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ORIGINAL ARTICLE

Assessing the older population acceptance of healthcare wearable in a developing Country: an extended PMT model

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Abstract
Wearable healthcare devices (HWDs) got prominence, especially during the COVID-19 pandemic. Aiming to know the proliferation of the HWDS, this study tries to evaluate the intentions of the old-age population to use the devices. To this end, the protection motivation theory (PMT) coupled with health information accuracy, perceived novelty, perceived ease of use, hedonic motivation, health anxiety, and health consciousness were investigated as predictors of HWDs among senior Pakistani citizens. A total of 310 participants who knew how the smartwatches could be used as a health monitoring device, were surveyed to empirically test the model. The required data were then analyzed using structural equation modeling. The findings reveal that the protective, utilitarian, and personal attributes of HWDs play a significant role in choosing the HWDs. While addressing their healthcare issues, senior citizens are highly receptive to perceived usefulness, accurate information accuracy, self-efficacy, perceived severity, health consciousness, and perceived vulnerability during COVID-19. These factors have a positive impact on their willingness to use HWDs. The study educates healthcare management and users to focus on the determining factors that can enhance the use of HWDs.

Keywords Protection motivation theory · Acceptance · Healthcare wearables · Pakistan

1 Introduction

In light of the recent advances in digital technologies and the COVID-19 pandemic, new healthcare technologies have highlighted the importance and usefulness of wearable medical devices (HWDs) (Fukuti et al. 2020). A wearable is an intelligent gadget linked to an electronic health record that helps patients, caregivers, and healthcare providers communicate (Bianchi et al. 2022). In light of the importance of addressing demographic trends, including an aging population, an increase in the prevalence of lifestyle illnesses, and the cost of healthcare, wearables are becoming more important (Levy 2014). HWDs provide patients with real-time information without visiting hospitals (Binyamin and Hoque 2020). HWDs can better enhance the healthcare system thereby assessing patients' health and providing them with timely medical treatment (Islam et al. 2020). Currently, the COVID-19 epidemic is spreading throughout the world. The tremendous impact of the COVID-19 pandemic on the elderly population in the world indicates the need to closely monitor their health problems (Pan et al. 2020). Seniors have comorbidities regularly, demanding continual monitoring to maintain optimum health (Kirwan et al. 2020). Wearable technology enhances the quality of life for older adults by facilitating healthier lifestyle choices (Elimelech et al. 2022; Popescu 2014).

Wearable devices like smartwatches and fitness trackers, as well as healthcare software, are believed to strengthen the overarching health of users (Aymerich-Franch and Ferrer 2022). Its primary purpose and usefulness largely influence customers' perceptions of a product and its application.

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Customers often choose practical advantages over aesthetics. As outlined in the technology acceptance model (TAM), individuals are more likely to adopt technology when they see its usefulness. Users are more likely to adopt the usage of HWDs and rate them highly in terms of perceived usefulness and intent to use if they believe that such devices aid in health monitoring, are reliable, and provide accurate results (Cheung et al. 2020). When people worry about their health, they are more likely to take advantage of available information technology to make positive changes in their health. HWD encourages individuals to use healthcare technology worn whenever they need to monitor or improve their health. Regarding health-related concerns and anxieties, HWDs can be considered protective technology.

According to the protection motivation theory (PMT) (Rogers 1975), perceived security and vulnerability perceptions play an important role in determining intentions to use HWDs. In general, the greater the health-related threat to individuals, especially seniors, the more likely they are concerned to improve their health (Prentice-Dunn and Rogers 1986). Past research shows that elderly users who face significant health risks are more likely to adopt health technology (Sun et al. 2013). Past research (Hsu and Lin 2016; Sicari, Rizzardi, Grieco, & Coen-Porisini, 2015) has demonstrated that information privacy concerns like data security, lack of human oversight, and device privacy reliance are limiting considerations in this setting (Mani and Chouk 2018; Tu 2018) identified perceived advantages and concerns as significant factors in accepting wearable devices. Additionally, data privacy is a significant problem, especially when utilizing wearable fitness trackers (Zhou and Piramuthu 2014). Technology adoption is influenced by social influences, such as peer assessments and recommendations from social circles (Gao and Bai 2014). Though wearable devices provide various advantages, especially in healthcare, their application is limited (Sultan 2015). Despite the apparent benefits of wearable technology for elder groups, young people are the primary consumers of these technologies (Kekade et al. 2018). In the United States, just 3.3% of HWDs users are 65 or older, whereas 17.1% are between 25 and 34. Another disadvantage of HWDs is their prolonged usage. Research (Junaeus 2015; Levy 2014) has shown that users abandon their wearable devices after less than six months. In the current pandemic environment, the usage of wearable devices is equally influenced by health and technological considerations. The HWDs are superior devices that aid in health monitoring and equip people to control their health at home. Though HWDs generate value for consumers by combining health and technological characteristics, there is little research on consumer concerns, perceptions, and acceptance intention, excluding rare empirical research by (Chau et al. 2019) and (Zhang et al. 2017). Regarding HWD acceptability, health professional studies dominate consumer behavior research (Junglas et al. 2009). Prior research has also neglected the role of self-efficacy in promoting HWD adoption (Abouzahra and Ghasemaghaei 2020).

Pakistan, the world's sixth most populous country, has an average daily income of less than US$10 and a literacy rate of about 60% (Dahri and Thebo 2020). Most of the population, over 70%, resides in rural regions, where they have worse accessibility to healthcare due to a lack of healthcare facilities and a qualified healthcare worker. In Pakistan, the ratio of patients to physicians is 1:1300, and only 22% of the inhabitants are covered by public hospitals and primary health institutions (Khan 2019). The inadequacy of the healthcare system, as seen by the limited availability of primary care, is a sufficient cause to prioritize one's health. The latest COVID-19 outbreak worsens the state of the country's healthcare system and prompts individuals to take more responsibility for their health by using technology (Dahri and Thebo 2020; Saheb, Sabour, Qanbary, & Saheb, 2022). With Pakistan's growing population and low health expenditures, digitizing healthcare is the only way out of the crisis (Hayat et al. 2022).

The COVID-19 infection has made senior citizens worried about their health. Concern about health leads to more health monitoring and preventive measures, which improves health conditions (Alam et al. 2020; Saheb et al. 2022). The hospitals are closed or operating below the potential to treat COVID-19 patients (Khan 2019). Healthcare technologies such as wearables devices, telemedicine, and mobile healthcare are rapidly gaining popularity among the general public (Dehghani et al. 2018). Technology-based medical health services enable patients to monitor and manage their health at home, avoiding hospital visits (Hayat et al. 2022; Kekade et al. 2018; Rajak and Shaw 2019). The HWDs are superior devices that facilitate health monitoring and enable people to control their health at home. Accordingly, this study aims to identify the technological factors influencing the adoption of HWDs and the role played by health awareness in influencing the acceptance of HWDs among the elderly. HWDs provide novel methods for measuring health and technology-related characteristics (Dehghani et al. 2018). Through the lenses of PMT and select utilitarian constructs, such as perceived usefulness from TAM, hedonic motivation from UTAUT2, and perceived novelty, this study examines the behavior of seniors when it comes to the adoption of health information. Furthermore, this study examines the influence of personal aspects, such as health consciousness and anxiety, on the intention to use and adopt HWDs. Thus, we contribute to this research field in many ways. First, this study examines the potential applicability of an extended protection motivation theory (PMT) for wearable technology by incorporating utilitarian constructs such as perceived usefulness from TAM, hedonic motivation from UTAUT2 developed by (Venkatesh et al. 2012), perceived novelty, and health information accuracy and personal attribute (health consciousness and health anxiety) as indirect antecedents of wearable technology acceptance through perceived usefulness. Second, this research examines the behavioural intention of healthcare wearable technology adoption among senior citizens in Pakistan. Finally, this study contributes to marketing practitioners by providing guidance on how to adopt and utilize wearable technology advances in Pakistan.

2 Relevant Literature and Hypotheses

2.1 Protection motivation theory and older citizen protection motivation

PMT presents a psychological model for comprehending what drives individuals to alter their behaviour in response to danger (Rogers 1975). Threat appraisals are the process of estimating the degree of danger associated with maladaptive actions by examining two aspects (1) how harmful and dangerous the threats would be to an individual (i.e., perceived severity), and (2) how susceptible an individual is to be exposed to the threats (i.e., perceived vulnerability). Moreover, coping appraisals relate to analyzing adaptive behaviour and show an individual's capacity to face and escape future risks. The coping appraisal factor is whether one can engage in the coping response (i.e., self-efficacy). The protection motivation grows with the intensity and probability of the risk, and when the coping approach is successful and achievable, it motivates people to modify their behaviour.

This study adopts PMT as the main theoretical framework along with some new constructs to make the model more comprehensive. The additional constructs are; health information accuracy, perceived usefulness taken from TAM, perceived novelty, hedonic motivation from UTAUT 2, health consciousness, and health anxiety. The justifications for considering these variables are provided below. Firstly, HWDs are intelligent wearable devices with automatic functionalities that record context information to create a personalized experience for the user. These gadgets are more ubiquitous among younger generations than older ones (Kekade et al. 2018). Nevertheless, recent research suggests that older generations support HWDs (Pan et al. 2020; Popescu 2014). However, their awareness of the rationale and utilization of HWDs was still in its infancy and still considered new by them. Thus, this research uses perceived usefulness from TAM. We add perceived usefulness as a predictor of intention since it is pertinent for technologies that match consumers' habits and lifestyles (Pan et al. 2020). The literature widely mentions perceived usefulness as a construct based on users' conceptions that may change due to users' interaction with a particular technology (Dutot et al. 2019). Specifically, research on HWDs and other fitness applications has shown that perceived usefulness is a powerful predictor of users' attitudes and willingness to utilize these services (Huang and Ren 2020). A few essential studies support the relevance of TAM's variable perceived usefulness from the viewpoints of prospective and existing users who may utilize such gadgets for personal comfort and health monitoring (Chen and Lee 2008; Y. Gao, Li, & Luo, 2015). Furthermore, older people with restricted mobility and self-efficacy need health devices to be user-friendly, have self-tracking capabilities, and be beneficial (Cilliers 2020). Therefore, PU is the primary characteristic that users demand in HWDs (Chen and Lee 2008).

Second, HWDs are considered new due to self-monitoring or self-care services (Malwade et al. 2018). Several studies have concluded that consumers consider the gadget a novelty and believe it will improve their overall health and well-being if adopted (Cheung et al. 2020). Unfortunately, these results are mainly validated in the setting of young users (Generation Z), while research on adults is sparse (Cheung et al. 2020; Kekade et al. 2018). Technology advancement is a clearly defined term that emphasizes a service's uniqueness, flexibility, and usefulness (Mani and Chouk 2018; Singh et al. 2020). The prior study demonstrates that in non-users, the anticipated users' acceptance of an invention or technology is influenced by the innovation's usefulness (Malwade et al. 2018). In addition, studies investigate the precision and credibility of HWDs, including the veracity of medical data supplied by HWDs and the security of users' privacy while employing such devices (Claes et al. 2015). Such considerations warrant more study, particularly from the perspective of adults, who are more averse to new technology than younger consumers. Literature indicates the favorable effect of health anxiety, health consciousness, hedonic motivation, novelty, and accuracy on the PU of HWDs, which increases customers' intention to adopt them (Ahmad et al. 2020; Bianchi et al. 2022; Cheung et al. 2020; Yang et al. 2022).

Third, Several studies have demonstrated that HWDs can reduce health stress and monitor users' health in critical situations (Gao et al. 2015). Concerning the elderly population, in particular, the studies indicate the need for health gadgets for reviewing health data, monitoring health, and taking preventative steps against developing a health condition (Jeong et al. 2017; Kekade et al. 2018). In most of these studies, PMT is used as the basis of the research (Ma et al. 2019). Several PMT-based studies have concluded that addressing only the technical characteristics of HWDs is not sufficient; it is necessary to examine their protective health factors (Jeong et al. 2017). Accordingly, PMT is applicable and acceptable for evaluating HWD users' protective motives in this setting. A unified framework explaining both technical and health-preventative factors of HWDs is needed during health-threatening circumstances like the COVID-19 pandemic, although this has not been addressed in prior research. The current research combines PMT with four essential utilitarian characteristics, i.e., perceived usefulness, perceived novelty, hedonic motivation, and health information accuracy and personal attributes (health consciousness and health anxiety) to better understand how the senior citizens develop their intentions to use HWDs, especially in pandemic, like COVID.

Finally, a dearth of research examines how the senior population view and use wearable technology (Kekade et al. 2018; Malwade et al. 2018). Furthermore, we identified a paucity of research that uses the PMT to evaluate people's intention to adopt HWDs, considering the significance of the model (Chen and Lee 2008; Gao et al. 2015; Ifinedo 2012). To the best of our knowledge, no previous research, particularly in Pakistan, has examined seniors' acceptance of PMTs for health services. Few studies focus on health-related issues during the pandemic discussing the aging citizens' behavior (Claes et al. 2015; Fraile, Bajo, Corchado, & Abraham, 2010). Such circumstances having threats restrict their activities and make them conscious. Multiple external constraints restrict the mobility and accessibility of older people to different health services and associated activities (Claes et al. 2015; Hung, Zhang, & Tai, 2004). This gap was the motivation to be filled by taking HWDs usage, especially for the elderly.

2.2 Hypotheses Development

2.2.1 Linking perceived vulnerability (PV) to BI

Perceived vulnerability (PV) signifies "the conditional probability that the threatening event will occur provided that no adaptive behaviour is performed or there is no modification of an existing behavioural disposition" (Rogers and Prentice-Dunn 1997). PMT argues that when the probability of encountering a risk is substantial, a person will use health information technology to reduce or avoid health risks (Prentice-Dunn and Rogers 1986). Previously, it has been demonstrated that when PV intensity is high, users feel more prepared and knowledgeable concerning the threat (Guo et al. 2015; Sun et al. 2013). Prior research has shown that PV dramatically significantly enhanced behavioural intent to utilize online banking (Jansen and Van Schaik 2018), IS security (Warkentin et al. 2016), cloud computing services (Rahman and Choo 2015), and smartwatches (Al-Emran 2021). A health belief model was developed due to early studies on the PV aspect in the health field (Becker, 1974). In situations such as the pandemic, when an individual's primary goal is safeguarding his or her health, PMT factors may accurately reflect a person's health behavior and predisposition to cardiovascular disease (Cilliers 2020). Addressing health concerns becomes increasingly essential in the setting of older persons, who are more susceptible to health risks (Kalantari 2017). Hence, this research posits the following hypothesis:

H1 PV positively influences intention towards HWDs.

2.2.2 Linking Perceived Severity (PS) to BI

PS assesses the level of danger posed by unhealthy behavior (Rogers 1975). Researchers have shown that individuals are more inclined to adopt health technology when there is a severe threat to their health (Rahi et al. 2021; Sergueeva and Shaw 2017). PMT defines threat severity as the extent to which a health threat may elicit a particular reaction (Rogers 1983). Prior study indicates that the intention to adopt HWDs stems from individual protective interests (Guo et al. 2015; Lv, Guo, Xu, Yuan, & Yu, 2012). Banerjee, Hemphill, and Longstreet (2018) demonstrated that customers regularly use HWDs, including smartwatches and activity trackers, to stay healthy and demonstrate their protective intent. Health risk mitigation or prevention is achieved using technology or healthcare wearables (Reyes-Mercado 2018). The previous study revealed a high positive correlation between users' protective intents and their inclination to utilize HWDs (Kaewkannate and Kim 2016; Reyes-Mercado 2018). Based on research, individuals use HWDs to avoid illness when they perceive a threat to their health (Prentice-Dunn and Rogers 1986).

H2 PS positively influences intention towards HWDs.

2.2.3 Linking Self-Efficacy (SE) to BI

Self-efficacy measures an individual's ability to perform the actions necessary to achieve a specific objective (Bandura 2012). From the perspective of PMT, self-efficacy refers to a person's optimism in their potential to participate in a coping behaviour (Jeong et al. 2017). Using technology confidently lowers resistance and makes them more likely to use it (Fraile et al. 2010). Previous research has shown that healthcare wearables allow the user to self-monitor health vitals and preserve their health; nevertheless, the determining element is the user's confidence in their ability to use the HWD's features (Cilliers 2020; Metcalf, Milliard, Gomez, & Schwartz, 2016). Incorporating self-efficacy characteristics into the design of health-related technology might boost the intent to utilize these technologies (Venkatesh et al. 2003). Accordingly, this research presumes the following:

H3 SE positively influences intention towards HWDs.

2.2.4 Linking Health Information Accuracy (HIA) to BI

HIA refers to the extent to which users feel that the information supplied by HWDs regarding their health state is reliable and believable (Chau et al. 2019). HWDs are being used more and more by those who care about their health to monitor their physical activity and those with chronic illnesses. The data gathered by the device must be accurate in any of these cases (Mahloko and Adebesin 2020). People will be more likely to assess their health when they believe that the information provided by HWDs is reliable (Ahmad et al. 2020). According to recent research, wearable technologies are usually reliable and error-free in 92–99% of cases (Vijayan et al. 2021). The accuracy of HWDs is a significant concern when integrating them with medical applications (Yang et al. 2022). When making health care decisions, individuals are likely to rely on the precision of HWDs' health information (Cheung et al. 2019). Accordingly, we hypothesize that:

H4 HIA positively influences intention towards HWDs.

2.2.5 Linking Perceived Novelty (PN) to BI

With their innovative characteristics, IoT devices have led to almost all fields' automation (Dholakia and Reyes 2013). As per E. Rogers (1995), Novelty is a crucial aspect of every innovation. Researchers in the literature about HWDs have explored technological innovation as a driving force for acceptance and usage (Chang et al. 2016). Y. Chang, Dong, and Sun (2014) and Wu, Talwar, Johnsson, Himayat, and Johnson (2011) have acknowledged the influence of innovation on mobile fitness application adoption. Kwee-Meier, Bützler, and Schlick (2016) analyzed the impact of a similar concept, 'technological excitement,' on the drive behind-hand wearable GPS devices. Prior empirical research has verified novelty as a factor significantly influencing customers' perceptions and use of any information technology-driven innovation (Wells et al. 2010; Zeng and Gao 2017). The current generation of smartwatches offers unique functions like oxygen monitoring and ECG, which increase users' desire to use the devices (Samol et al. 2019). In times of pandemic, these traits are advantageous. Along with tracking steps and heart rate, the innovative gamification function has made health monitoring more enjoyable; users enjoy accumulating and competing for badges (Sharma and Biros 2019). Thus, this research presumes the following:

H5 PN positively influences intention towards HWDs.

2.2.6 Linking Perceived usefulness (PU) to BI

A technology-based service or product's most critical aspect is its utilitarian or functional purpose. According to the PU, adopting a technology-based system would enhance efficiency and productivity for the user (Davis 1989). For example, if someone feels that having an HWD like a smartwatch has improved their health by monitoring vitals such as blood pressure, steps are taken, and so on, this will increase their intent to use the device (Kim and Shin 2015). Previous research has shown that individuals who grasp the benefits of the Internet of Things (IoT) devices for health are more likely to utilize them (Njomane and Telukdarie 2022). As per the PMT, utility comes from extrinsic motivation. Alternatively, it may be argued that the usefulness of smartwatches may also be attributed to consumers' belief that smartwatches will make them more efficient and organized (Dehghani et al. 2018). Hong, Jeong, Cho, Lu, and Kim (2019) research on smartwatch customers found a significant association between utilitarian value and behavioral intention. Hence, this research suggests the following:

H6 PU positively influences intention towards HWDs.

2.2.7 Linkage hedonic motivation (HM) to BI

The UTAUT2 framework defines hedonic motivation as "the fun or pleasure of using a technology" (Venkatesh et al. 2012). In the case of this research, HM is distinct as personal pleasure. Davis, Bagozzi, and Warshaw (1992) proposed that intrinsic motivations like subjective enjoyment may influence acceptance behavior. Consequently, enjoyment determines customers' attitudes toward adopting new technology (Gu et al. 2016; Magni, Taylor, & Venkatesh, 2010). Wearable devices, like HWDs, enable users to monitor their physical state continuously, especially for healthcare applications. Prior research has demonstrated that HM is a significant factor in wearable technology acceptance in the United States, China, and Saudi Arabia (Gu et al. 2016;

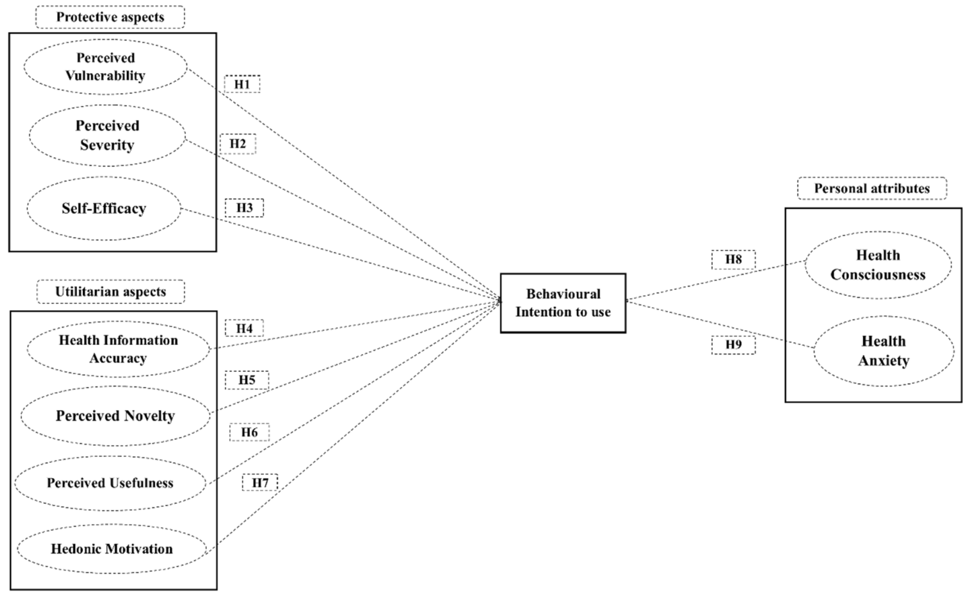

Fig. 1 Conceptual Framework
Source: Adapted from (Guo et al. 2015) and (Rogers 1975).

Sergueeva, Shaw, & Lee, 2020; Talukder, Chiong, Bao, & Hayat Malik, 2019). Therefore, we propose that:

H7 HM positively influences intention towards HWDs.

2.2.8 Linking Health consciousness (HC) to BI

A person's health consciousness refers to the degree to which health issues are integrated into daily life (C.-C. Chang, 2020). A vital link exists between HCS and healthy behavior. Health-cognizant individuals understand their health better, are attentive to health matters, and take precautions to maintain a healthy lifestyle (Lee et al. 2014). Also, people who are conscious of their health will want the right information to monitor it (Lee and Lee 2018; Paluch and Tuzovic 2019). Their health indicators will be continuously monitored, and they will utilize the product's healthcare services (Meng et al. 2019). HWDs intend to alter people's health behaviors and increase well-being (Zhang et al. 2017; Sergueeva et al. 2020) suggest that HC significantly forecasts health-related preventative behavior. Accordingly, a higher HC means a more positive outlook and willingness to use HWDs on the person's part. Hence, this research posits the following hypothesis:

H8 HC positively influences intention towards HWDs.

2.2.9 Linking Health anxiety (HA) to BI

An individual who suffers from HA is preoccupied with researching their health situation and is convinced that they are suffering from a serious undiagnosed illness (Sang and Cheng 2020). Further, HA is a feeling of discomfort or fear caused by bodily symptoms indicating severe illness (Meng et al. 2020). As a general rule, health anxiety contributes to safety-seeking behavior, aiming to protect and control one's health (F.-F. Huang, 2015). Older citizens with anxieties are more inclined to adopt healthcare technology because they want to feel more in control of their lives (Sang and Cheng 2020). In addition, individuals with a high HA level utilize more healthcare technologies and are more likely to use HWDs. Therefore, in the context of HWDs, we expect seniors with higher degree of health anxiety will have a higher intention to adopt the technology. In light of the above discussion, we propose the following hypothesis:

H9 HA positively influences intention towards HWDs.

3 Methodology

3.1 Proposed research model and survey development

The model was established by extending the PMT to integrate additional variables (i.e., perceived usefulness, hedonic motivation, perceived novelty, health information accuracy, health consciousness, and health anxiety as predictors to investigate the intention to use and adopt HWDs in Pakistan. Figure 1 displays the model with the hypotheses. The research adopts a comprehensive methodology using a sample questionnaire to gather data—measures and scales from previous studies we used. The survey used a seven-point Likert scale (strongly agree = 1 to disagree = 7 strongly). Perceived vulnerability, perceived severity, and self-efficacy were taken from (Gao et al. 2015; Jeong et al. 2017; Patrick, Griswold, Raab, & Intille, 2008; G. F. C. Rogers, 1983). The health information accuracy scale was adopted (Perkins and Annan 2013). The Perceived novelty scale was adopted from (Wells et al. 2010) and (Truong 2013). The Perceived usefulness scale was adopted from (Kulviwat, Bruner II, Kumar, Nasco, & Clark, 2007; Y. Park & Chen, 2007). We borrowed the health consciousness scale from (Dutta-Bergman 2004). The health anxiety items were borrowed from (Kim et al. 2019). Finally, the scale of behavioral intention was adopted from (Gong et al. 2004).

3.2 Sample and data collection process

We conducted a pilot study in which the first 25 responses were used to determine whether the statements used to quantify several factors were accurate and valid. The data collection process was done online to ensure consistency. The study's targeted participants were older people (individuals older ≥ than 60) residing in Islamabad, Karachi, Lahore, and Peshawar. The data was collected between November 2020 and January 2021 online who were aware of using smartwatches for health monitoring. A screening question, "Are you aware of the use of smartwatches for health monitoring?" was added to the questionnaire at the beginning. Only respondents who said "YES" and also met the age of 60 years were considered in the sample for this study. The responses received from less than 60 were excluded from the data set. In order to gather data, convenience sampling was employed, a method of non-probability (Ramayah et al. 2013). It is utilized to collect data from nearby and conveniently reachable individuals and to pick responders who are accessible to the researcher. We contacted senior citizens via our (near and extended) network of friends and relatives and then asked that they provide references. Participants were notified of the purpose of the research and ensured their privacy and confidentiality. The survey collected data over a period of three months and resulted in 310 responses (37.7% females and 62.3% males). Despite a more significant percentage of male participants, the sample makeup is comparable with past research on technology usage in Pakistan (Khan et al. 2017). Table 1 presents the sample characteristics.

Table 1 Demographic characteristics

Demographics Characteristics	Frequency	Percentage
Gender	193	62.3%
Male	117	37.7%
Female		
Average monthly income		
Below USD 160	35	11.3%
USD 161–360	105	33.9%
USD 361–500	73	23.5%
USD 501–700	40	12.9%
USD 701–1000	32	10.3%
More than USD 1000	25	8.1%
Number of hours spent with smartwatches (per day)		
Less than 2 h	103	33.3%
2–4 h	138	44.5%
4–6 h	41	13.2%
More than 5 h	28	9.0%
Frequency of use (per week)		
1–3 times a week	99	31.9%
4–6 times a week	125	40.3%
7–10 times a week	51	16.5%
More than ten times a week	35	11.3%

4 Data analysis and findings

A structural equation model (SEM) was used to analyze the data. Rendering to Bollen (1989), SEM is a powerful, multivariate second-generation approach for evaluating theoretical frameworks, thereby supporting the assessment of integrative models soundly. We use a three-step process to examine the data, which includes (1) the suggested model was tested by engaging CFA to analyze the constructs' reliability and validity, (2) testing the theoretical and extended HWDs adoption model, (3) Applying post hoc analysis to investigate the attitude of healthcare wearables as technologies.

4.1 Measurement model

CFA was employed to investigate the factors' convergent validity, discriminant validity (DV), and internal consistency (Slade et al. 2015). This study adopted Anderson and Gerbing (1988) three ad hoc tests standardized FL, CR, and AVE to evaluate the convergent validity of latent variables. The standardized FLs varied between 0.656 and 0.917, thus meeting the mandatory 0.50 cutoff value (Gefen et al. 2000). Furthermore, the CR values showed the latent constructs' internal consistency, with values exceeding the 0.70 criterion (Hair et al. 1992; Nunnally and Bernstein 1978). Lastly, the results presented in Table 2 signify the convergent validity (average variance extracted [AVE]). The values are more significant than 0.50, thus meeting the suggested standard level of AVE (Fornell and Larcker 1981). The latent construct succeeded for the convergent validity test when its values exceeded the three tests' predefined threshold (Anderson and Gerbing 1988).

Table 2 Construct validity

Constructs	FL	α	CR	AVE	Skewness	Kurtosis	VIF
PV		0.886	0.894	0.680	-0.51	-0.57	4.183
PV1	0.822						
PV2	0.897						
PV3	0.822						
PV4	0.749						
PS		0.880	0.762	0.519	-0.415	-0.634	2.373
PS1	0.850						
PS2	0.840						
PS3	0.868						
SE		0.872	0.858	0.606	-0.467	0.529	3.429
SE1	0.702						
SE2	0.669						
SE3	0.868						
SE4	0.854						
HIA		0.860	0.817	0.600	-0.99	0.174	2.912
HIA3	0.819						
HIA2	0.835						
HIA3	0.657						
PN		0.870	0.911	0.721	-0.496	-0.711	2.366
PN1	0.840						
PN2	0.917						
PN3	0.880						
PN4	0.749						
PU		0.871	0.848	0.585	-0.521	-0.56	3.376
PU1	0.775						
PU2	0.797						
PU3	0.820						
PU4	0.656						
HM		0.885	0.886	0.661	-0.638	-0.424	2.725
HM1	0.765						
HM2	0.854						
HM3	0.792						
HM4	0.839						
HC		0.866	0.854	0.594	-0.865	0.17	2.936
HC1	0.703						
HC2	0.789						
HC3	0.801						
HC4	0.785						
HA		0.854	0.858	0.604	-0.86	0.066	2.946
HA1	0.819						
HA2	0.835						
HA3	0.657						
HA4	0.785						
BI		0.757	0.762	0.519	-0.52	-0.558	
BI1	0.717						
BI2	0.813						
BI3	0.618						

Note: AVE = Average Variance Extracted, CR = Composite Reliability, FL = Factor Loading

The measurement model's general fit was evaluated using five commonly used metrics: CMIN/DF, AGFI, CFI, RMSEA, TLI, GFI, and NFI. The results for all model-fit indices are above the required levels, indicating a satisfactory fit to the given data: chi-square/df = 2.13, GFI = 0.80, AGFI = 0.75, CFI = 0.93, TLI = 0.91, NFI = 0.87, and RMSEA = 0.084 (Gefen et al. 2000; J. F. Hair, Black, Babin, Anderson, & Tatham, 2006). The DV is gained by calculating the square root of convergent validity, and the results are above 0.70 for all constructs, thus meeting the recommended standard levels (Fornell and Larcker 1981). Table 3 demonstrates the descriptive statistics and correlation among constructs.

4.2 CMB

Even though the questionnaire was compiled consuming a self-reporting method, CMB may threaten the validity of the results. This research uses the Harman single-factor test (Podsakoff et al. 2003). Technically, the dataset may include CMB if the test result for a single component is 50% or more prominent. In this study, all variables were fixed on factor 1, and the total amount of variances that can be explained is 47.72% (lower than 50%). Consequently, it is determined that the given data are CMB-free. The skewness and kurtosis values were within the acceptable range ± 2, indicating that the data are normal as recommended by (George and Mallery 2010). In addition, the VIFs of the constructs range between 2.37 and 3.18, which falls below the threshold of 5 (Kline 1998), signifying that CMB is not an issue in the study (CM in PLS-SEM: A Full Collinearity Evaluation Technique).

4.3 Structural model

We used AMOS 21.0 to calculate the path coefficient. The structural model was evaluated to measure the relationship between the latent variables highlighted in Fig. 2. Before we conduct a path analysis of the proposed model, an appropriate model fit index must be developed for the structural model. Results demonstrate the fitness of the model, for example, chi-square/df, GFI value, AGFI, TLI, and NFI, to be within the satisfactory ranges (Hu and Bentler 1999) and (Deligianni et al. 2016) recommended that the values should be beyond 0.90 for GFI, NFI, and CFI for a stronger model fit. Structural model fit indices estimation criteria yielded acceptable results. CMIN/DF 1.89, GFI = 0.81, AGFI = 0.75, CFI = 0.94, TLI = 0.91, NFI = 0.88, and RMSEA = 0.075 were well within their anticipated thresholds. All indicators show a good fitness value. The findings of the structural model analyses demonstrate a good model fit. After developing sufficient fit indices for the structural model, path analysis is appropriate. A summary of the hypotheses testing results is shown in Table 4. Only 7 hypotheses were supported, namely HI (β = 0.400, S.E = 0.047, C.R = 8.433), H2 (β = 0.082, S.E = 0.032, C.R = 2.605,), H3 (β = 0.212, S.E = 0.035, C.R = 5.994), H4 (β = 0.140, S.E = 0.039, C.R = 3.565), H6 (β = 0.109, S.E = 0.029, C.R = 3.715), H7 (β = 0.064, S.E = 0.031, C.R = 2.039), H8 (β = 0.285, S.E = 0.045, C.R = 6.321),, H5 (β = −0.011, S.E = 0.029, C.R = −.384), and H9 (β = 0.056, S.E = 0.034, C.R = 1.641) are insignificant.

Table 3 Correlation

	Mean	S.D	PV	PS	SE	PU	PN	HIA	HM	HC	HA	BI
PV	4.878	1.405	1									
PS	4.516	1.646	0.486**	1								
SE	4.671	1.392	0.731**	0.599**	1							
PU	4.702	1.468	0.781**	0.443**	0.701**	1						
PN	4.883	1.569	0.714**	0.493**	0.638**	0.620**	1					
HIA	5.372	1.402	0.728**	0.400**	0.581**	0.630**	0.611**	1				
HM	5.004	1.388	0.655**	0.387**	0.575**	0.571**	0.591**	0.629**	1			
HC	5.327	1.292	0.626**	0.300**	0.525**	0.565**	0.586**	0.690**	0.752**	1		
HA	5.235	1.287	0.657**	0.398**	0.623**	0.645**	0.615**	0.734**	0.652**	0.702**	1	
BI	4.862	1.368	0.774**	0.497**	0.714**	0.703**	0.635**	0.601**	0.668**	0.660**	0.653**	1

*** $p < .001$; ** $p < .01$, * $p < .05^{NS}$.

Table 4 Hypotheses testing results

Hypotheses	Paths	Estimate	S. E	C.R	P	Results	Decision
HI	BI <--- PV	0.400	0.047	8.433	***	Significant	Supported
H2	BI <--- PS	0.082	0.032	2.605	0.009**	Significant	Supported
H3	BI <--- SE	0.212	0.035	5.994	***	Significant	Supported
H4	BI <--- HIA	0.140	0.039	3.565	***	Significant	Supported
H5	BI <--- PN	0.011	0.029	0.384	0.701	insignificant	Not Supported
H6	BI <--- PU	0.109	0.029	3.715	***	Significant	Supported
H7	BI <--- HM	0.064	0.031	2.039	0.041*	Significant	Supported
H8	BI <--- HC	0.285	0.045	6.321	***	Significant	Supported
H9	BI <--- HA	0.056	0.034	1.641	0.101	Insignificant	Not Supported

Note: *** p < .001, **p < .01, NS p > .05.

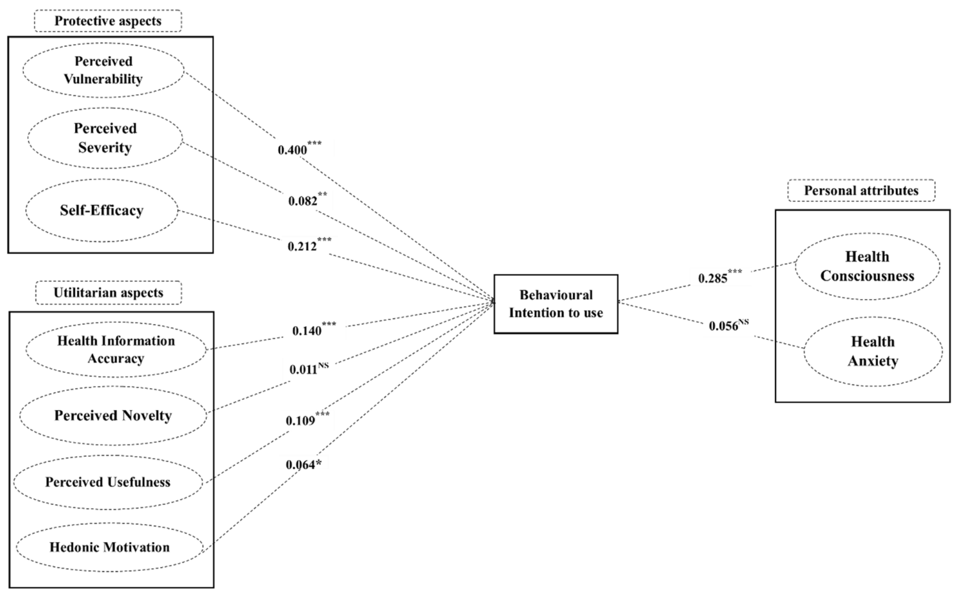

Fig. 2 Structural Model
Source: Adapted from (Guo et al. 2015) and (Rogers 1975).

5 Discussion and implications

This study examines the adoption of wearable healthcare devices with perceived vulnerability, perceived severity, self-efficacy, health information accuracy, perceived usefulness, hedonic motivation, perceived novelty, health consciousness, and health anxiety among senior Pakistani citizens. The results indicate that PMT factors influence seniors' behavioral intention to utilize HWDs to minimize health-related anxieties primarily caused by COVID-19 and encourage preventive health behavior (Kaewkannate and Kim 2016; Shen, Li, & Sun, 2018). Consistent with the results of previous experimental research (Al-Emran et al. 2022; Chan, Estève, Fourniols, Escriba, & Campo, 2012), there is a significant correlation between perceptions of vulnerability and seniors' intentions to utilize HWDs. This result is aligned with earlier research on adopting wearable technology in education, where perceived vulnerability is also a decisive motivating factor for adopting wearable technology (Al-Emran et al. 2022). Next, the research findings indicate that WHDs-based self-efficacy significantly affects the adoption of WHDs, suggesting that seniors' understanding of the risks and dangers associated with WHDs will influence their intention to utilize these wearables for personal use and health objectives. This result is similar to findings from previous research (Marakhimov and Joo 2017). Accordingly, senior citizens may be more inclined to use WHDs for health monitoring purposes if they are confident they can use them without difficulties. In line with the current literature (Chan et al. 2012; Marakhimov and Joo 2017), This research revealed a strong positive significant relationship between perceived severity and the behavioral intent to use WHDs among older adults. It is comprehensible that if older individuals feel very ill, they will be more inclined to utilize HWDs. Evidently, those with a high perception of vulnerability are more likely to become more self-protective (Burns et al. 2017); consequently, it is more evidence that they want to utilize HWDs. The findings indicated that health information accuracy significantly influenced individuals' intentions to use HWDs. This result is consistent with findings from previous investigations (Zhang et al. 2017). A technology's health information accuracy assesses its potential to provide customers with precise data and reliable services (Zhang et al. 2017). Studies have shown that health information websites are credible and provide accurate health-related information to users (Cilliers 2019; E. Park, Kim, & Kwon, 2016; Sharon, 2017). The findings of this research also pose questions about the insignificance of the influence of perceived novelty on intentions to accept HWDs and the function of this variable in PMT. Although our research findings do not entirely corroborate PMT model predictions referring to perceived novelty, other studies have demonstrated insignificant impacts of usability on consumer acceptability of wearable technology (e.g., (Cilliers 2019; Park et al. 2016; Patel, Asch, & Volpp, 2015). This study failed to reveal a relationship between perceived novelty and customers' intention to employ HWDs. Concerning their health, older adults may be more concerned about the device's precision and use than its novelty. Following earlier investigations (Park et al. 2016; Patel et al. 2015), this study revealed a substantial positive association between perceived usefulness and seniors' behavioural intent to utilize handheld devices.

Furthermore, the research asserts that hedonic motivation has substantially fostered the adoption of HWDs among study participants. It is in line with previous research on wearable adoption, which suggests that hedonic motivation is an important factor driving the acceptance of wearable devices such as watches, wristbands, and fitness trackers. However, in these studies, hedonic motivation has played a more minor role than perceived utility in driving wearable adoption (Lee and Lee 2018; Talukder, Sorwar, Bao, Ahmed, & Palash, 2020). Hedonic motivation seems to be a strong driver of seniors' usage of wearable technology in Pakistan, even for devices primarily employed for utilitarian purposes, such as healthcare. In addition, HC substantially inclined the decision to use the HWDs. This finding coincides with that of research by (Sergueeva et al. 2020), who indicates that personal HC influences the intention to use WMDs. However, the study results revealed that health anxiety is not a significant determinant of HWDs adoption among the senior citizen of Pakistan. This result contradicts the outcome of (Meng et al. 2020), who suggest that HA may not lead to the development of the desire to deploy WMDs.

5.1 Theoretical contribution

Despite a paucity of academic research on the subject, this study contributes to the body of research on the acceptance of HWDs in Pakistan, specifically on the little research conducted regarding wearable technologies in health care (Sergueeva et al. 2020). The research extends the PMT with the utilitarian aspects (perceived usefulness, perceived novelty, hedonic motivation, and health information accuracy) and personal aspects (health consciousness and anxiety) that nurtured healthcare technology adoption. The incorporation will give a more accessible explanation of both technology and the protective approach to find factors that might increase the intention of users to utilize HWDs during the pandemic. Health behavior–related research has integrated PMT, although its applicability to health-related technology, such as HWDs, remains restricted. Consequently, the current research bridges the gap by including protective and utilitarian characteristics and personal attributes. This research explains why PMT is useful in the present context for older users in their later years. It identifies the significant influence of perceived severity, self-efficacy, and perceived vulnerability on an individual's behavioral intention (Cilliers 2020; Ifinedo 2012). PMT indicators assess users' vulnerability and severity to health-related concerns and provide adaptive strategies for minimizing such threats (Haghi et al. 2017; Herath and Rao 2009). In the case of HWDs specifically, there has been a dearth of high-quality research linking PMT to user intent (Cilliers 2019). No research has been performed from the perspective of rising markets such as Pakistan.

5.2 Managerial implications

According to the study's findings, both technical and protection attributes should be considered by developers of HWDs. As providers, PN, HIA, HM, HA, HC, and PU are essential dimensions for marketing the services, promoting the consumer's interest in technology adoption, and taking responsibility for improving the consumer's intent to adopt the technology. Therefore, practitioners should address consumer expectations regarding the features and functions of these devices, including self-regulation features, reliable medical record systems, accurate health statistics, and daily health tracking. As a result, the accuracy of the device, as well as the usage intention of the customers, will be improved. It is essential to provide users with manuals or videos describing HWD's functional and security aspects. A significant contribution to this objective is made by this study, which recognizes pertinent factors that impact the intention to use HWDs.

Additionally, marketers should communicate the risks of not using HWD devices daily to their customers. Despite lifestyle changes and pandemics such as COVID-19, PMT is relevant in Pakistan due to the emergence of infectious and non-infectious diseases and their consequences on health (Asri et al. 2022). Older individuals are more susceptible to these diseases due to low immunity, shorter life expectancy, etc. (Claes et al. 2015). In light of the findings of this study, it can be concluded that customers are aware of the potential health risks associated with COVID-19 and the severity of the consequences that may result. This is relevant to their protective behavior. Customers are encouraged to adopt health-protective behaviors and made aware of their responsibility to maintain their health by HWDs. Moreover, the study shows that self-efficacy is vital to improving protective behavior and acceptance of HWDs. Providing better functionality, quality, and ease of use to HWDs and connected services could improve users' self-efficacy. Moreover, HWD developers should train users about the design and function of their products to enhance self-efficacy.

6 Limitations and future study

This study has made theoretical contributions by incorporating utilitarian dimensions and personal attributes into PMT; however, it has several limitations. First, the survey was delivered online due to the Covid- 19 epidemic. It was challenging for senior residents to comprehend the questionnaire, and obtaining timely replies was difficult to manage; thus it limits the generalizability to other regions and countries. In order to obtain comprehensive responses from older citizens, a future study must combine face-to-face and online data collection techniques. Second, the data are based solely on the elderly population in Pakistan, this may not apply to the elders of other countries. Future research must gather data from numerous geographic locations for the model to be generalizable and more accurate. Currently, the research focuses on the limiting factors influencing HWDs' intention and adoption. To investigate the adoption of HWDs, future research must include critical elements such as perceived value and mass adoption of HWDs. Because the usage of HWDs is still in its infancy in Pakistan, the participants in this research are likely early adopters who are more knowledgeable and self-motivated to explore IoT technology than typical customers. Conversely, the model can be extended by including some new moderating variables with interaction effects.

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