Assessing the factors that influence the adoption of healthcare wearables by the older population using an extended PMT model

Abstract

The present study aims to assess the intention of the older population to use healthcare wearable devices (HWDs) for wellness during life-threatening situations like COVID-19. The target population for the study was senior citizens (individuals aged above 60) living in Delhi and the national capital region. The respondents were aware that smartwatches could be used to monitor their health. Data from 534 respondents was collected using a structured questionnaire and nonprobability-based sampling method. The partial least squares structure equation model (PLS-SEM) was used to test the hypothesised model derived from the protection motivation theory (PMT) and constructs from previous studies on HWDs. Healthcare wearables offer new perspectives for gauging both health and technology-related dimensions. The present study is important as unlike existing studies, it discusses not only the utilitarian characteristics of HWDs but also their health-protective dimensions, which are crucial in times of life-threatening situations such as the COVID-19 pandemic. The findings indicate that there is a significant impact of both the protective and utilitarian dimensions of HWDs. The study assesses the perceived vulnerability and severity of the older population in COVID 19 and the intention to use HWDs to handle such health crises. The study confirms that perceived usefulness and information accuracy of HWDs, as well as self-efficacy, perceived severity, and perceived vulnerability of senior citizens are high during the COVID-19 pandemic, which significantly influences their intention to use HWDs.

Keywords: Protection motivation theory, novelty, usefulness, health information accuracy, intention to use

1. Introduction

The current COVID-19 pandemic has underlined the significance and usefulness of wearable medical devices (Fukuti et al., 2020). Wearables are intelligent devices that can be connected with electronic data records and help in facilitating communication between patients, caretakers/relatives, and healthcare providers (Sharifi et al., 2021). Since wearables address demographic trends such as ageing population, rising rates of lifestyle diseases, and rising healthcare expenses, therefore they are essential (Levy, 2014). Patients benefit from healthcare wearable devices (HWDs) because they give patients real-time data without requiring them to go to hospitals (Munos et al., 2016). With HWDs, the healthcare system may significantly improve its ability to remotely monitor patients' health and deliver prompt medical care (Islam et al., 2020).

The significant impact of the COVID-19 epidemic on the older population across the world demonstrates that they need intensive monitoring and care (Pan et al., 2020). Seniors frequently experience comorbidities, necessitating ongoing monitoring to ensure optimal health (Kirwan et al., 2020). Wearable technology encourages older people to remain independent and enhances the quality of their lives by helping them lead healthier lifestyles (Popescu, 2014; Elimelech et al., 2022).

Wearable device technology used in smartwatches and fitness trackers, and healthcare software is seen to help enhance consumers' overall health (Aymerich-Franch and Ferrer, 2022). A customer's perception of a product and its use is primarily related to its core function and utility. Customers prioritise utilitarian benefits more generally than aesthetic benefits. According to the technology acceptance model (TAM), people tend to react favourably when they feel that technology is useful. If the user perceives that HWDs help monitor health, and are trustworthy and free from errors, the user's intention to use them will consequently improve be greater and their perceived usefulness also increases (Cheung et al., 2019).

Individuals are motivated to use information technology to improve their health when they feel that their health is at risk. In the context of HWD, individuals are inspired to employ wearable healthcare technology when they are concerned about their health. HWDs can be considered protective technology, as they protect users against fears and concerns about health. According to the protection motivation theory (PMT) (Rogers, 1975), perceived security and vulnerability are the key factors that intention to use HWDs. The more acute the health threat to individuals, particularly amongst the older population, the higher the probability that they will show positive attitudes to take steps to change their condition (Prentice and Rogers, 1986). There is validation from other studies that older users with severe health risks are highly likely to adopt healthcare devices (Sun et al., 2013). Previous studies (Hsu and Lin, 2016; Sicari et al., 2015) have shown that information privacy issues such as data protection, absence of human control, and dependence on devices are limiting factors in this context (Mani and Chouk, 2018). Tu (2018) found perceived benefits and perceived worries to be significant determinants in the adoption of wearable devices. Data privacy is also a pressing concern, primarily when using a wearable fitness tracker (Zhou and

Piramuthu, 2014). Social influences, such as feedback from peers and social circle advice, has a positive impact on the intention to use devices (Gao and Bai, 2014).

Although wearable devices offer numerous benefits, particularly in the context of healthcare, the use of wearable devices is low (Sultan, 2015). Despite the obvious advantages of wearable technology for older generations of individuals, it is young people who are primarily drawn to these gadgets (Kekade et al., 2018). Only 3.3 per cent of HWD users in the United States are 65 or older, compared to 17.1 per cent who are between the ages of 25 and 34 (Wurmser, 2019).

Another drawback associated with HWDs is their long-term use. Studies (Levy, 2014; Junaeus, 2015) have reported that consumers stopped using their wearables in less than six months. In the present pandemic situation, wearable device use is driven as much by health factors as by technology-related factors. Previous empirical studies (Wuenderlich et al., 2015) followed TAM, focusing on the technological precursors that preceded users' intention to adopt HWDs, leaving gaps of awareness in other areas. Although HWDs combine health and technology traits to create value for consumers, studies on consumers' concerns, their health beliefs and adoption intention are limited, except for a few empirical studies by Chau et al., (2019) and Zhang et al. (2017). On the topic of acceptance of HWDs, more studies are focused on health professionals rather than consumer behaviour studies (Junglas et al., 2009). Prior studies have also overlooked the influences of self-efficacy in advancing the adoption of HWD (Abouzahra and Ghasemaghaei, 2020).

India is used as the context in this study as it has one of the lowest per capita healthcare expenditures globally (Bahuguna et al., 2018). Like most developing nations, the concept of geriatric (senior) healthcare is comparatively new in India. With India's increasing population and low budget spending on healthcare, the only solution to the crisis is the digitisation of healthcare (Mills and Hilberg, 2020). As per the discussion above, this study addresses the following research questions.

RQ1: What drives senior citizens to adopt HWDs?

RQ2: Does the senior citizens perceive HWD as a utilitarian (technology) product, health-related product, or both?

HWDs provide new approaches to gauging health and technology-related dimensions (Dehghani et al., 2018). The study attempts to understand the use adoption behaviours of senior citizens through the lens of PMT and selected utilitarian constructs, including perceived usefulness from TAM, perceived novelty, and health information accuracy. From a practical perspective, wearable device designers must understand the factors that affect HWD adoption and sustained use, particularly amongst the older population, as a complex device (or complicated application) will result in negative perceptions.

The remainder of this article is structured as follows. Section 2 discusses the theoretical background and development, followed by the research methodology (Section 3) applied to the study. Section 4 presents the findings, which are discussed in Section 5, along with implications of the study. Section 6 provides the conclusion.

2. Theoretical background, conceptual model, and development of hypotheses

Factors that influence the adoption of technology and its actual use have been discussed widely in previously published literature (Wang et al., 2015; Singh et al., 2020). Specific to healthcare wearable technologies, extant literature is based on several theories, such as the innovation theory, TAM, expectations confirmation theory (ECT), unified theory of acceptance and use of technology (UTAUT), theory of planned behaviour, and protection theory. These theories explain that users are inclined to use HWDs for functional benefits (Chang et al., 2014; Wang et al., 2015), health-related benefits (Jeong et al., 2017; Ma et al., 2019), self-monitoring (Fraile et al., 2010), health protection (Wang et al., 2015), etc. These studies largely explored the variables of HWDs, including innovativeness, attitude, social norms, usefulness, credibility, risk, and other technological attributes motivating utilitarian belief.

The present study uses PMT and extends it with the following antecedents: perceived usefulness from TAM, the construct of health information accuracy, and perceived novelty. The reasons for choosing these factors are set out below. First, HWDs are new smart wearable devices with automated functions that capture contextual information of users to provide a personalised experience. These devices are more popular among the younger than the older generation (Kekade et al., 2018). However, a few recent studies indicate the inclination of the older generation towards HWDs (Pan et al. 2020; Popescu, 2014). However, their understanding of the purpose and usefulness of HWDs was still in a nascent stage. These devices are still perceived as new by them (Munos et al., 2016). Therefore, this study uses perceived usefulness from TAM. We focus on perceived usefulness to predict intention because it is highly relevant for technologies that fit customers' routines and lifestyles (Pan et al., 2020). Perceived usefulness is commonly found in literature as a perception-based construct that can alter depending on the user's contact with a certain technology (Singh et al. 2017). Particularly in studies on HWDs and other fitness apps, perceived usefulness is shown to be a strong predictor of users' attitude and intention to use these services (Huang and Ren, 2020). A few significant studies confirm the applicability of the variable perceived usefulness from TAM from the perspectives of potential and actual users who may use such devices for personal convenience and health monitoring (Chen and Lee, 2008; Wang et al., 2015). Moreover, older individuals with limited mobility and self-efficacy expect health technologies to have easy-to-use features and self-tracking facilities and be useful (Cilliers, 2020). Therefore, usefulness is the main function that consumers desire in HWDs (Chen and Lee, 2008).

Second, HWDs are viewed as novel because of their self-monitoring or self-care services (Malwade et al., 2018). According to studies, consumers regard the device as very innovative, and that its adoption would enhance their health and well-being (Cheung et al. 2020). However, these findings are primarily supported in the context of young consumers (Generation Z), with limited research on adults (Kekade et al., 2018; Cheung et al., 2020). Technological innovation is a well-defined concept that focuses on a service's novelty, adaptability, and usefulness (Mani and Chouk, 2018; Singh et al. 2020). Earlier research confirms that in the non-users' context, the intended users' adoption of an innovation or technology is based on innovation that influences its usefulness (Singh et al. 2017; Malwade et al., 2018). Studies also explore the accuracy of HWDs and credibility, such as the reliability of medical information provided by HWDs and the protection of users' privacy while using such devices (Claes et al., 2015). Such concerns require additional investigation, especially in the context of adults, who are more resistant to new technologies than younger consumers (Singh et al., 2017). Literature demonstrates the positive impact of novelty and accuracy on the perceived usefulness of HWDs, which intensifies consumers' intention to use them (Ahmad et al., 2020; Cheung et al. 2020). Thus, the model in this study includes perceived novelty and health information accuracy as utilitarian aspects.

Third, some studies also understand the importance of HWDs in alleviating health stress and monitoring users' health during critical times (Wang et al. 2015). With respect to the older population in particular, the studies confirm that health devices are required to review health statistics, monitor health, and take primary measures to combat the risk of developing a health problem (Jeong et al., 2017; Kekade et al., 2018). Most of these studies use PMT as a base model (Ma et al., 2019). Studies based on PMT suggest that discussing only technological aspects of HWDs will not be sufficient, and their protective health dimensions should be measured (Jeong et al., 2017). Therefore, the use of PMT is relevant and appropriate in the current context to assess the protective motives of HWD users. When health-threatening situations, for example, COVID-

19 pandemic, are prevalent, there is a need for an integrated framework that explains both technical and health preventive determinants of HWDs, which has not been tested in previous studies. Therefore, the present study integrates PMT with three relevant utilitarian dimensions – perceived usefulness, perceived novelty, and health information accuracy – to assess users' behavioural intention to use HWDs during the pandemic.

Finally, very few studies discuss the perception of the elderly population on the actual use of wearable devices (Kekade et al., 2018; Malwade et al., 2018). In addition, we found very few studies that use PMT to assess individuals' intention to adopt HWDs despite its high relevance to the concept (Chen and Lee, 2008; Ifinedo, 2012; Wang et al., 2015). No known study examines old age groups and their adoption of wearable devices for health services based on protective motives using PMT. There are limited studies conducted in a dependent environment (pandemic) where elderly users' mobility is restricted (Fraile et al., 2010; Claes et al., 2015). Such situations limit their activities, and several). Several external impositions are faced by older users, limiting their movement and accessibility to various health services as well as their activities (Hung et al., 2004; Claes et al., 2015). The appropriate use of HWDs, particularly for the older population, can fill this gap.

2.1. **Protection motivation theory (*PMT*)**

Past studies have found PMT to be relevant in the context of stressful events or any situations that threaten health, and widely discussed (Jeong et al., 2017; Shen et al., 2018). Health-related factors are highly relevant when older individuals are more vulnerable due to comorbidities and belong to a high-risk zone (Jeong et al., 2017). PMT explains individuals' protective actions towards a threatening event that is likely to occur or has already occurred (Rogers, 1975). The theory consists of two motivation strategies used by individuals: threat appraisal and coping appraisal (Herath and Rao, 2009). The first determines the probability of the severity or seriousness of the situation (Guo et al., 2015). On the other hand, the second measures the user's efficacy to cope with such situations (Guo et al., 2015). The PMT constructs, perceived vulnerability (PV) and perceived severity (PS) as threat agents have been studied in various contexts, such as, mobile information services in tourism (Fuchs et al., 2011), mobile health services (Lv et al., 2012), cloud computing classrooms (Shiau and Chau, 2016), and advanced driver assistance systems (Jun et al., 2019). PMT is relevant in the current situation, as it includes threat identification (impact of pandemic) and coping mechanisms (measures to remain healthy). A few studies used PMT on senior people to highlight their vulnerability to health risks and suggest behavioural changes to avoid such threats in the future (Chen and Lee, 2008; Lv et al., 2012). Concerning health-related issues, the PMT model is used and extended with various technological, psychological, and behavioural factors in several significant studies (Bansal and Gefen, 2010; Ifinedo, 2012; Jeong et al., 2017). Specifically, amongst the older population, studies confirmed that when they are vulnerable to diseases, HWDs help in early detection and management of health (Kekade et al., 2018; Malwade et al., 2018). HWDs help users in managing stress and protecting their health (Kim et al., 2019). Hence, PMT is applicable in this context (Jeong et al., 2017).

2.2. Conceptual framework and development of hypotheses

Based on the gaps in existing research literature, a conceptual framework is developed and presented in Figure 1.

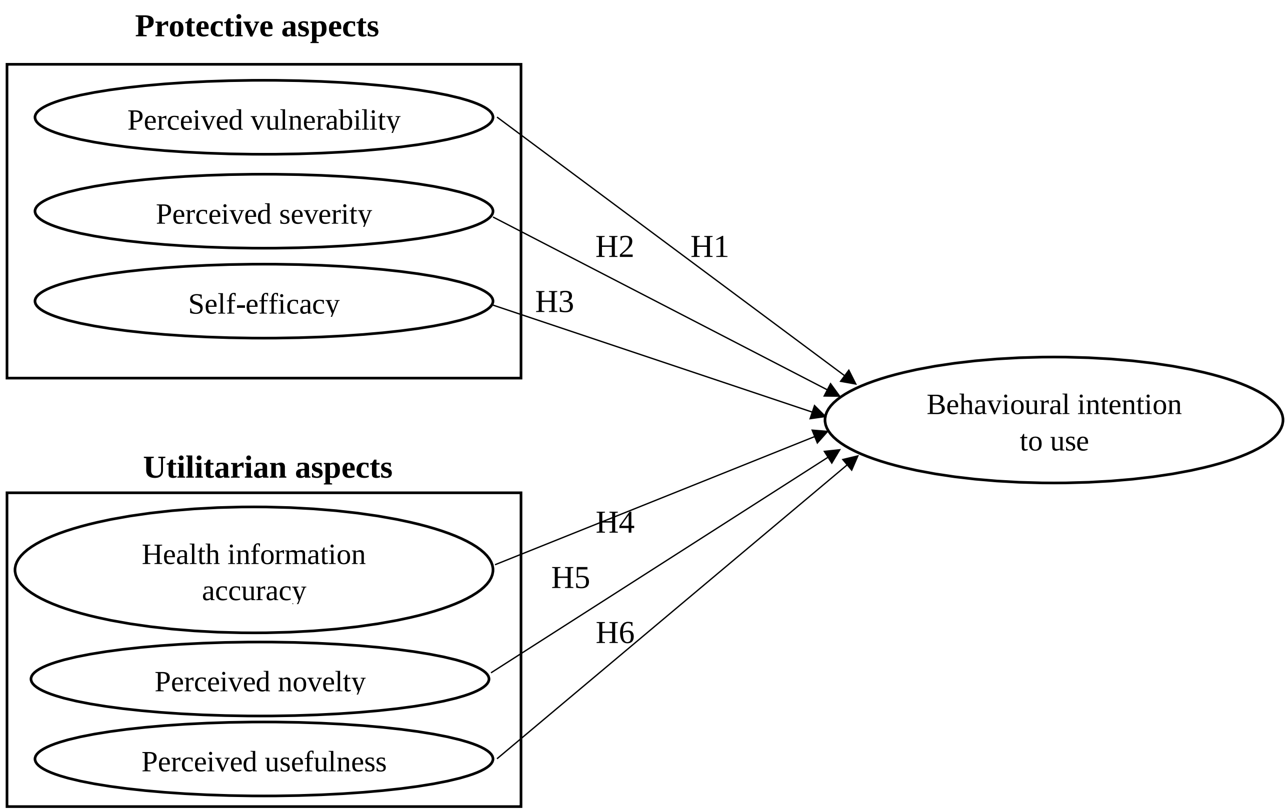

Fig. 1. Conceptual framework

Source: Adapted from Guo et al. (2015) and Davis (1989)

2.2.1 **Perceived Vulnerability (***PV***)** *and behavioural intention*

PV is the assessment of the probability that people will experience a threat to their health (Wang et al. 2015). PV is an essential element of the threat appraisal process, suggesting that people actively determine their risk (Rogers, 1983). PMT states when there is a high likelihood of coming across a risk, a person adopts health information technology to lessen or prevent health threats (Prentice & Rogers, 1986). Previous studies on PMT reported that when PV was high, users become more worried about their knowledge and preparedness to deal with the risk (Sun et al., 2013; Guo et al., 2015). The earliest work on the PV dimension in the health discipline aimed to understand why people use health services, which guided the development of the health belief model (Becker, 1974). In situations like the pandemic, where the main agenda of an individual is to protect health, PMT determinants may better explain an individual's health behaviour and inclination towards HWD (Cilliers, 2020). Understanding health threats becomes more critical in the context of elderly people, as they are more vulnerable to health threats (Kalantari, 2017). Based on these arguments, the first hypothesis is proposed as follows:

H1: PV will positively influence intention towards HWDs.

2.2.2 **Perceived Severity (***PS***)** *and behavioural intention*

PS describes the degree of threat resulting from unhealthy behaviours (Rogers, 1975). Studies show that when there is a significant risk to their health, people are more likely to use health technology (Sergueeva & Shaw, 2017; Rahi et al., 2021). PMT defines threat severity as the ability to influence the strength of the response to a health threat (Rogers, 1983).

According to prior research, the intention to use HWDs is derived from individual protective motives (Lv et al., 2012; Guo et al., 2015). Banerjee et al. (2018) claimed that consumers frequently use HWDs, such as smartwatches and activity trackers, to stay healthy and show protective intentions. Consumers employ technology or healthcare wearables to resist or reduce risks to their health (Wang et al., 2015; Reyes-Mercado, 2018). Previous research demonstrated a strong and positive relationship between a user's protective intentions and their intention to utilise HWDs (Reyes-Mercado, 2018, Kanitthika et al., 2016). According to studies, people adopt HWDs to prevent ill-health when they appear to be at risk from threats (Prentice-Dunn and Rogers, 1986; Guo et al., 2015).

H2: PS will positively influence intention towards HWDs.

2.2.3. Self-efficacy (SE) and behavioural intention

An individual's perception of their ability to successfully carry out the tasks required to achieve the desired intent are referred to as self-efficacy (Bandura, 2012). In the PMT context, the degree of self-confidence a person has in their ability to engage in a coping behaviour is known as self-efficacy (Jeong et al., 2017). When people utilise technology confidently, it reduces resistance and intensifies the intention to use (Fraile et al., 2010). Past studies confirmed that healthcare wearables enable a user to self-monitor health vitals and protect their health, however, the determinant factor is their belief that they are competent to deploy the functionality of the HWD (Cilliers, 2020; Kim et al., 2019; Metcalf et al., 2016). The fostering of self-efficacy features in designing health-related technologies could increase the intention to use (Venkatesh et al., 2003). Based on the above-mentioned discussion, we propose that:

H3: Self-efficacy will positively influence behavioural intention towards HWDs.

2.2.4. Perceived usefulness (PUF) and behavioural intention

The most critical factor in using any technology-driven service or product is the utilitarian or function-oriented motivation. PUF is the user's perception that using a technology-driven system or service will help improve their performance and increase output (Davis,1989). In the case of a HWD like a smartwatch, if the user believes that using the device has benefited their health by helping them monitor their vitals like blood pressure, steps taken, etc., it will increase the user's intent to use (Kim and Shin, 2015). Previous studies showed that people who understand the benefit of Internet of Things (IoT) devices on health will have significantly higher motivation to use the device (Cheung et al., 2019; Njomane and Telukdarie, 2022). As per the motivation theory, utility is a consequence of extrinsic motivation. The utility of smartwatches can also be understood as users' belief that smartwatches will enhance their productivity by helping them be more planned and productive (Dehghani et al., 2018). The study by Hong et al. (2019) of smartwatch consumers ascertained a positive relationship between utilitarian value and behavioural intention. Based on the arguments above, we propose the following hypothesis:

H4: Perceived usefulness will positively impact behavioural intention towards HWDs.

2.2.5. Perceived novelty (PN) and behavioural intention

IoT devices with their novel attributes have contributed to automation in nearly all disciplines (Dholakia and Reyes, 2013). As per Rogers (1995), an essential feature of any innovation is its novelty. In the literature on HWDs, researchers have studied technology innovativeness as a motivation for adoption and continued use (Chang et al., 2016). Wu et al. (2011) and Chang et al. (2014) have recognised the impact of innovativeness on adopting mobile fitness applications. Kwee-Meier et al., 2016 studied the effect of a similar construct, ‘technical enthusiasm’, on the motivation behind wearable GPS devices. Previous empirical studies have validated novelty as a factor that has a significant impact on consumers’ attitudes and utility for using any innovation-driven by information technology (Wells et al., 2010, Zeng & Gao, 2017). The new generation of smartwatches includes innovative features such as oxygen monitoring and ECG, which also drive consumers’ intention to use (Samol et al., 2019). These features are beneficial in pandemic times. The novel gamification tool has made health tracking more fun; in addition to tracking steps and heart rate, users enjoy collecting badges and competing against their friends (Sharma & Biros, 2019). Based on the arguments above, we propose the following hypothesis.

H5: PN positively impacts behavioural intention towards HWDs.

2.2.6. Health information accuracy (IA) and behavioural intention

The degree to which consumers believe that the data provided by HWDs about their health status is trustworthy and credible is referred to as health information accuracy (Cheung et al., 2019). HWDs are increasingly used by health-conscious people to track physical activity as well as by people with chronic disease conditions for remote monitoring (Pobiruchin, 2017). The data the gadget collects must be correct in both these scenarios (Mahloko & Adebesin, 2020). When consumers believe that information they receive through HWDs is accurate, they are willing to use it to assess their health (Ahmad et al., 2020). One recent study says that wearable devices are usually 92–99% accurate and precise (Vijayan, 2021). One of the main concerns about integrating HWDs with medical applications is the device’s precision (Yang et al., 2022). The accuracy of HWDs’ health information increases the likelihood that people will rely on it when making decisions regarding their health (Cheung et al., 2019).

H6: HIA positively influences behavioural intention towards HWDs.

3. Research methodology

This is a descriptive study that intends to identify the factors that affect a user’s intention to use HWDs. The conceptual model presented in Figure 1 shows various protection factors (PV, PS, and SE) and other factors (health information accuracy, perceived novelty, and perceived usefulness) derived from previous studies on HWDs. These variables are used as predictors of behavioural intention (BI) to use smartwatches to monitor health.

3.1. Scale description

The scales included in this study were carefully selected from published sources after considering their applicability to the present study and their use in the relevant literature. These measures were further refined to confirm reliability. Next, to ensure face validity, the instrument was given to two experts, an academic and an IT professional, for their feedback. Two statements were slightly modified to improve the understanding of variables based on the feedback received from experts. The questionnaire contained three sections. Section one comprised the screening question, while section two measured demographic profiles such as gender and annual income, as well as time spent using IoT devices. The third section measured the study's constructs. Each variable in the survey was measured on a seven-point Likert scale (1 = 'Strongly disagree'; 7 = 'Strongly agree').

Perceived vulnerability: It is defined as the possibility that an individual experiences some threat to their health (stated problems) (Patrick et al., 2008). The measure of perceived vulnerability used five items from the study by Gao et al. (2015). For example, two of the measurement items were 'It is likely that I will suffer the health problems' and 'I am at risk for suffering from the health problems'.

Perceived severity: Perceived severity is defined as the existence of a threat to one's health when not using HWDs (Rogers, 1983). The four-item scale for perceived severity is adopted from the study by Gao et al. (2015) with minor alterations. 'If I suffered the health problems, it would be severe' and 'If I suffered the health problems, it would be serious' are two sample measurement items used to measure perceived severity.

Self-efficacy: Self-efficacy measures one's belief in the capability and competency to use HWDs (Jeong et al., 2017). To measure self-efficacy, a five-item scale was adapted from Gao et al. (2015). For example, 'I can use wearable devices to self-monitor my physical conditions' and 'I can use wearable devices to self-monitor my physical conditions without much effort' were two of the measurement items used.

Health information accuracy: This construct was measured using a three-item scale, adapted from the study by Daniel and Jonathan (2013). Two sample statements used to capture data on information accuracy were: 'Services offered by wearable devices like smartwatches are secure' and 'Wearable devices like smartwatches provide accurate data related to my health'.

Perceived novelty: Any innovative product is perceived as novel if it has essential features and offers some unique application/s (Rogers, 1995). A four-item scale was followed, using studies by Truong (2013) and Wells et al. (2010). Examples of statements used to measure perceived novelty are: ‘Wearable devices like smartwatches are different from the other devices’ and ‘Wearable devices like smartwatches are unique’.

Perceived usefulness: The usefulness of wearable devices like smartwatches is defined as users’ belief that such devices will help them plan better for their health (Dehghani et al., 2018). To measure perceived usefulness, a five-item scale was adapted from Kulviwat et al. (2007) and Park and Chen (2007). Two of the sample statements used to measure perceived usefulness were: ‘I find wearable devices like smartwatches very useful in my daily life’ and ‘Using wearable devices like smartwatches help me to complete my tasks efficiently’.

Behavioural intention to use: A three-item scale was adapted from Gong et al. (2004) to measure behavioural intention to use smartwatches. Two measurement items used were, ‘I intend to use wearable devices like smartwatches in the next 12 months’ and ‘I am likely to disclose my personal information to use wearable devices like smartwatches in the next 12 months’.

3.2. Sample and data collection

A pilot study was conducted with the first 20 responses received to check the precision and completeness of statements used to measure various variables. The target population for the study was senior citizens (individuals aged above 60) living in Delhi and the National Capital Region. A screening question (‘Have you heard about usage of smartwatches for health monitoring?’) was added at the beginning of the questionnaire. The respondents who answered ‘NO’ were excluded from the analysis. Convenience and reference sampling are used for data collection. We used our contacts amongst friends and family (close and extended) to reach out to senior citizens and then these respondents were requested to give references. The respondents were informed about the study’s objective and assured of anonymity and confidentiality of responses. Approximately 700 questionnaires were distributed through e-mail, followed by phone calls. We received 580 responses. As the screening criterion was awareness of smartwatches, 34 responses were excluded from further analysis, since they had never heard of smartwatches. An additional 12 responses were removed for having straight-line problems (Arias et al., 2020). A total of 534 responses were used for the final analysis.

We used various descriptive techniques such as standard deviation, skewness, kurtosis, p-p plots, and q-q plots, to assess the normality of the data. Almost all the variables used in the study were found to be skewed and this was the main reason for choosing the partial least squares structure equation model (PLS-SEM) to test the structural equation model. Applying PLS-SEM does not require any normality assumption, unlike covariance-based SEM (Hair et al., 2020). The minimum sample size required for PLS should be at least 10 times the maximum number of inner model paths pointing towards a particular construct (Barclay et al., 1995). The sample size for the present study satisfies this condition well.

3.3. Common method bias

Common method bias is a systematic bias that is present in measures by means of the measurement method (Doty and Glick, 1998) and usually occurs when all the study variables were measured using the same method or source (Richardson et al., 2009). To control common method bias, a few procedural remedies, such as protecting the anonymity of respondents (Tehseen et al., 2017), keeping the scale short and simple, and avoiding double-barrelled questions (Tourangeau et al., 2000) are followed. Further, partially out of common factor (Podsakoff and Todar, 1985) and full collinearity assessment approach (Kock, 2015) are used as statistical measures to rule out the possibility of common method bias. Under the first statistical approach, a very small increase in the R-square value is observed. In addition, using the full collinearity assessment approach, the variation inflation factor (VIF) value for the inner model was well below the threshold value of 5 (Hair et al., 2011). The result indicates that there are fewer chances of common method bias in our data.

4. Results

4.1. Demographics of respondents

The demographic details of the respondents are presented in Table 1. Approximately 60 per cent are male, and 40 per cent are female respondents. The monthly income of more than 70 per cent of respondents is less than two hundred thousand rupees (INR 200,000). Out of all the respondents, approximately 69 per cent of respondents used IoT devices for more than one hour a day and used IoT devices more than two times a week.

Table 1. Demographic profile of respondents

Demographics	Frequencies (Percentage)
Gender	
Male	316 (59.18)
Female	218 (40.82)
Household monthly income (in INR)	
Less than 200,000	376 (70.41)
200,000–500,000	158 (29.59)
More than 500,000	0 (00.00)
Number of hours spend with smartwatches (per day)	
Less than 1 hour	168 (31.46)
1–3 hours	221 (41.39)
3–5 hours	88 (16.48)
More than 5 hours	57 (10.67)
Frequency of use (per week)	
1–2 times a week	161 (30.15)
3–5 times a week	189 (35.39)
6–10 times a week	87 (16.29)
More than 10 times a week	97 (18.16)

4.2. Evaluation of measurement model

Various items related to each construct in the model were subjected to the measurement model using the Smart PLS3 software. We examined the goodness of all variables, i.e., PV, PS, SE, HIA, PN, PU, and BI to establish reliability and validity (Hair et al., 2014). To establish reliability, we used both indicator reliability and internal reliability. The findings confirmed indicator reliability, as all the outer loadings were more than 0.70 (Hair et al., 2017). The results also established internal reliability with all values of Cronbach's Alpha and composite reliability (CR) higher than the threshold value of 0.60 (Nunnally, 1978) and 0.70 (Fornell and Larcker, 1981). To confirm reliability, we also checked Rho_A values, and the results showed Rho_A values to be well above the accepted value of 0.60 (Henseler et al., 2016). The values for item-wise mean, standard deviation, outer loadings and construct-wise Cronbach alpha values, Rho_A values, average variance extracted (AVE), and CR values are presented in Table 2.

Table 2. Validity of constructs

	Factor Loading	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**Cronbach's Alpha**	**Rho_A**	**Composite Reliability**
Perceived Vulnerability				0.930	0.930	0.947
PV1	0.891	4.796	1.550			
PV2	0.893	4.940	1.500			
PV3	0.881	4.850	1.519			

PV4	0.883	4.837	1.541			
PV5	0.871	4.876	1.526			
Perceived Severity				0.891	0.891	0.932
PS1	0.901	4.843	1.326			
PS2	0.916	4.858	1.315			
PS3	0.902	4.993	1.414			
Self-Efficacy				0.916	0.917	0.937
SE1	0.889	5.045	1.578			
SE2	0.875	4.942	1.526			
SE3	0.814	4.712	1.561			
SE4	0.875	4.912	1.574			
SE5	0.870	4.925	1.584			
Health information accuracy				0.892	0.892	0.933
HIA1	0.897	4.794	1.361			
HIA2	0.912	4.873	1.396			
HIA3	0.912	4.850	1.390			
Perceived Novelty				0.915	0.915	0.940
PN1	0.908	4.919	1.578			
PN2	0.878	4.775	1.570			
PN3	0.893	4.888	1.586			
PN4	0.891	4.903	1.665			
Perceived usefulness				0.935	0.935	0.950
PU1	0.900	5.024	1.547			
PU2	0.887	4.904	1.529			
PU3	0.888	4.968	1.531			
PU4	0.819	4.871	1.549			
PU5	0.900	4.955	1.579			
Behavioural Intention to use				0.868	0.871	0.920
BI1	0.855	4.723	1.406			
BI2	0.895	4.966	1.394			
BI3	0.920	4.993	1.412			

Note: Items removed due to high inter-item correlation (PS4)

We calculated convergent and discriminant validity to establish the validity of the constructs. Convergent validity was confirmed using AVE for all the factors. As per the results, AVE values for each construct are above the accepted value of 0.50 (Fornell and Larcker, 1981). Further, discriminant validity was established using two methods: first, the Fornell-Larcker criterion and second, HTMT ratios. As a condition of Fornell-Larcker, the value of correlation coefficients (along with other constructs) need to be less than the square root of AVE for all constructs in the model. Whereas, when HTMT ratios are used, all ratios must be less than the threshold value of

0.90 (Henseler et al., 2016). The results confirming convergent validity are presented in Table 2 and the results demonstrating discriminant validity are presented in Table 3. According to the results, the measurement model was confirmed to be a good fit.

Table 3. Discriminant validity

	BI	HIA	PN	PS	PU	PV	SE
BI	0.890						
HIA	0.751 (0.867)	0.907					
PN	0.699 (0.895)	0.658 (0.839)	0.893				
PS	0.733 (0.847)	0.742 (0.844)	0.669 (0.851)	0.906			
PU	0.739 (0.829)	0.683 (0.857)	0.799 (0.872)	0.710 (0.887)	0.891		
PV	0.686 (0.874)	0.753 (0.836)	0.592 (0.750)	0.686 (0.864)	0.603 (0.753)	0.884	
SE	0.731 (0.830)	0.672 (0.854)	0.786 (0.867)	0.709 (0.795)	0.710 (0.783)	0.718 (0.778)	0.865

Note: Diagonal elements in the matrix represent the square root of AVE, off-diagonal elements represent correlation coefficients, and values in parentheses represent HTMT ratios.

4.4. Evaluation of structural model and hypothesis testing

We used the PLS-SEM method to test the hypotheses proposed in this study. Bootstrapping procedure with 5,000 sub-samples was used to check the significance of the relationships proposed in the conceptual model. We established the good fit of the model by measuring the standardised root mean square residual (SRMR). The value is 0.033, following the threshold value of 0.08 (Henseler et al., 2014). While assessing the PLS model, we examined R-square, f-square and Q-square values, as Henseler et al. (2016) have suggested. These helped us evaluate the predictive power, effect size, and predictive relevance of dependent variables. Our model explains a total of 82 per cent variance in the intention to use HWDs. An R-square value of 0.820 indicates that our model shows good predictive accuracy (Hair et al., 2017).

Next, we tested the effect size of independent variables on BI using f-square values. As per Cohen (1988), small, medium, and large effect sizes are indicated through the f-square values greater than 0.02, 0.15, and 0.35, respectively. The results showed that PN has no effect, whereas other variables have small-to-medium effect sizes with an f-square value ranging from 0.02 to 0.18.

Further, we examine Q-square values, which focus on the predictive sample reuse technique (Stone, 1974). We used the blindfolding method with omission distance 7 to calculate the Q-square value. Although a Q-square value of more than zero reflects the predictive relevance, a higher Q-square value represents better predictive relevance (Hair et al., 2017). In the present study, the Q-square value of BI is 0.640, which indicates that the model has good predictive relevance.

Table 4. Structural relationships and hypothesis testing

Hypotheses	Standardized Beta coefficients	Std Error	t-value	Decision
H1 (PV -> BI)	0.114	0.048	2.355*	Supported
H2 (PS-> BI)	0.158	0.052	3.015*	Supported
H3 (SE -> BI)	0.163	0.059	3.089*	Supported
H4 (HIA -> BI)	0.299	0.057	5.269*	Supported
H5 (PN -> BI)	0.025	0.053	0.461	Not Supported
H6 (PU -> BI)	0.226	0.066	3.440*	Supported

*Significant at 0.001 using 5,000 iterations of bootstraps

After establishing the model fit for the structural model, we calculated coefficients for two hypothesized paths. Table 4 exhibits the standardized beta coefficients, standard error, and t-value obtained from the bootstrapping procedure. Figure 2 presents the results obtained for the conceptual model. The outcomes suggest that both protective aspects (PV, PS, and SE) and utilitarian aspects (HIA and PU) have a significant impact on BI. However, the effect of PN could not be established on BI. These results support H1–H4 and H6. Moreover, to evaluate the impact of demographic variables on BI, we included control variables such as gender, monthly household income, hours spent, and weekly frequency of use, but the result showed no significant effect on the behavioural intention to use smartwatches.

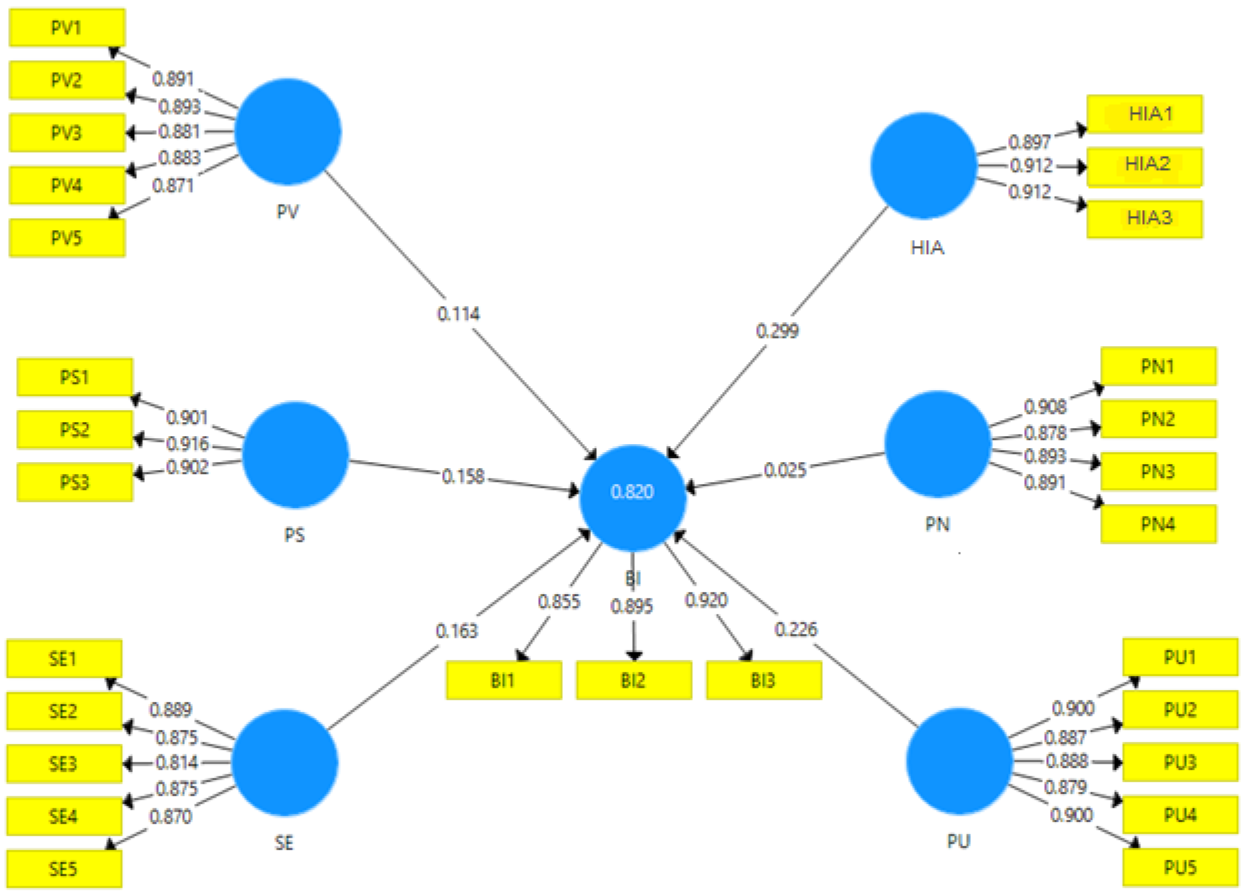

Fig. 2. Validated research model

5. Discussion

The present study supports existing studies in confirming that PMT determinants have an impact on users' behavioural intention to use HWDs to avoid health-related concerns, including those arising from COVID-19, and promote protective health behaviour (Chan et al., 2012; Guo et al., 2015; Kanitthika et al., 2016; Shen et al., 2018). The results of the study confirm that perceived vulnerability, self-efficacy, and perceived severity significantly influence the protective health behaviour of senior citizens and have a positive impact on behavioural intention (Chan et al., 2012; Marakhimov and Joo, 2017). From the literature, few studies confirm the effect of protective motivators on users' intention to use wearable devices (Rogers, 1975; Wang et al., 2015; Shen et al., 2018). Users who are conscious of their health and related diseases or threats are more inclined to use such devices to monitor their health parameters and reduce health risks (Guo et al., 2015). Findings from this study indicate that self-efficacy is the most significant protective motivator which influences the intention of senior citizens to use HWDs. The second important protective motivator was found to be their perceived severity. It is understandable that if senior citizens perceive themselves to fall severely ill, they are more likely to have the intention to use HWDs. It is apparent that people with high perceived vulnerability show a greater possibility of being more self-protective (Burns et al., 2017) and hence their intentions to use HWDs is greater in evidence.

Next, the study used a few utilitarian motivators – perceived usefulness, perceived novelty, and health information accuracy – to determine their impact on users' behaviour and intention to use HWDs. The effect of perceived novelty was not found to be significant. These variables were selected carefully after reviewing the features of these devices and their relevance in the current COVID-19 situation. Many studies discuss the significance of these determinants in the context of technology use (Cilliers, 2019; Patel et al., 2015; Park et al., 2016), but only a few significant studies discuss the impact of these utilitarian features on users in the healthcare context (Kim et al., 2019). These latter studies confirm that HWDs are perceived as valuable and innovative (novelty) as they are self-tracking devices, and are used to track individuals' sleep, food intake, sugar levels, calories levels, etc. (Wang et al., 2015; Jin et al., 2017; Sharon, 2017). In addition, studies suggest that HWDs are novel and highly efficient as they assist users in managing their health and generating health information to make lifestyle decisions (Metcalf et al., 2016; Singh et al., 2020). Perceived novelty may be an important variable in the context of HWDs, but findings from this study did not establish its significance on users' intention to use HWDs. One reason for this could be that in matters of health, senior citizens are more concerned about the accuracy and usefulness of the device rather than its novelty.

Information accuracy of wearable devices is also discussed and validated in a few studies Wang et al., 2015; Zhang et al., 2017). The health information accuracy of a device measures its efficiency to provide accurate data and reliable services to users (Zhang et al., 2017). Previous studies confirmed that HWDs provide accurate and reliable health-related information to users and is perceived to be credible (Cilliers, 2019; Park et al., 2016; Sharon, 2017; Wang et al., 2015).

5.1. Theoretical implications

This study attempts to assess the perception of senior citizens towards the COVID-19 pandemic and measure their intention to use HWDs. After reviewing extant research on the topic of HWDs and examining their characteristics, we have developed a conceptual model to show how senior consumers' intention to adopt/use HWDs is affected. Compared to other HWD adoption references (Chuah et al., 2016; Gao et al., 2015), our integrated model will provide an extensive understanding of senior consumers' decisions to adopt HWDs more specifically during periods of crisis. Our study has integrated the utilitarian aspects (PU, PN, IA) with protection motivators (PVU, PT, and SE).

The inclusion of PMT is highly relevant in the current health crisis. It talks about the protective health behaviour of an individual and its influence on wearable devices. Next, to explain behavioural intention regarding health-related technology – HWDs in this case – the study also used dimensions of perceived usefulness from TAM, perceived novelty, and health information accuracy. The integration will provide a more comprehensible description of both technology and protective perspective to identify variables that could intensify users' intention to use HWD during the pandemic. The application of PMT has been incorporated in health behaviour–related studies, but its application to health-related technologies, such as HWDs, is still limited. Therefore, the present study fills the gap by integrating both protective and utilitarian aspects.

The present work explains the relevance of PMT in the current situation for elderly users. It determines the high impact of perceived severity, self-efficacy, and perceived vulnerability of a user on behavioural intention (Ifinedo, 2012; Wang et al., 2015; Cilliers, 2019). PMT determinants measure users' vulnerability and severity to health-related threats and suggest coping mechanisms to avoid such threats (Herath and Rao, 2009; Haghi et al., 2017). Specific to HWDs, very few significant studies have linked PMT to a user's intention (Wang et al., 2015; Cilliers, 2019). No known study has been done in the emerging market context, including India.

5.2. Managerial implications

The findings suggest that HWD developers should consider both technical and protection attributes of healthcare wearables. For providers, PN, IA, and PU are important dimensions that promote consumers' interest and play an essential part in improving the intention to adopt technology adoption. The results show that practitioners should pay attention to consumer expectations about the attributes and functions of these devices, particularly those related to self-regulating functions, accurate health statistics, daily health tracking facility, reliable medical results, and other benefits. This will improve the device's accuracy and customers' intention to use. Companies must create manuals or videos to explain the functional and security aspects of HWD to users to enhance their acceptance. The present study contributes to this by recognising relevant factors that influence the intention to use HWDs.

Furthermore, it is imperative for marketers to highlight the effects of PMT constructs, by communicating to customers the benefits of using HWDs in daily life and stressing the risks of not using the devices. The use of PMT is relevant particularly in the Indian context, as the country currently suffers from three categories of diseases, including infectious and non-contagious diseases, due to lifestyle changes and pandemics like COVID-19 and their health-related outcomes (Narain, 2016). Individuals in the older age groups are more vulnerable to these diseases due to low immunity, low life expectancy, etc. (Claes et al., 2015). The findings of this study show that customers are aware of health-related vulnerabilities and severity of consequences that may occur due to COVID-19, which influences their protective behaviour. The results suggest that practitioners make customers aware that they are responsible for their health and should be motivated to consider health-protective behaviour by using HWDs. The study further confirms that self-efficacy is crucial for improving protective behaviour and acceptance of HWDs. Providers should enhance the functionality, quality, and ease of handling of HWDs and connected services, which will possibly improve the self-efficacy of users. In addition, HWD developers should offer training to users about their design and functions to improve self-efficacy.

5.3. Social and policy implications

During the current pandemic, HWDs have played an essential role in minimising contact between patients and healthcare professionals through remote monitoring of health vitals and by shifting service and care from hospital to home, thus reducing hospitals' load. The current study contributes towards improving the perception of HWDs, particularly when health resources are limited, health facilities are overwhelmed, and the use of remote monitoring with the aid of HWDs becomes more critical. According to Boulos and Al-Shorbaji (2014), the data from connected devices may be linked to hospital databases, facilitating real-time information about the health status of patients, thus supporting the provision of better health management decisions. HWDs can be used to monitor the seriousness of a COVID-19 patient by monitoring the patient's respiratory functions, including SpO_2, RR, and lung sounds. If the device reports the parameters to be within range, the patient can be under observation at home, reducing the healthcare burden. Health information accuracy is a crucial factor in adoption.

A few policy changes may be suggested based on the results of this study. First, the accuracy of customer/user information is found to be vital to improve the utilitarian benefits of HWDs. Policymakers should ensure data privacy or anonymity of users by offering standard guidelines for medical data usage, sharing, and distribution. These privacy standards must also address the current privacy concerns of customers. Second, the study shows that users are aware of health-related vulnerabilities and severity of consequences during COVID-19 and exhibit protective behaviour. To support this, the government should develop policies that will improve medical infrastructure, support the integration of technology and healthcare, reinforce the existing health system, and expand medical insurance coverage, especially for high-risk communities in the country.

5.4. Limitations and future research directions

The present study has made theoretical contributions in extending PMT with selected utilitarian dimensions; however, there are certain limitations in this research. First, data was collected for the empirical analysis only once, restricting explanations about consumers' perception of HWDs. The challenge with the HWDs is their continuous use, which can be better explained by longitudinal research. Second, the study has included only smartwatches and related mobile applications; research can be extended in future to study other innovative wearable technology in the market. As the investigation in this study is primarily focused on senior citizens' (older population), perception of HWDs, analysing other demographic variables such as gender, age, and profession as moderators will provide greater insights. In addition, the present study focuses on variables measuring the effectiveness of HWDs, specifically in a crisis. Future studies may include physical and mental monitoring effectiveness, care management of lifestyle diseases, assessing depression/anxiety, hedonic motivations etc., to understand the significance of HWDs in detail. Future studies may also explore findings on various demographics such as people with co-morbidities, lifestyle changes, and high vulnerabilities to refine the results further. There may be a correlation between the number of hours of use and the frequency of use of smartwatches, which can be assessed in future studies.

Since adoption of HWDs is still in the initial stages in India, the respondents who participated in this study are probably early adopters who are more aware and self-driven to experiment with IoT technology than conventional consumers. Another limitation of the study is that the survey respondents belong to the Delhi and NCR region, representing the urban Indian perspective. Therefore, testing in a cross-cultural context would be beneficial.

6. Conclusion

The current study contributes to existing literature on health wearable technologies. The study assesses the behavioural intention of the older population in using HWDs during life-threatening crises. The study uses PMT constructs and utilitarian aspects such as health information accuracy, perceived usefulness, and perceived novelty as main determinants to measure the older people's intention to use HWDs. The study confirms that high self-efficacy in older people indicates a high probability of them using HWDs to monitor their health regularly. The study identifies perceived vulnerability and perceived severity as the main protective determinants of using HWDs. On the other hand, the information accuracy and perceived usefulness of HWDs are determined as the most important utilitarian dimensions considered by older people. The current findings suggest that marketers highlight HWD accuracy and useful features to improve perception among users. Further, HWDs must be promoted to users as credible devices to self-monitor health vitals and assess health risk at various stages of life and in stressful situations such as COVID-19. Very few current studies have talked about the protective motives of HWDs predominantly in the context of an older population.

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