try to improve their health status. Such consumers may find information about the usefulness of SWH devices improves their perceptions of the usefulness of SWH devices. Having strong health beliefs influences the behavioral intention of consumers to use SWH devices. We therefore hypothesize:

H4: Health belief has significant impacts on (a) perceived usefulness (b) behavioral intention to use SWH devices.

Health Information Accuracy (HIA)

Health information accuracy (HIA) refers to the extent that users believe that the information related to their health status provided by a SWH device is credible and reliable (Cheung et al., 2019). SWH devices acquire user health data continuously, then analyze it and present diagnostic reports for the user about their health status. Inaccurate health information caused by inaccurate health services has no value and such inaccurate health services can cause a great deal of damage (Zhang et al., 2017). To examine the link between a consumer's effective response to health informatics and the credibility of health data, Shin et al. (2017) demonstrated that health data credibility has significant effects on consumer's adoption of health informatics. The credibility of health data is important, because health-related decisions are based on health data. Inaccurate data from SWH devices leads to the mismanagement of health (Marakhimov & Joo, 2017). On the other hand, the accuracy of health information delivered by SWH devices has positive effects on consumer willingness to use health information for decisions related to their health, which in turn positively affects their perceptions of the usefulness of SWH devices (Kawakami & Parry, 2013; Shin et al., 2017). On this basis, this study assumes that the accuracy of health information has positive effects on perceived usefulness. Therefore, we hypothesize:

H5: Health information accuracy has significant impacts on perceived usefulness.

Compatibility (COMP)

According to the diffusion of innovation theory (DIT), compatibility refers to the degree to which users believe that a specific innovation complies with their needs, lifestyle, experience, and existing values (Rogers, 1995). Users adopt an innovation if they find it compatible with their needs and lifestyle (Cheng, 2015). J. Li et al. (2019) investigated the health monitoring of older adults through wearable technologies, and found significant effects of compatibility on perceived usefulness and ease of use. Similar results were found in other studies, also in the context of wearable devices (Choi & Kim, 2016; Jeong et al., 2017; Schmidthuber et al., 2020). SWH devices are compatible with existing smart devices (smartphones, PCs and wireless sensor network) and monitored information about health status can be transferred to these devices. If consumers find a SWH device to be compatible with their lifestyle, and their needs are fulfilled, they will adopt SWH devices. We thus expect that compatibility will have positive significant effects on perceived usefulness and perceived ease of use in the context of this study. We thus hypothesize:

H6: Compatibility has significant impacts on (a) perceived usefulness, and (b) perceived ease of use.

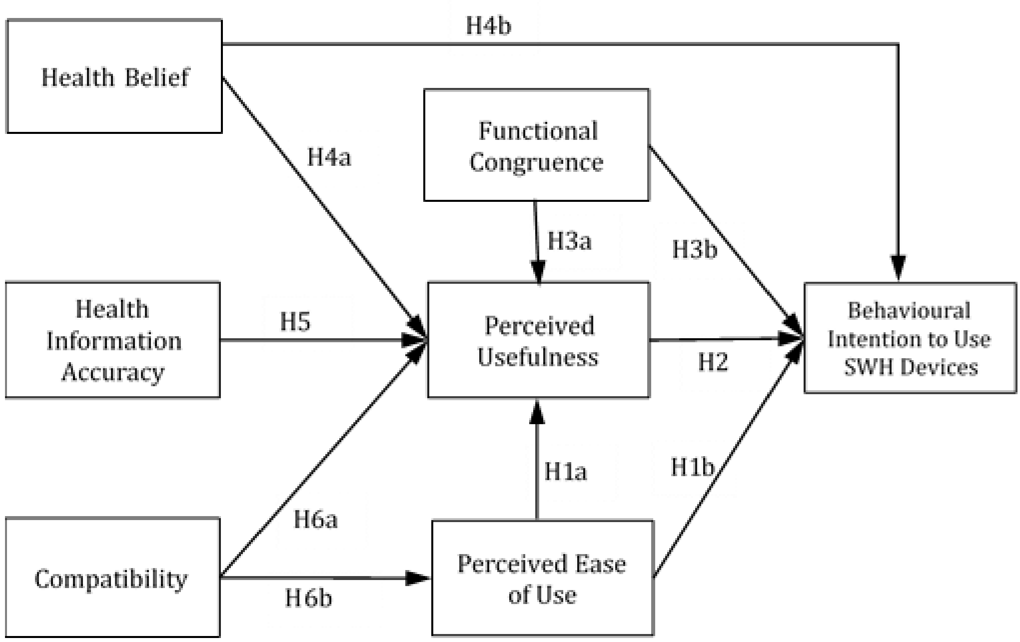
The proposed model of the study is depicted in Figure 1 below.

RESEARCH METHODOLOGY

Instrument Development

This study used a quantitative approach. The main purpose of quantitative data collection is to produce reliable, generalizable, effective and valid measures (Creswell, 2003). The quantitative approach is useful in achieving higher levels of reliability of the collected data (Balsley, 1970). The survey, used to collect data, contained a total of 23 items. Scales have been adapted from well-established research to measure the latent constructs of the proposed model. Functional congruence, compatibility, and perceived ease of use were measured using three items, each adapted from Talukder et al. (2020), Sohail & Al-jabri (2013), and Park (2020) respectively. Four items for perceived usefulness were adapted from Papa et al. (2020) and Park (2020). Health belief and behavioral intention were measured

Figure 1. Proposed model of the study



using four items, each adapted from Cheung et al.(2019) and Alalwan et al. (2017). Health information accuracy was measured using two items Cheung et al. (2019). A pilot survey with 41 SWH device users was carried out before distributing the final survey to ensure the clarity and accuracy of the questions. After the necessary revisions and satisfactory results from the pilot study, the questionnaire was distributed for data collection. Likert scales (1-5) ranging from "Strongly Disagree" to "Strongly Agree" were used for all items. The measurement items of this study are listed in Appendix 1.

Data Collection & Sample

The sample was collected from respondents in Saudi Arabia by employing expert sampling form of the purposive sampling technique. The survey was served online to respondents from four public universities, six contracting and trading companies. The questionnaires were also served to individuals by using their social media contacts. Hardcopies of survey were also served to respondents in different cities of Saudi Arabia like Riyadh, Dammam, Jeddah, Taif, Abha, Jazan, Madinah, and Tabuk to cover all the geographic areas of the country. Data collection was carried during July-August 2020 and June 2021. A screening question was added at the beginning of the survey "Do you use any smart wearable healthcare device?" The aim of this question was to focus on respondents who have been using SWH devices.

As this study uses SEM-ANN approach, therefore, the appropriate sample considerations for both SEM and ANN methods are needed. The rule of thumb for minimum sample size in a PLS-SEM model is equivalent to 10 times the maximum number structural paths directed to a latent variable anywhere in the model (Hair Jr, Hult, Ringle, & Sarstedt, 2017). According to Stevens (2002), 15 cases per predictor construct are recommended in least squares multiple regression. For reliable and meaningful ANNs, the minimum number of cases should be 10 times the number of weights in the network (Abu-Mostafa, 1995; Haykin, 2009). Our ANN model B has the highest number of weights which is 29. Thus the minimum sample size for ANN model is 10 x 29 = 290. We used a sample of 473 which is fulfilling the criteria both for PLS-SEM and ANN models.

A total of 492 responses were gathered. Nineteen cases were discarded during the data-screening phase due to missing data. The remaining 473 cases were used for data analysis. In this sample, 52.4% of respondents were males, and 47.6% were female. Within the respondents, 28.5% were aged 15-to-25 years, 27.1% were from 26-to-35 years, 24.3% were from 36-to-45 years, and 20.1% were above 45 years. In terms of their educational qualifications, 27.5% were high school, 35.5% undergraduate, 30.2% had master's degrees, and 6.8% PhDs.

Statistical Analysis

We used the partial least squares - structural equation modelling (PLS-SEM) method to test the relationships within the conceptual model. Unlike covariance-based SEM, PLS-SEM can handle complicated models that contain a large number of constructs (Urbach & Ahlemann, 2010). According to Leong, Hew, Ooi, Lee, & Hew (2019), examining multivariate assumptions (such as linearity, normality, and multicollinearity) is important before the multivariate analysis. An ANOVA test was carried out to determine the linearity of relationships. The results in Table 1 indicate that four relationships were non-linear (V. H. Lee, Hew, Leong, Tan, & Ooi, 2020). We used the one-sample Kolmogorov-Smirnov test to assess the normality of data, and the results showed that the data distribution was non-normal. The PLS-SEM is an appropriate method to assess the model if the data distribution is non-normal (Hew, Tan, Lin, & Ooi, 2017). The variance inflation factor (VIF) was examined to ascertain the multicollinearity. The VIF values ranged between 1.67 to 2.84, which suggests that multicollinearity was not an issue in the data (Leong et al., 2019).

PLS-SEM is a better method than factor-based SEM as the data distribution is non-normal (Hew, Tan, et al., 2017). The presence of non-linear relationships in the model means that dual-stage analysis, where the PLS-SEM analysis is followed by ANN analysis, is more beneficial as composite-based SEM and factor-based SEM cannot handle the non-linear relationships (V. H. Lee et al., 2020; Leong et al., 2019).

Table 1. ANOVA table

ANOVA Table		Sum of Squares	df	Mean Square	F	Sig.	Linear
BI * FUC	Deviation from Linearity	36.924	57	0.648	1.156	0.215	Yes
BI * HB	Deviation from Linearity	132.657	124	1.070	2.218	0.000	No
BI * PEU	Deviation from Linearity	39.077	32	1.221	2.400	0.000	No
BI * PU	Deviation from Linearity	123.923	91	1.362	3.539	0.000	No
PU * COMP	Deviation from Linearity	64.948	64	1.015	1.459	0.017	No
PU * FUC	Deviation from Linearity	43.438	57	0.762	1.203	0.159	Yes
PU * HB	Deviation from Linearity	110.037	124	0.887	1.468	0.004	No
PU * HIA	Deviation from Linearity	7.963	13	0.613	1.153	0.312	Yes
PU * PEU	Deviation from Linearity	63.435	32	1.982	3.537	0.000	No
PEU * COMP	Deviation from Linearity	41.622	47	0.886	1.359	0.077	Yes

Note: BI: Behavioural Intention: FUC: Functional Congruence; HB: Health Belief; PEU: Perceived Ease of Use; PU: Perceived Usefulness; COMP: Compatibility; HIA: Health Information Accuracy

The ANN is a modelling technique which can obtain knowledge through its learning process (Hew, Leong, Tan, Lee, & Ooi, 2018). The ANN resembles the human brain, in containing neurons, synapses, and axons (Talukder et al., 2020). The ANN can be trained to improve its performance

(Hew, Badaruddin, & Moorthy, 2017). The learning ability of ANN distinguishes it as a superior method to other conventional multivariate analytical methods (V. H. Lee, Foo, Leong, & Ooi, 2016). The ANN links the input and output data using artificial neurons and their interrelationships in the hidden layers to improve prediction capability without a theoretical model (Leong et al., 2019). The black box operation means that the ANN is unable to determine the significance level of casual relationships, which makes it unsuitable for hypotheses testing (V. H. Lee et al., 2020). For this reason, combining the two methods, SEM and ANN, is beneficial in order to take advantage of both methods (Ooi, Hew, & Lin, 2018). Both SEM and ANN provide a more rigid data analysis by complementing each other (Hew, Badaruddin, et al., 2017; Leong et al., 2019). To conduct this dual-stage analysis, the PLS-SEM is first used to evaluate the statistical significance of the exogenous constructs, then the ANN analysis is carried out to understand the importance of exogenous constructs towards their endogenous constructs (V. H. Lee et al., 2020; Ooi, Lee, Tan, Hew, & Hew, 2018).

Common Method Bias

The bias caused by using the same source for collecting data about dependent and independent variables is referred to as common method bias (CMB). CMB is produced if a single factor explains most of the variance (Philip M, Scott B, Jeong-Yeon, & Nathan P, 2003). Harman's single-factor test was used to evaluate CMB. The results of the test indicate that a single factor explains 42.9% of the variance, which is less than the threshold value 50%. CMB is thus not an issue in our data. The latent variables' VIF values were also examined to assess CMB. Kock & Lynn (2012) recommended that VIF values less than 3.3 indicate the non-existence of CMB. Collinearity test results produced VIF values less than 3, which further confirmed that there was no CMB in our data.

PLS-SEM Analysis

Assessment of Measurement Model

To assess the measurement model, in first stage, the internal consistency reliability, composite reliability and indicator reliability were tested to assess the reliability as recommended by Hair Jr et al. (2017). We used the criteria Cronbach's alpha>0.6 for internal consistency while the threshold values (>0.7) was used for composite reliability and indicators' reliability. The results of reliability tests are shown in Table 2. The Cronbach's alpha, composite reliability and indicator reliability are higher than the threshold values. The results thus indicate that the measurement items can measure consistently the required concept to be measured.

In second stage of measurement model assessment, validity of the model was tested. Two tests, convergent validity and discriminant validity, were conducted to check the validity of the measurement model. For convergent validity testing, we examined the AVE (average variance extracted) values as listed in Table 3. All AVE values are more than the threshold value of 0.5 which indicates the establishment of the convergent validity of the scales.

Fornell-Lacker's Criterion and Heterotrait-Monotrait Ratio (HTMT) were assessed to examine discriminant validity. Table 4 below shows the results of discriminant validity. The diagonal elements indicate Fornell-Lacker's Criterion. The diagonal elements demonstrate that the square root of the AVE of each construct is higher than its corresponding correlations with other variables. It establishes the discriminant validity. The elements above the diagonal elements show the HTMT ratio. Henseler, Ringle, & Sarstedt (2015) suggested that the HTMT value between any two variables should be below 0.9. The results of HTMT further confirm that discriminant validity is established.

Structural Model Analysis

The bootstrapping procedure was applied with 5000 bootstrap samples to test the hypotheses. The path coefficients with corresponding t values and p values were assessed to evaluate the significance of the

Table 2. Reliability & convergent validity tests summary

Construct	Cronbach's alpha	Composite Reliability	Items	Indicators' reliability
	>0.6	>0.7		>=0.7
Behavioural Intention	0.888	0.923	BI1 BI2 BI3 BI4	0.870 0.864 0.873 0.853
Compatibility	0.826	0.896	COMP1 COMP2 COMP3	0.828 0.870 0.885
Functional Congruence	0.831	0.899	FUC1 FUC2 FUC3	0.904 0.886 0.804
Health Belief	0.837	0.892	HB1 HB2 HB3 HB4	0.746 0.859 0.853 0.821
Health Information Accuracy	0.843	0.927	HIA1 HIA2	0.924 0.935
Perceived Ease of Use	0.804	0.885	PEU1 PEU2 PEU3	0.849 0.894 0.798
Perceived Usefulness	0.872	0.913	PU1 PU2 PU3 PU4	0.858 0.868 0.863 0.812

Table 3. Convergent validity

Construct	AVE>0.5	Construct	AVE>0.5
BI	0.749	**HIA**	0.864
COMP	0.742	**PEU**	0.719
FUC	0.749	**PU**	0.723
HB	0.674		

relationships. Table 5 presents the results of hypotheses testing. Figure 2 depicts the bootstrapping results. All the hypothesized relationships are supported with a minimum significance level of $p < 0.05$.

According to our findings, the PEU significantly influences PU (β: 0.185, p: 0.001) and BI (β: 0.307, p: 0.000), and thus H1a and H1b are accepted. The effects of PU on BI (β: 0.175, p: 0.000) were found to be significant which supports hypothesis H2. FUC was found to have a significant impact on PU (β: 0.179, p: 0.000) and BI (β: 0.304, p: 0.000), thus confirming our hypotheses H3a and H3b. Health belief was found to have significant effects on PU (β: 0.163, p: 0.000), and BI (β: 0.210, p: 0.000). Therefore, H4a and H4b are accepted. The impacts of HIA on PU (β: 0.367, p: 0.000) were found to be significant, which supports hypothesis H5. Furthermore, the impacts of compatibility on

Table 4. Discriminant validity

	BI	COMP	FUC	HB	HIA	PEU	PU
BI	**0.865**	0.541	0.765	0.698	0.642	0.787	0.743
COMP	0.463	**0.861**	0.480	0.597	0.534	0.521	0.604
FUC	0.657	0.401	**0.866**	0.541	0.653	0.608	0.696
HB	0.605	0.499	0.456	**0.821**	0.551	0.622	0.663
HIA	0.556	0.447	0.548	0.465	**0.929**	0.598	0.797
PEU	0.667	0.425	0.496	0.512	0.491	**0.848**	0.700
PU	0.655	0.514	0.595	0.569	0.685	0.588	**0.850**

***N*ote: The diagonal elements express the square root of the AVE. The elements above the diagonal are HTMT ratios. While elements below the diagonal elements are the correlations between the constructs**

PU (β: 0.118, p: 0.001) and PEU (β: 0.425, p: 0.000) were also found to be significant, thus providing support for our hypotheses H6a and H6b.

In short, the empirical results validated our conceptual model and all hypotheses of this study are supported. The validated model accounts for 64.5% of the variance explained in BI to use SWH devices.

Table 5. Summary of structural model path coefficients

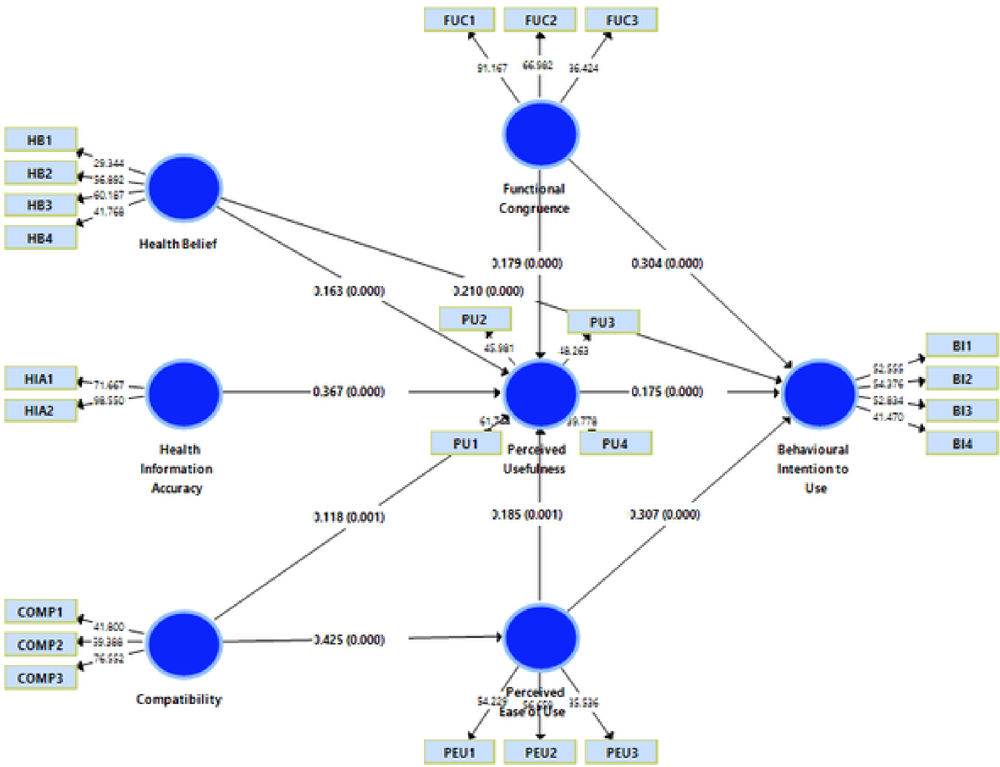
Hyp. #	Path	Path Coefficient	Standard Deviation	T Statistics	P Values	Sig. Level
H1a	PEU → PU	0.185	0.057	3.271	0.001	***
H1b	PEU → BI	0.307	0.049	6.250	0.000	***
H2	PU → BI	0.175	0.047	3.702	0.000	***
H3a	FUC → PU	0.179	0.042	4.281	0.000	***
H3b	FUC → BI	0.304	0.050	6.126	0.000	***
H4a	HB → PU	0.163	0.043	3.760	0.000	***
H4b	HB → BI	0.210	0.046	4.577	0.000	***
H5	HIA → PU	0.367	0.047	7.856	0.000	***
H6a	COMP → PU	0.118	0.037	3.194	0.001	***
H6b	COMP → PEU	0.425	0.041	10.295	0.000	***

*Note: *p < 0.1; **p < 0.05; ***p < 0.01; NS= Not Significant.*

Coefficient of Determination (R^2)

The R^2 values obtained are PU (0.620), PEU (0.180), and BI (0.645). The R^2 values of PU (0.620) and BI (0.645) are higher while R^2 value of PEU is rather weak. These results indicate that the model provides moderate level of predictive accuracy to explain the consumers' behavioral intention to use SWH devices.

Figure 2. SEM analysis of conceptual model



Goodness of Fit Indices

To examine whether the measurement model is able to explain the actual observed data, we assessed the model in terms of model fit indices like standard root means square residual (SRMR), and normed fit index (NFI). The SRMR value is 0.053. An SRMR value less than 0.10 or 0.12 shows a sound-fitting model (Hair Jr et al., 2017; Hu & Bentler, 1999). The NFI value is 0.822 which is close to the threshold (>0.9). The model fit indices indicates the fitness between the observed data and the hypothesized model.

Effect Size f^2

The effect size f^2 is the degree of change in the value of R^2 by omitting a specific exogenous construct from the model to evaluate whether the omitted construct has a substantive effect on the endogenous construct (Hair Jr et al., 2017). In our model, compatibility has medium effect (0.220) on PEU. The effects of COMP, FUC, HB, HIA, and PEU on PU are 0.025 (small), 0.051 (small), 0.042 (small), 0.21 (medium), and 0.055 (small) respectively. FUC (0.159) and PEU (0.156) have medium effects on BI while HB (0.077) and PU (0.042) have small effects on BI that indicates that omitting HB and PU will bring a small change in the R^2 value of BI while omitting FUC and PEU can exert a medium size change in R^2 value of BI.

Predictive Relevance Q^2 value

The Q^2 value (Stone-Geisser's Q^2) is the measure of the predictive relevance of an exogenous construct for an endogenous construct under consideration (Hair Jr et al., 2017). Q^2 value larger than zero for a particular reflective endogenous latent construct indicates that the endogenous construct is predicted properly by the indicators. We used blindfolding procedure to evaluate Q^2 values by keeping omission distance 7. The Q^2 values for all the dependent variables PEU (0.128), PU (0.443), and BI (0.475) are larger than zero. Hence, the predictive relevance of the model is established.

Mediating Effects of PU and PEU

For mediation analysis, bootstrapping procedure was used as mentioned in the previous section. The direct and indirect effects were examined to assess the mediation. Appendix 2 lists the direct and indirect effects. Partial and full mediating effects of PU and PEU were confirmed on different relationships. The indirect effects of PEU on BI (t= 2.283, p= 0.022) via PU are significant. The direct relationship PEU → BI is also significant, therefore, we conclude that PU partially mediates the relationship between PEU and BI. The relationship between FUC and BI is also partially mediated by PU as the direct (t= 6.126, p= 0.000) and indirect effects (t= 2.178, p= 0.029) of FUC on BI are significant. The relationship HB → BI is also mediated partially by PU as HB has significant direct (t= 4.557, p= 0.000) and indirect effects (t= 2.288, p= 0.022) on BI. The PEU partially mediates the relationship COMP → PU as both the direct effects of compatibility (t= 3.194, p= 0.001) and indirect effects (t= 3.229, p= 0.001) on PU are significant. The direct effects of compatibility on BI (t= 0.665, p= 0.506) are non-significant. While its indirect effects on BI via COMP→PU→BI (t= 1.993, p= 0.043) and COMP → PEU → BI (t= 5.489, p= 0.000) are significant. Thus, PU and PEU fully mediates the relationship COMP → BI. The PU also fully mediates the HIA → BI relationship as the direct effects of HIA on BI (t= 0.961, p= 0.337) are not significant while its indirect effects on BI (t= 2.718, p= 0.007) via PU are significant. Hence, our findings provide strong empirical support for the mediating role of PU and PEU in our model.

The Moderating Effects of Age, Gender, and Level of Education

The data used for this study contain heterogeneous groups like age, gender, and level of education. The relationships between the variables may be affected by the group specific characteristics. We divided the data in two groups each based on age, gender and level of education. The data was divided age-wise into two groups namely youngers (age less than 36 years, n=263) and elders (age greater than 36 years, n=210). Male (n=248) and female (n=225) groups were formed gender-wise. Undergraduates and lower were kept in lower_education group (n=298) while graduates and post-graduates were kept in higher_education group (n=175).

To analyze the group specific characteristics, permutation test and multi-group analysis (MGA) tests were carried. The MGA supported the results produced by permutation. In terms of age, significant differences were found only in three structural paths COMP→PEU, FUC→BI, and PEU→BI. The relationship between COMP and PEU is significantly different at 1% (p=0.001) with youngers (β=0.548) and elders (β=0.283). The FUC→BI is significantly different at 10% (p=0.087) with youngers (β=0.373) and elders (β=0.197). The effect between PEU and BI is significantly different at 10% (p=0.054) with youngers (β=0.246) and elders (β=0.428). Gender-wise differences were found significant only in one relationship COMP→PEU at 10% (p=0.062) significance level. The relationship is stronger for male (β=0.498) and weaker for female (β=0.339). Similarly, group specific differences for education level were significant (p=0.087) at 10% significance level in one path COMP→PU which is stronger for users with higher education (β=0.207) and weaker for users with lower education level (β=0.073).

ANN Analysis

We used the statistical tool SPSS 23 and employed a multi-layer perception ANN that consisted of input, hidden, and output layers to perform ANN analysis. In ANN, a large processor consists of simple processing units known as neurons that can acquire knowledge for future use (Ooi, Lee, et al., 2018). The neurons acquire knowledge through a learning process and store it in the interneuron connection strengths, also known as synaptic weights (Leong, Hew, Tan, & Ooi, 2013). The synaptic weights are adjusted during the learning process to achieve an objective (Hew, Leong, Tan, Ooi, & Lee, 2019). The hidden layer's neuron nodes learn to present the input layer's neuron nodes in an easy way so as to anticipate the output neuron node (Lecun, Bengio, & Hinton, 2015).

This study employed two hidden layers of deep learning ANN architecture for each of the output neurons with the aim of deeper learning (Mahdavifar & Ghorbani, 2019). We used a ten-fold cross-validation technique to overcome the overfitting problem. 90% of the data was allocated for the training of the neural network model, and the remaining 10% of the data for testing the prediction accuracy of the trained model (V. H. Lee et al., 2020). We used the sigmoid activation function for both hidden and output layers and the number of hidden layers was selected to generate automatically (Ooi, Lee, et al., 2018). Since the BI, PU and PEU have several significant predictors, three ANN models were formed for BI, PU and PEU, as shown in Figure 3, Figure 4, and Figure 5.

To assess the predictive accuracy, the root mean squares of errors (RMSE) were calculated for the training and testing processes based on the sum of squares error (SSE). The RMSE values listed in Table 6 indicate that the RMSE values are negligible and all ANN models show higher levels of predictive accuracy (V. H. Lee et al., 2020; Leong et al., 2019). To further investigate the performance of the ANN models, we calculated the percentage of variance explained by the ANN models following the approach used by Leong et al. (2019) using the formula where S^2 is the variance of preferred output. Appendix 3 presents S^2 values. The results indicate that the input neurons are able to predict 78.4%, 79.4% and 83% of the variance in BI, PU and PEU respectively. The R^2 values for BI (R^2: 78.4%), PU (R^2: 79.4%), and PEU (R^2: 83%) attained from the ANN model are considerably higher than the R^2 values calculated through the PLS-SEM model which are BI (R^2: 64.5%), PU (R^2: 62%), and PEU (R^2: 18%). This indicates that the ANN models have endorsed the PLS-SEM results and provided better explanations for the endogenous constructs.

A sensitivity analysis was carried out to rank the exogenous constructs (input nodes), based on their normalized importance (Leong et al., 2019). In Appendix 4, the results of ANN model A indicate that perceived ease of use (90%) is the most important predictor of behavioral intention to use SWH devices, followed by functional congruence (77%), health belief (76%), and perceived usefulness (53%). Further, the normalized importance values of ANN model B show that functional congruence (89%) is the most important predictor of PU tailed by health belief (85%), perceived ease of use (71%), compatibility (66%), and health information accuracy (60%).

DISCUSSION AND CONCLUSIONS

This study explored the determinants of consumer behavioral intention to use SWH devices and to provide empirical support for the proposed model of the study. This study thus extended TAM by incorporating additional constructs, namely health beliefs, health information accuracy, compatibility and functional congruence, and presented an empirically validated model with 64.5% explanation power to explain the consumers' behavioral intentions to use SWH devices. Our results confirmed that functional congruence, health belief, perceived usefulness, and perceived ease of use have direct impacts on behavioral intention to use SWH devices, while health information accuracy and compatibility have indirect impacts on behavioral intention to use SWH devices. The following insights can be highlighted to improve the adoption of SWH devices.

The findings of the study indicate that functional congruence not only has a significant relationship with behavioral intention but it is the most important predictor of behavioral intention also. This result is consistent with prior research (Talukder et al., 2020). This finding shows that users will adopt SWH devices if their expectations about the functional features of SWH devices are fulfilled.

Table 6. RMSE values during training and testing stages

	Model A (R^2=78.4%)				Model B (R^2=79.4%)				Model C (R^2=83%)			
	Training		Testing		Training		Testing		Training		Testing	
	N	RMSE	N	RMSE	N	RMSE	N	RMSE	N	RMSE	N	RMSE
ANN1	423	0.095	50	0.086	422	0.101	51	0.097	418	0.142	55	0.131
ANN2	413	0.090	60	0.095	418	0.098	55	0.093	424	0.141	49	0.128
ANN3	417	0.092	56	0.094	432	0.104	41	0.095	425	0.144	48	0.129
ANN4	428	0.101	45	0.086	425	0.097	48	0.100	436	0.139	37	0.165
ANN5	421	0.092	52	0.089	416	0.101	57	0.108	431	0.144	42	0.148
ANN6	426	0.089	47	0.091	432	0.108	41	0.104	416	0.144	57	0.117
ANN7	418	0.088	55	0.072	416	0.102	57	0.080	435	0.142	38	0.149
ANN8	424	0.099	49	0.087	425	0.099	48	0.095	426	0.144	47	0.123
ANN9	426	0.088	47	0.084	421	0.103	52	0.098	436	0.143	37	0.119
ANN10	416	0.089	57	0.100	421	0.109	52	0.096	431	0.141	42	0.134
Average		0.092		0.088		0.102		0.097		0.142		0.134
St Dev		0.005		0.007		0.004		0.007		0.002		0.015

Notes:

1. N = number of samples, RMSE = root mean square of errors.
2. In Model A, Functional Congruence, Health Belief, Perceived Ease of Use, and Perceived Usefulness served as the input neurons; while behavioral intention served as the output neuron.
3. In Model B, Compatibility, Functional Congruence, Health Belief, Health Information Accuracy, and Perceived Ease of Use served as the input neurons; while Perceived Usefulness served as the output neuron.
4. In Model C, Compatibility served as the input neuron; while Perceived Ease of Use served as the output neuron.
5. $R^2 = 1 - RMSE/S^2$, where S^2 is the variance of the desired output for the test data.

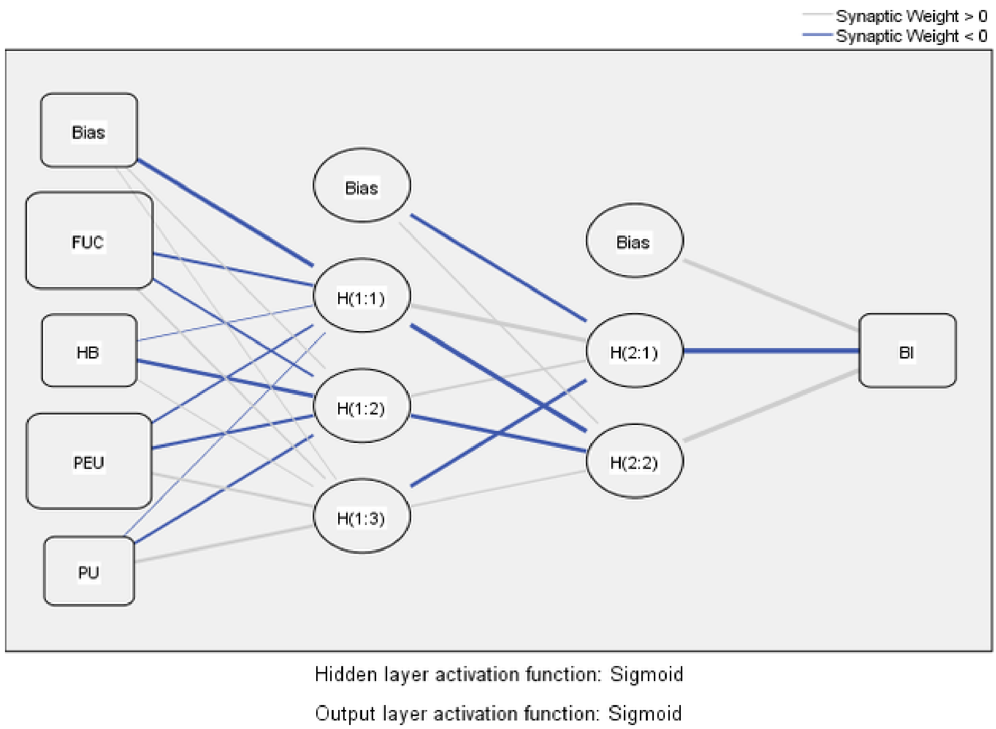
Notes: FUC: Functional Congruence; HB: Health Belief; PEU: Perceived Ease of Use; PU: Perceived Usefulness; BI: Behavioral Intention

The hypotheses testing showed that health belief is an important predictor of behavioral intention. The sensitivity analysis of the ANN model showed that health belief is the second most important predictor of behavioral intention. Significant impacts of health belief were also confirmed on perceived usefulness. These findings are consistent with prior studies (Cheung et al., 2019; Zhang et al., 2017). Empirical results also confirmed the significant effects of health information accuracy on perceived usefulness, and the ANN model showed that health information accuracy is the second most important predictor of perceived usefulness. These findings indicate that individuals who are more sensitive about their health are more likely to use SWH devices and that they will perceive them as more useful. The accuracy of health information also leads them to improved perceptions of usefulness that in turn affect intention to use SWH devices.

Compatibility has proved to be a significant predictor of perceived usefulness and perceived ease of use. These results are consistent with prior research (Choi & Kim, 2016; Jeong et al., 2017; Schmidthuber et al., 2020). These findings reveal that if users find SWH devices compatible with their lifestyle and needs, their perceptions about usefulness and ease of use of SWH devices are improved, which affects their intention to use SWH devices. The manufacturers of SWH devices should consider compatibility features when manufacturing SWH devices.

The findings of the study also confirmed that perceived ease of use has significant effects on both perceived usefulness and behavioral intention to use. Furthermore, it was demonstrated that perceived ease of use and perceived usefulness are important predictors of behavioral intention. Many previous studies endorse such findings (V. H. Lee et al., 2020; Loh, Lee, Tan, Hew, & Ooi, 2019).

Figure 3. ANN model A

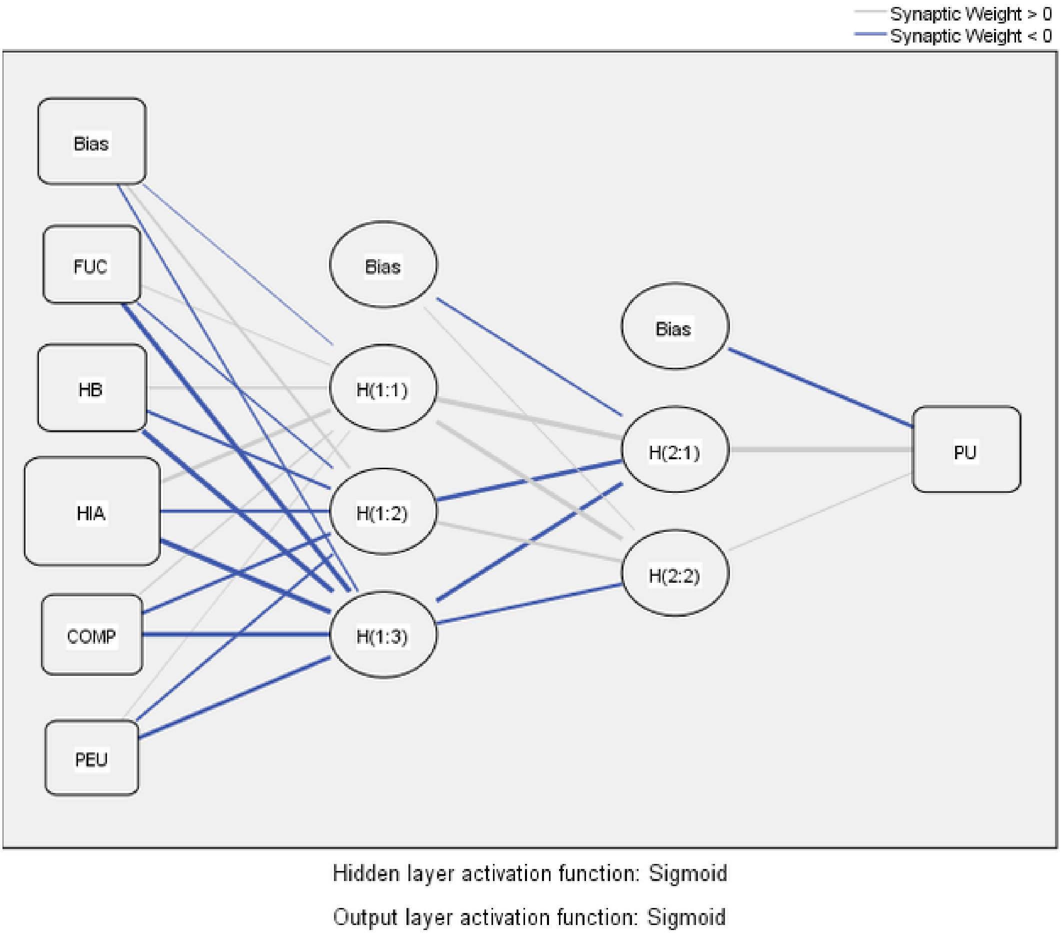


Notes: COMP: Compatibility; FUC: Functional Congruence; HB: Health Belief; HIA: Health Information Accuracy; PEU: Perceived Ease of Use; PU: Perceived Usefulness

The outcomes of the study established the mediating role of PU and PEU in seven relationships. The PEU partially mediates in one path COMP→PU and fully mediates in one path COMP→BI. The PU mediates partially in three relationships (PEU→BI, FUC→BI, HB→BI) and fully mediates in two relationship COMP→BI and HIA→BI. These results indicate the critical roles of PU and PEU in influencing the users' intentions to use SWH devices.

Our findings confirmed age-wise group specific significant differences in three paths COMP→PEU, FUC→BI, and PEU→BI. The effects of compatibility on PEU are stronger for young users and weaker for elders. It indicates that the young users are more concerned about the compatibility of the SWH devices with their life style in comparison with the elders. The FUC→BI relationship is also stronger for young users. These findings are showing natural tendencies because youngsters are more interested in availability of more features and compatibility of the devices with their life style and experiences. The relationship between PEU and BI was found stronger for elders and weaker for users with less age. It reveals that the elders' intentions are affected more by PEU while the youngsters are comparatively less concerned about ease of use. COMP→PEU was found weaker for females and stronger for males. It shows that males are more interested in compatibility of the SWH devices in comparison with the females. Similarly, the relationship between compatibility and PU was found stronger for users with higher education. This result indicates the tendency of the users with more education towards compatibility of the devices with their life styles. In brief, compatibility is the most dominating factor for group-wise differences which is more important for young users, male users, and users having higher education levels.

Figure 4. ANN model B

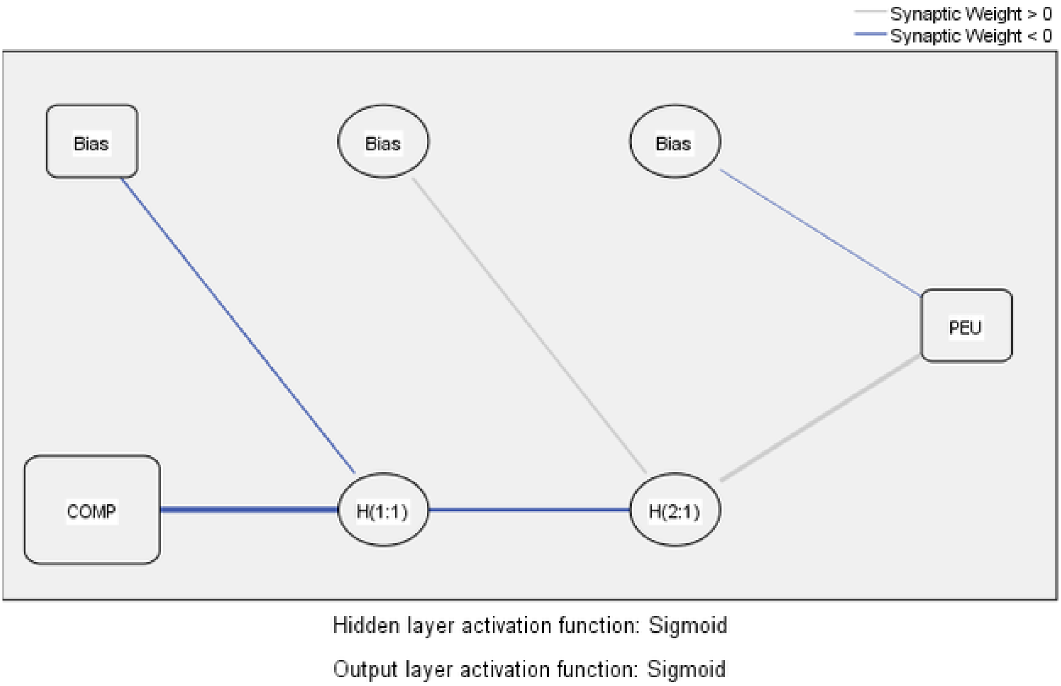


Notes: COMP: Compatibility; PEU: Perceived Ease of Use

Theoretical Implications

This research is important for academic and research purposes in the context of smart wearable technology. Most of the previous studies in the context of wearable technology have focused on adoption by older people (Abouzahra & Ghasemaghaei, 2020; J. Li et al., 2019). Since SWH devices have equal importance for both younger and older people, this study focused on the adoption of SWH devices by both young and older consumers. This study extends the existing wearable technologies literature by incorporating health attributes (health beliefs and health information accuracy), and technology attributes (compatibility and functional congruence) in the TAM framework. Further, the study enhances the TAM framework in the human-technology communication context and examines which health attributes along with technological attributes influence the consumers' intentions to use SWH devices. It thus complements both innovation implementation, and consumer attributes. The validated model of the study is suitable for acceptance of SWH devices, comprising factors such as health attributes, technology attributes, and behavioral attributes. The study also provides evidence that TAM is an effective model with which to examine healthcare wearable technologies.

Figure 5. ANN model C



This study used a dual-stage SEM-ANN approach to empirically validate the proposed model and prioritize the factors that influence behavioral intentions to use SWH devices by evaluating the relative importance of each significant construct. The findings of this study agree with existing research (Cheung et al., 2019; Talukder et al., 2020). The SEM-ANN approach provides deeper insights into linear and non-linear relationships. This is a methodological advance from a SWH device perspective. Such a hybrid approach can serve as a new statistical analytical approach for statistical analysis in the contexts of technology adoption and continuance.

Managerial Implications

In terms managerial implications, results of the study indicate that health belief and health information accuracy play a vital role in influencing user perceptions about the usefulness of SWH devices. Marketers should therefore promote the usefulness of SWH devices in improving user health by addressing health concerns. Manufacturers should ensure the accuracy of health information so that the consumer concerns about the mismanagement of their health due to inaccurate information acquired from SWH device can be minimized. When consumers realize the effectiveness of SWH devices in improving their health, and understand that the health information obtained from SWH devices is accurate, their perceptions of the usefulness of SWH devices are boosted and in turn, their behavioral intention to use SWH devices is influenced positively.

The findings of the present study also reveal the significant effects of compatibility on perceived usefulness and perceived ease of use, which have indirect impacts on consumer behavioral intention to use SWH devices, while functional congruence has direct significant impacts on consumer behavioral intention to use SWH devices. The manufacturers of healthcare wearable devices should focus on functional features such as comfort, material, and long-lasting battery. These findings also reveal that ease of use must be considered while preparing SWH devices so that the users with little or no experience can easily use such devices. User perceptions about the usefulness of SWH devices are improved by ease of use, which positively affects their intentions to use.

The manufacturers should concentrate on group specific differences in terms of age, gender, and level of education. They should be aware of the users' preferences and demands while designing manufacturing healthcare devices for different consumers' groups based on age, gender, or level of education. For young users, the compatibility and functional congruence need to be focused while for elders the devices should be made easier to use.

Decision-makers can improve SWH devices by equipping these devices with product-related functional features and making them more compatible with consumer needs and lifestyles. Manufacturers should design user-friendly interfaces that are easy to use, equipped with the relevant features and the ability to provide accurate health information, which can improve consumer health.

Limitations and Future Research Avenues

Despite the useful contributions to theory and practice, some limitations are associated with this research. The sample of the study was confined to Saudi Arabia, which means that the findings of the study show the status of a particular country. To broaden the scope of research on SWH devices, it is suggested that future research may use cross-country data. Second, this study used the TAM framework as the base model and incorporated other factors. Future studies could use UTAUT and other frameworks as base models to investigate consumer adoption of SWH devices. Third, the current research collected and analyzed data from experienced users. Future studies could validate the model of this study by comparing the behaviors of users and non-users. Fourth, a quantitative method was used to validate the proposed model of this study. Future research could employ a mixed-method approach, which can provide deeper insights into the phenomenon. Fifth, the proposed model of the study was tested using a cross-sectional survey. Since consumer behaviors vary over different periods, longitudinal studies may be more helpful to examine the subject matter. Sixth, this study tested the model in the context of SWH devices adoption. The validated model can be tested in other information system settings. Lastly, this research used a dual-stage SEM-ANN approach to explore consumer adoption of SWH devices. Scholars could use this approach to validate models in other contexts of information systems.

CONCLUSION

The objective of this research is to understand the aspects of wearable device adoption in global healthcare systems. This research explored wearable technologies in healthcare worldwide as noninvasive and autonomous devices that capture and analyze to improve personal health and well-being. This study contributes to explore the factors affecting the consumers' behavioral intention to use SWH devices and presents an empirically validated model with a predictive capability of 64.5%. This research enhances the extant literature on wearable healthcare technologies by extending the TAM framework. This study explored the determinants of consumer behavioral intention to use SWH devices and provided empirical support for the proposed model of the study. This study thus extended TAM by incorporating additional constructs, namely health beliefs, health information accuracy, compatibility, and functional unity, and presented an empirically validated model explanation power to explain the consumers' behavioral intentions to use SWH devices. The study employs the SEM-ANN approach to validate the model and rank the constructs of the model. The hybrid approach provides deeper insights when the model is composed of linear and non-linear relationships. The approach prioritizes the factors that influence behavioral intentions to use smart wearable healthcare devices by evaluating the relative importance of each significant construct. The SEM-ANN hybrid approach can serve as a new statistical analytical approach for statistical analysis in the contexts of technology adoption and continuance. Based on the outcomes of the study, this research presents important recommendations to the practitioners and manufacturers about the important characteristics and features of the healthcare devices. Group specific characteristics like age, gender, and level of education have also been highlighted. The study suggests that the SWH devices can be improved if these devices are equipped with product-related functions, user-friendly interfaces, ease of use, compatibility, and the ability to provide accurate health information. Devices with such features can improve the health status of the consumers. The future work will look into the challenges, including data security, trust issues, and ethical hurdles. The prospective study will address the benefits to healthcare systems due to wearable devices, including personalization, early diagnosis, remote patient monitoring, adherence to medication, information libraries, and better decision making while reducing healthcare costs.

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APPENDIX A. (MEASUREMENT ITEMS)

Functional Congruence adopted from (Talukder et al., 2020)
FUC1: Wearable health devices are expected to be comfortable.
FUC2: Wearable health devices are expected to be fashionable.
FUC3: Wearable health devices are expected to be priced appropriately considering their quality.
Health Information Accuracy adopted from (Cheung et al., 2019)
HIA1: The health information provided by the wearable healthcare technology is accurate
HIA2: The health information provided by the wearable healthcare technology is trustworthy
Compatibility adopted from (Sohail & Al-jabri, 2013)
Comp1: Smart wearable devices are compatible with my lifestyle
Comp2: Smart wearable devices fit well with the way I like to manage my health
Comp3: Using smart wearable devices fit into my working style
Health Belief adopted from (Cheung et al., 2019)
HB1: I realize that bad living habits will cause harm to my health
HB2: I perceive that bad living habits will cause harm to my health
HB3: I hope I can change my bad habits and thus to minimize damage to health
HB4: I think I can improve my health status effectively in many ways like sports
Perceived Usefulness adopted from (Papa et al., 2020; Park, 2020)
PU1: I think that smart wearable devices are useful for my life
PU2: Using smart wearable devices increases my productivity
PU3: Using smart wearable devices helps me conveniently perform many tasks
PU4: Using smart wearable devices would improve my health performance
Perceived Ease of Use adopted from (Park, 2020)
PEU1: My interaction with smart wearable devices is clear and understandable
PEU2: Using smart wearable devices is easy for me
PEU3: Interacting with smart wearable devices does not require mental effort
Behavioral Intention to Use adopted from (Alalwan et al., 2017)
BI1: I intend to use smart wearable devices in the future.
BI2: I will always try to use smart wearable devices in my daily life.
BI3: I plan to use smart wearable devices in future.
BI4: I predict I would use smart wearable devices in the future.

APPENDIX B. (DIRECT AND INDIRECT EFFECTS)

Direct Effects					Indirect Effects				
Path	Path Coefficient	Standard Deviation	T Statistics	P Values	Path	Path Coefficient	Standard Deviation	T Statistics	P Values
PEU → BI	0.307	0.049	6.250	0.000	PEU → PU → BI	0.027	0.012	2.283	0.022
FUC → BI	0.304	0.050	6.126	0.000	FUC → PU → BI	0.026	0.012	2.178	0.029
HB→ BI	0.210	0.046	4.577	0.000	HB → PU → BI	0.024	0.011	2.288	0.022
COMP →PU	0.118	0.037	3.194	0.001	COMP → PEU → PU	0.079	0.024	3.229	0.001
COMP→ BI	0.023	0.035	0.665	0.506	COMP → PEU → BI	0.128	0.023	5.489	0.000
					COMP → PU ® BI	0.017	0.009	1.993	0.043
HIA → BI	0.043	0.044	0.961	0.337	HIA → PU → BI	0.054	0.020	2.718	0.007

*Note: *p < 0.1; **p < 0.05; ***p < 0.01; NS= Not Significant.*

APPENDIX C. (SUM OF SQUARES ERRORS (S2) VALUES DURING TRAINING AND TESTING STAGES OF ANN)

	Model A		Model B		Model C	
	Training	Testing	Training	Testing	Training	Testing
	SSE	SSE	SSE	SSE	SSE	SSE
ANN1	3.794	0.368	4.299	0.475	8.474	0.947
ANN2	3.315	0.537	4.035	0.480	8.479	0.799
ANN3	3.535	0.493	4.691	0.371	8.760	0.794
ANN4	4.325	0.333	4.019	0.482	8.433	1.013
ANN5	3.535	0.413	4.264	0.659	8.889	0.925
ANN6	3.373	0.392	5.005	0.444	8.596	0.785
ANN7	3.215	0.289	4.347	0.362	8.786	0.847
ANN8	4.151	0.374	4.206	0.435	8.838	0.709
ANN9	3.293	0.331	4.476	0.500	8.967	0.520
ANN10	3.287	0.567	5.039	0.482	8.568	0.752
Average SSE	3.582	0.410	4.438	0.469	8.679	0.809

APPENDIX D. (SENSITIVITY ANALYSIS WITH NORMALIZED IMPORTANCE)

Neural Network	Model A (Output Neuron: BI)				Model B (Output Neuron: PU)					Model C (Output Neuron: PEU)
	FUC	HB	PEU	PU	COMP	FUC	HB	HIA	PEU	COMP
ANN1	0.354	0.262	0.335	0.048	0.171	0.204	0.375	0.132	0.117	1.0
ANN2	0.354	0.166	0.342	0.138	0.161	0.184	0.367	0.083	0.205	1.0
ANN3	0.309	0.255	0.309	0.126	0.127	0.212	0.408	0.154	0.099	1.0
ANN4	0.328	0.292	0.338	0.041	0.154	0.209	0.416	0.069	0.153	1.0
ANN5	0.320	0.158	0.341	0.180	0.160	0.186	0.348	0.096	0.209	1.0
ANN6	0.307	0.205	0.313	0.175	0.132	0.215	0.257	0.162	0.234	1.0
ANN7	0.434	0.218	0.265	0.084	0.138	0.186	0.406	0.111	0.159	1.0
ANN8	0.295	0.213	0.256	0.237	0.131	0.160	0.386	0.073	0.251	1.0
ANN9	0.296	0.231	0.325	0.148	0.163	0.206	0.341	0.114	0.175	1.0
ANN10	0.353	0.208	0.354	0.085	0.237	0.156	0.242	0.197	0.167	1.0
Average relative importance	0.335	0.221	0.318	0.126	0.157	0.192	0.355	0.119	0.177	1.000
Normalized relative importance (%)	77%	76%	90%	53%	66%	89%	85%	60%	71%	100%

Notes:

BI: Behavioral Intention: FUC: Functional Congruence; HB: Health Belief; PEU: Perceived Ease of Use; PU: Perceived Usefulness; COMP: Compatibility; HIA: Health Information Accuracy

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