Article

Understanding Factors Influencing Elderly Diabetic Patients' Continuance Intention to Use Digital Health Wearables: Extending the Technology Acceptance Model (TAM)

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Abstract: Elderly diabetic patients in developed countries have been widely using digital health wearables for many years to manage their diabetes-related health data accurately. To encourage the increased adoption of digital health wearables among elderly diabetic patients in a developing country, Bangladesh, this study investigated the factors that influenced the existing elderly users' continuance intention to use this technology. The Technology Acceptance Model (TAM) has been used here as a theoretical basis. A model using structural equation modelling was developed for the elderly diabetic patients' continuance intention to use digital health wearables. Survey-based data were collected in Bangladesh from 223 diabetic patients aged sixty years and older. This study found that all six constructs, namely, perceived usefulness ($\beta = 0.183$), perceived ease of use ($\beta = 0.165$), perceived irreplaceability ($\beta = 0.138$), perceived credibility ($\beta = 0.165$), compatibility ($\beta = 0.285$) and social influence ($\beta = 0.226$) had a positive influence on elderly diabetic patients' continuance intention to use digital health wearables. Along with the theoretical contributions, the findings of this study can be used by developers of digital health wearables, manufacturers, marketers and health practitioners in developing better strategies to increase the elderly diabetic patients' continuance intention to use this technology.

1. Introduction

The diffusion of innovation (e.g., artificial intelligence, big data, design thinking and robotics, etc.) has offered groundbreaking solutions to various needs and challenges of the global healthcare industry. With the advances in healthcare technology and increased health consciousness among many people, the ageing population is growing worldwide. In 2015, there were around 900 million people who were 60 years old or more; in 2017, there were around 980 million [1], and it is expected that by 2050 this figure will have more than doubled and will represent around 16% of the total population of the world [2]. According to Khanam et al. [3], 80% of elderly people have at least one chronic disease, and 60% of elderly people have more than one chronic disease. Diabetes is one of the common chronic diseases among the global population, and people older than 60 years of age are more

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susceptible to it [4]. In 2017, there were around 425 million diabetic patients worldwide [5]. According to the International Diabetes Federation (IDF) [6], there were around 5.10 million diabetic patients in Bangladesh in 2013, and by 2035, this number will increase to around 8.20 million. Diabetic patients are required to visit hospitals or clinics on a regular basis to monitor diabetes-related parameters; however, this poses a great challenge for them in terms of their weakened physiological condition, transportation and associated costs [7]. Diabetic patients in Bangladesh, which is one of the developing countries of the world, are especially challenged in this regard, compared to those in developed countries. In this circumstance, the role of efficient digital health wearables is pivotal.

Digital health wearables have been used for some time by elderly people to monitor changes in their physical and mental health and to provide treatment accordingly for a healthier life [8]. In recent years, digital health wearables in various forms have gained the attention of both practitioners and users for dealing with diabetes [9]. According to Lyons, Lewis and Mayrsohn [10], digital health wearables incorporate efficient and evidence-based behaviour change techniques in targeting diabetes risk factors in a very cost-effective way, which is also easily accessible by the users or caregivers/physicians. Due to the notable benefits for elderly people of using digital health wearables, many studies have already covered elderly people's intention to use them and identified the relevant antecedents [1,8]. However, no study has yet been conducted to investigate the factors that influence elderly people's continuance intention to use the digital health wearables once they have been adopted for use. There is a glaring gap in the business and healthcare literature about elderly diabetes patients' continuance intention to use digital health wearables, especially in the context of a developing country. Thus, the main aim of this study is to investigate the factors influencing elderly diabetic patients' continuance intention to use digital health wearables in the context of Bangladesh.

Empirical data were collected from 223 respondents, and structural equation modelling (SEM) was used to test the proposed conceptual model. This study provides meaningful implications for theory as well as practice. From the theoretical perspective, the extended Technology Acceptance Model (TAM) with additional constructs, such as perceived irreplaceability, perceived credibility, compatibility and social influence, provides a comprehensive understanding of elderly diabetic patients' continuance intention to use digital health wearables. From the practical perspective, digital health wearable manufacturers, caregivers and physicians who deal with diabetic patients will have a better understanding of elderly diabetic patients' continuance intention to use digital health wearables, and they will be able to make the necessary adjustments to their policies and strategies.

2. Literature Reviews

2.1. Digital Health Wearables

Digital health wearable devices are supported by electronic technology and can be worn directly on the human body [11]. It is expected that, by the end of 2020, this industry will generate revenue of around $22.9 billion [12]. There are mainly two kinds of digital health wearable devices available in the market, namely, fitness and medical wearable devices [13]. Fitness-based digital health wearables, such as fitness wristbands and smartwatches, have become very popular in the healthcare sector [14]. Digital health wearables for fitness are primarily used for monitoring users' health status and activity levels, such as sleep, calories burned, heart rate and distance travelled [15]. Other types of digital health wearables falling into the medical wearable device category, such as smart clothes, implantable devices and skin devices, have also gained popularity, along with wrist-worn medical wearables [16,17]. By using medical wearable devices, users can monitor fitness-related data such as their blood pressure, oxygen level and glucose level. These devices also assist patients to identify any early harmful signs of different types of chronic diseases, such as diabetes [18]. In this study, we have focused on the latter, medical wearable devices.

2.2. Digital Health Wearables and Diabetes Management

Diabetes has been classified as a chronic disease in which the pancreas does not produce the required amount of insulin and, as a result, a variety of health-related complications arise [19]. For diabetes management, diabetes patients using digital health wearables receive immediate feedback, reminders and alerts about the glucose levels in their blood [20]. Diabetes patients use digital health wearables mainly to track glucose levels. The digital health wearables are used not only by diabetes patients to maintain their blood sugar levels but also by health professionals to provide the correct treatment. There are two types of digital health wearables, namely, invasive and non-invasive, available to diabetic patients for monitoring and controlling their blood glucose level, which reduces the risk of other health-related issues, especially cardiovascular complications [21]. Non-invasive digital health wearables (i.e., those requiring no finger-pricking or needle insertion) for diabetic patients make self-monitoring of glucose less time-consuming and more convenient and also allow them to change the dose of insulin if required [22]. Invasive digital health wearables for continuous glucose monitoring (CGM) were introduced in 1999; they consist of a few blood glucose sensors and require skin pricking to collect the measurements [21]. Glucose levels in the blood are measured repeatedly by the sensors, which transmit the average measurement to the receiver every couple of minutes [23]. Wrist-worn digital health wearables for diabetes management are the most common among diabetic patients these days. Due to rapid technological advances, other types of digital health wearables, such as garment-integrated and body-worn sensors, that can provide multidimensional data, are also being used for diabetes management in a limited scope [24].

Digital health wearables have opened up a new paradigm in terms of collecting data for diabetes patients both offline and in real time. Continuous glucose monitoring (CGM) allows both diabetes patients and health professionals to track glucose levels in real time. In this case, the biosensors in digital health wearables play a significant role.

2.3. Technology Acceptance Model (TAM)

This study applied the Technology Acceptance Model (TAM) [25] as the theoretical basis to investigate the factors influencing elderly diabetic patients' continuance intention to use digital health wearables. In the past, TAM was used for understanding the adoption of technologies only within organisations [26]. However, due to TAM's excellent performance and simplicity, it has become one of the widely used models for understanding users' behaviour with regard to the acceptance, adoption and continuation of use of a variety of technologies (Okumus and Bilgihan, [27]). However, "Perceived Usefulness" (PU) and "Perceived Ease of Use" (PEOU) are the two explanatory variables that TAM uses to explain a user's intention to adopt a particular technology and their continuance intention to use this technology [28].

Many studies have already used TAM to better understand information technology adoption in the healthcare context. For example, Beglaryan et al. [29] and Kohli and Tan [30] used TAM in their studies on health practitioners' intention to use electronic health records (EHR). Zhang et al. [31] made a bold statement in their article about the difference between healthcare technologies and general technologies. Therefore, the simple TAM model with only two explanatory variables, namely, PU and PEOU, would not be adequate for this study to meet the desired objective. Having considered this, our study warrants the adoption of TAM with a few more variables to understand factors influencing elderly diabetic patients' continuance intention to use digital health wearables, which has not been examined in previous studies.

3. Development of Hypotheses

3.1. Perceived Usefulness (PU), Perceived Ease of Use (PEOU) and Continuance Intention (CI)

In the first version of TAM, Davis [25] identified perceived usefulness (PU) and perceived ease of use (PEOU) as the key factors influencing users to adopt and continue to use a new technology.

He defined PU and PEOU as the degree to which an individual trusts that a particular technology would benefit them, and would be easy to use, respectively. For digital health wearables, PU refers to the benefits that a user expects to get from them, and PEOU refers to how little effort a user expects to make when using them.

Bhattacherjee [32] defined continuance intention (CI) as an individual's intention to continue to use a particular technology after the initial adoption process. In the same article, he further mentioned that an individual's continuance intention to use a particular technology is influenced by its perceived usefulness and perceived ease of use. In the healthcare space, Cho [33] found that perceived usefulness and perceived ease of use influence a user's continuance intention to use a healthcare-related technology. Therefore, we postulated that:

Hypothesis (H1). *Perceived usefulness is positively associated with elderly diabetic patients' continuance intention to use digital health wearables.*

Hypothesis (H2). *Perceived ease of use is positively associated with elderly diabetic patients' continuance intention to use digital health wearables.*

3.2. Perceived Irreplaceability (PIR)

Schifferstein and Zwartkruis-Pelgrim [34] defined perceived irreplaceability (PIR) as the symbolic meaning of a product to a user that they perceive cannot be found in other identical products. They further added that users are more likely to continue to use those products that they consider as irreplaceable. Unique functionalities and attributes of digital health wearables will influence elderly diabetic patients to continue to use them. Thus, the hypothesis related to PIR is as follows:

Hypothesis (H3). *PIR is positively associated with elderly diabetic patients' continuance intention to use digital health wearables.*

3.3. Perceived Credibility (PCR)

Based on two elements, namely, data accuracy and security, perceived credibility (PCR) refers to the degree to which a user makes their decision to use a particular technology [35]. Studies in the past established a positive correlation between perceived credibility and a user's continuance intention to use a new technology [35,36]. For elderly diabetic patients using digital health wearables, the accuracy of their health data and the security of this data are of optimum importance under the factor of credibility to influence their continuance intention to use them. Thus, we propose the following hypothesis:

Hypothesis (H4). *PCR is positively associated with elderly diabetic patients' continuance intention to use digital health wearables.*

3.4. Compatibility (COM)

Yang et al. [37] defined compatibility (COM) as the degree to which a new technology works with other existing technologies without altering any functionalities to a great extent. A higher degree of compatibility of a new technology with existing ones has been found to be positively connected with a user's continuance intention to use them [38]. For digital health wearables, COM in terms of their ability to transfer health-related information to remote mobile devices and improve the user's well-being will influence elderly patients' continuance intention to use them. Accordingly, the following hypothesis is proposed:

Hypothesis (H5). *COM is positively associated with elderly diabetic patients' continuance intention to use digital health wearables.*

3.5. Social Influence (SI)

Social influence (SI) refers to the degree to which a user's decision to use a particular technology is influenced by their family members, friends and colleagues [39,40]. A positive connection between SI and a user's continuance intention to use a healthcare-related technology has been established in previous studies [41,42]. For elderly diabetic patients, digital health wearables are a relatively new technology, and SI plays an important role here in their continuance intention to use them. Therefore, the following hypothesis is suggested:

Hypothesis (H6). *SI is positively associated with elderly diabetic patients' continuance intention to use digital health wearables.*

Six hypotheses have been proposed in this study based on the Technology Acceptance Model (TAM) to test the relationship among seven variables, namely, perceived usefulness, perceived ease of use, perceived convenience, perceived irreplaceability, perceived credibility, compatibility, social influence and continuance intention. Figure 1 summarises the model that we have developed for this study.
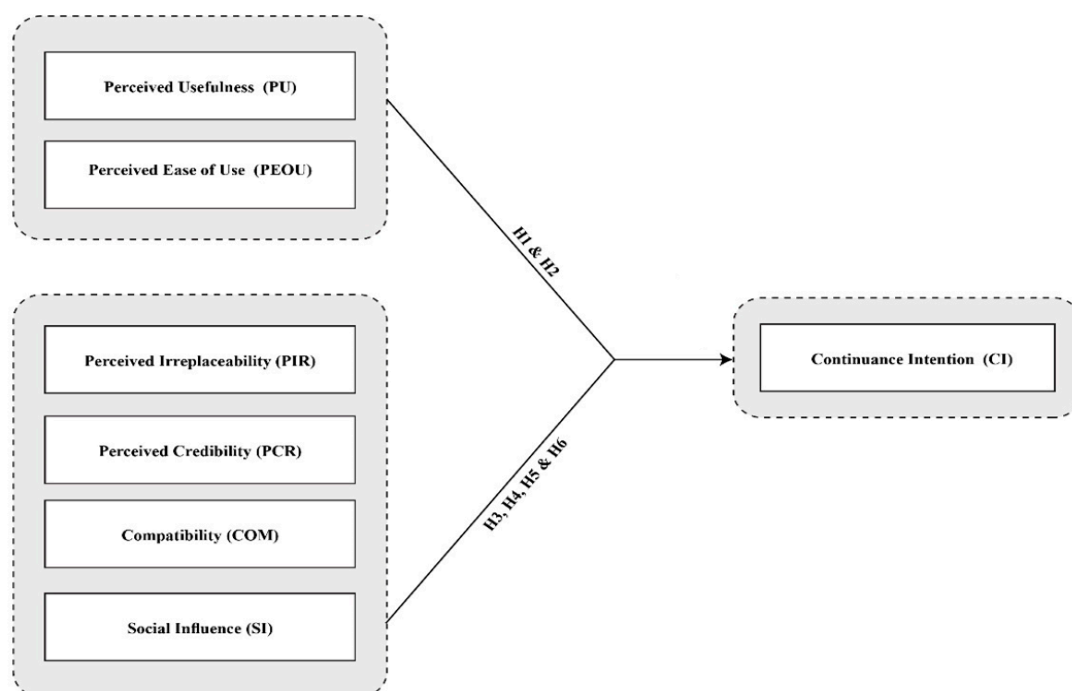
Figure 1. Conceptual Model of CI (Source: Authors' research).

4. Questionnaire Design and Data Collection

4.1. Sample

To test the research hypotheses of this study, we chose the quantitative research method to collect data from random elderly diabetic patients in Bangladesh who use digital health wearables to monitor their well-being. All data were collected by a paper-based survey. The survey questionnaire had two sections, namely, Part A and Part B. Questions on demographics, such as age, gender and educational qualification, were included for the respondents in Part A. All questions relating to the seven variables (27 items) of this study that we included in the proposed model were included in Part B.

A pilot study was conducted with a random sample of 27 respondents who were elderly diabetic patients and used digital health wearables, followed by the main study. The main reason for the pilot study was to make sure there would not be any issues during the main data collection phase. No significant issue was identified, apart from a few wording-related issues which were subsequently fixed. It is worth noting that, after the pilot study, a pool of experts further checked our structured questionnaire, especially for Part B where there were a total of twenty-seven questions. Having considered the lack of knowledge of English of some of the survey participants, we translated our questionnaire into Bengali, and we allowed the participants to answer questions in either English or Bengali. It is worth noting that Bengali is the first language for the people of Bangladesh, and English is widely used as well. Every respondent was asked to fill in a consent form at the beginning of the survey, and they were also provided with the relevant information sheet, which described the purpose of our study. In total, there were 232 respondents, and we had to exclude nine incomplete questionnaires.

Of the respondents, 60.1% were male and 39.9% were female. Respondents aged between 60 and 64 years represented the largest group in the sample (41.7%), followed by respondents aged 65 to 69 years (30.0%). The other two age groups, the respondents between 70 and 74 years old and those 75 years and older, represented 18.4% and 9.9% of the total population, respectively. According to marital status, the majority of the respondents (55.6%) were married and 30.9% had never married; 10.3% of the respondents mentioned that they were separated/divorced, and 3.1% were widowed. As for the educational level of the respondents, the majority (53.4%) had completed an undergraduate degree, while 30.0% had completed a postgraduate degree. Among the rest, 11.2% of the respondents had completed a diploma-level qualification, and 5.4% had not pursued any further study after high school. In terms of employment, the majority of the respondents (70.9%) were employed full time, 8.5% were part-time workers and 15.7% were not in the labour force. Only 1.8% of the respondents were away from work, while 3.1% were unemployed. Within the employed full time category, we included people who run their own businesses (business owners) on a full-time basis. Table 1 presents the demographic characteristics of the respondents.

Table 1. Demographic profile of the respondents (n = 223) (Source: Authors' research).

	Absolute Numbers	**%**
Gender		
Female	89	39.9%
Male	134	60.1%
Age		
60–64 years	93	41.7%
65–69 years	67	30.0%
70–74 years	41	18.4%
75+ years	22	9.9%
Marital status		
Married	124	55.6%
Never married	69	30.9%
Separated/Divorced	23	10.3%
Widowed	7	3.1%
Employment status		
Work Full Time	158	70.9%
Work Part Time	19	8.5%
Away from Work	4	1.8%
Unemployed	7	3.1%
Not in the Labour force	35	15.7%
Highest level of education		
High School	12	5.4%
Diploma	25	11.2%
Undergraduate degree	119	53.4%
Postgraduate degree	67	30.0%

4.2. Measures and Instrument Development

For this study, based on the previously validated scales, we designed a paper-based survey instrument which was adjusted to suit the context of digital health wearables. Items to measure perceived usefulness were adapted from Thong et al. and Venkatesh et al. [43,44]. Four items to measure perceived ease of use were adapted from Davis, Brinkman et al., Hung et al., Wang and Wei et al. [25,39,43–47]. Four items were adapted from Bhattacherjee and Barfar, Venkatesh and Goyal, and Venkatesh et al. [44,48,49] to measure continuance intention. Three items were adapted from Flavián and Gurrea, and Schifferstein and Zwartkruis-Pelgrim [34,50] to measure perceived irreplaceability. Perceived credibility was measured based on the items adapted from Wang et al. [36]. Three items were adapted from Bradford and Florin, and Li et al. [51,52] to measure compatibility. Finally, five items were adapted from Venkatesh et al. and Chong et al. [53,54] to measure social influence.

We used structural equation modelling (SEM) to evaluate the relationship among the proposed hypothesised concepts and to validate the proposed conceptual research model. SEM is one of the widely used credible multivariate statistical analysis techniques that has been used in many studies [55]. AMOS (v. 22) software was used in our study to analyse the collected data. We used the five-point Likert scale ranging from strongly disagree (1) to strongly agree (5) to measure all the constructs in the research model, [56] except the demographic profile. The responses were later recoded on a scale from strongly disagree (−2) to strongly agree (2) for the data analysis.

5. Data Analysis and Results

5.1. Measurement Model

The data were analysed using AMOS (v. 22). A confirmatory factor analysis (CFA) was performed to test the construct validity of the variables under study. The factor loadings of all the items relative to their constructs were greater than 0.5 [57], which showed that the scales had construct validity (Table 2). To ensure the internal consistency for the constructs under study, Cronbach's alpha was calculated for all the scales, and the alphas for all the scales were greater than the recommended value of 0.7 [58].

Table 2. The measurement model and cross-loading matrix (Source: Authors' research).

Constructs	Items	Loadings	Mean	SD
PU AVE = 0.501 CR = 0.800 C-Alpha = 0.799	PU1 PU2 PU3 PU4	0.679 0.780 0.668 0.700	4.72	1.71
PEOU AVE = 0.560 CR = 0.840 C-Alpha = 0.835	PEOU1 PEOU2 PEOU3 PEOU4	0.780 0.721 0.710 0.779	5.33	1.76
PIR AVE = 0.674 CR = 0.861 C-Alpha = 0.861	PIR1 PIR2 PIR3	0.795 0.836 0.831	4.01	1.46
PCR AVE = 0.573 CR = 0.843 C-Alpha = 0.842	PCR1 PCR2 PCR3 PCR4	0.787 0.784 0.712 0.742	5.40	1.83
COM AVE = 0.530 CR = 0.770 C-Alpha = 0.757	COM1 COM2 COM3	0.563 0.748 0.842	3.99	1.34

Table 2. *Cont.*

Constructs	Items	Loadings	Mean	SD
SI	SI1	0.578		
AVE = 0.520	SI2	0.808		
CR = 0.841	SI3	0.873	6.33	2.11
C-Alpha = 0.848	SI4	0.620		
	SI5	0.681		
CI	CI1	0.834		
AVE = 0.734	CI2	0.874		
CR = 0.917	CI3	0.888	4.04	1.74
C-Alpha = 0.922	CI4	0.829		

Note: PU—Perceived Usefulness, PEOU—Perceived Ease of Use, PIR—Perceived Irreplaceability, PCR—Perceived Credibility, COM—Compatibility, SI—Social Influence, CI—Continuance Intention, AVE—Average Variance Extracted, Composite Reliability—CR.

Additionally, to ensure convergent validity, the average variance extracted (AVE) and composite reliability were computed for every construct (Table 2). AVEs for all the scales were greater than the recommended value of 0.5, and the composite reliabilities exceeded the recommended value of 0.70 [59]. To ensure discriminant validity, correlations between constructs under study were compared with the square root of the AVE [59]. As can be seen in Table 3, the square root of the AVE for each construct was greater than the correlations with other factors.

Table 3. Descriptive statistics, correlation matrix and square root of the average variance extracted (Source: Authors' research).

	CI	PU	PEOU	PIR	PCR	COM	SI
CI	**0.857** [a]	-					
PU	0.291 ***	**0.708** [a]	-				
PEOU	0.297 ***	0.349 ***	**0.748** [a]	-			
PIR	0.287 ***	0.099 ns	0.256 **	**0.821** [a]	-		
PCR	0.249 **	0.108 ns	0.100 ns	0.192 *	**0.757** [a]	-	
COM	0.311 ***	0.193 *	0.078 ns	0.288 ***	0.107 ns	**0.728** [a]	-
SI	0.279 ***	0.194 *	0.241 **	0.163 *	0.111 ns	0.127 ns	**0.721** [a]

Note: The square root of AVE is on the diagonal; lower-diagonal values are inter-construct correlations; ns = not significant; [a] = Square root of AVE for each latent variable; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

5.2. Structural Model Testing

The results of the structural model tested for this study are presented in Table 4. The perceived usefulness of the digital health wearables significantly predicted the elderly diabetic patients' continuance intention to use them (H1: β = 0.183, $p < 0.05$). The results show that a one-unit change in PU directs a 0.183 unit change in CI. Likewise, elderly diabetic patients' perceived ease of use of digital health wearables was also a significant predictor of CI (H2: β = 0.165, $p < 0.05$). These results are consistent with many studies that have found that customers' perceived usefulness and perceived ease of use related to a new technology influenced their initial intention to use them and additionally influenced their continuance intention to use them as well [60–62].

CI was also significantly predicted by customers' beliefs about irreplaceability as a one-unit change in PIR directed 0.138 units change in CI (H3: β = 0.138, $p < 0.05$). Studies point out that those customers who have a favourable attitude towards new technologies and consider them important are more likely to continue using such technologies. The perceived credibility of the digital health wearables was also found to be a significant predictor of CI in this study (H4: β = 0.165, $p < 0.05$). A plethora of scholarly literature suggests that the perceived credibility of applications is a significant determinant of customers' continuance intention to use them [31,63–65]. Elderly diabetic patients

who consider digital health wearables to be reliable are more likely to continue using them and even repurchase advanced versions.

Table 4. Structural model (Source: Authors' research).

Hypothesis	Path	B	T Statistics	Comments
H1	PU → CI	0.183	2.258	Supported *
H2	PEOU → CI	0.165	2.305	Supported *
H3	PIR → CI	0.138	2.120	Supported *
H4	PCR → CI	0.165	2.429	Supported *
H5	COM → CI	0.285	2.815	Supported **
H6	SI → CI	0.226	2.429	Supported *

Note: * $p < 0.05$; ** $p < 0.01$.

The compatibility of such digital health wearables with elderly diabetic patients' existing technologies and other aspects of life shaped their intention to continue using them (H5: $\beta = 0.285$, $p < 0.05$). Of all the variables included in the model, perceived compatibility was the prime determinant of continuance intention to use digital health wearables. This finding is well supported by scholarly literature that has found perceived compatibility to be significantly related to customers' favourable attitude towards a new technology and the likelihood of their continuing to use it [62,66–69]. Humbani and Wiese [66] found that customers who found a new technology to be compatible with their needs and lifestyles were more likely to continue their usage. Social influence also turned out to be a major contributor towards elderly diabetic patients' continuance intention to use digital health wearables, as the results suggested that a one-unit change in SI created a 0.226 unit change in CI (H6: $\beta = 0.226$, $p < 0.05$). A lot of evidence suggests that, in addition to perceived ease of use, usefulness, and compatibility, social influence exerted by peers and significant others is an important factor shaping intention to continue to use a new technology [27,64,70,71].

To see the relative fit of data to the model (Table 5), the ratio of chi-square to degrees of freedom (χ^2/df), the Goodness-of-Fit (GFI) Index, Adjusted Goodness-of-Fit Index (AGFI), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Normed Fit Index (NFI), and Root-Mean-Square Error of Approximation (RMSEA) were used [57,72,73]. According to Hair et al. [74], the value of χ^2/df should be less than 3 to meet the accepted standard. The value of GFI = 0.840 was very close to the recommended value of 0.90. Nevertheless, scholars such as Baumgartner and Homburg [72] have suggested that a value greater than or equal to 0.8 is also a good fit. Similarly, the value of NFI = 0.825 was very close to the recommended value, and it has been suggested by many studies that a value greater than 0.8 can be considered as a good fit [75]. Gefen et al. [76] and Singh et al. [77] recommended that the value of AGFI, CFI and NFI should be more than 0.8. The value of RMSEA has been recommended to be less than 0.8 [78].

Table 5. Model fit (Source: Authors' research).

Fit Indices	Recommended Value	Research Model
χ^2/df	≤3.00	1.716
GFI	≥0.90	0.840
AGFI	≥0.80	0.810
CFI	≥0.90	0.918
TLI	≥0.90	0.910
NFI	≥0.90	0.825
RMSEA	≤0.08	0.057

6. Discussion and Conclusions

The objective of this study was to investigate the factors that influence elderly diabetic patients' continuance intention to use digital health wearables. Along with the original constructs of TAM,

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namely, perceived usefulness and perceived ease of use, this study used four other additional constructs, such as perceived irreplaceability, perceived credibility, compatibility and social influence, to meet the objective of this study. The following insights have been drawn, based on the findings, to allow a deeper understanding of the objective of this study.

In this study, we found that perceived usefulness (β = 0.183) has significant influence on elderly diabetic patients' continuance intention to use digital health wearables, which is consistent with the findings of previous studies [31,32]. This implies that digital health wearables' performance that meets elderly diabetic patients' expectations of, for example, increased productivity and convenience, influence their continuance intention to use this technology. The results also demonstrated that the other original construct of TAM, namely, perceived ease of use (β = 0.165), has a positive influence on elderly diabetic patients' continuance intention to use digital health wearables, which is aligned with the previous studies [31,79]. It was implied here that an easy learning process for the elderly diabetic patients to operate digital health wearables was the main influence on their continuance intention to use this technology.

In addition, this study found that four other constructs, namely, perceived irreplaceability (β = 0.138), perceived credibility (β = 0.165), compatibility (β = 0.285) and social influence (β = 0.226), had a positive influence on elderly diabetic patients' continuance intention to use digital health wearables, which is supported by a number of relevant studies [31,41,42,80]. The first finding related to perceived irreplaceability suggests that digital health wearables are functionally different from similar traditional devices (e.g., passometers) in meeting the elderly diabetic patients' health-related requirements; therefore, they will continue to use them. The second finding related to perceived credibility suggests that digital health wearables protect elderly diabetic patients' personal health information, so they are happy to continue to use them. The third finding related to compatibility implies that digital health wearables are compatible with elderly diabetic patients' existing devices (e.g., smartphones), so they will continue to use them without any hesitation. The fourth finding related to social influence suggests that friends, family members and colleagues influence elderly diabetic patients' continuance intention to use digital health wearables, because elderly diabetic patients value their opinions; therefore, without exception, they will continue to use this technology.

6.1. Implications for Theory

In the realm of technology adoption and continuance intention to use it, this study provides merit for relevant academic literature and theories. Being the first of its kind, this study proposes a conceptual model to investigate the factors that influence elderly diabetic patients' continuance intention to use digital health wearables in a developing country, Bangladesh. In the past, studies on digital health wearables technology focused on different age groups [81] where the relevance of a chronic disease, such as diabetes, was not taken into account. In addition, a combination of digital health wearables, elderly people, diabetes as a chronic disease and Bangladesh as a developing country has made this study unique in the context of relevant literature and theory. This implies that the proposed conceptual model of this study can be taken into account and applies to a similar segment in other developing countries as well.

Another major theoretical contribution of this study is that it focuses on the factors that influence elderly customers' continued intention to use digital health wearables, whereas most of the prior studies [1] in this domain focused on customers' intention to purchase and initial adoption process of digital health wearables. More particularly, this study makes a solid contribution by validating the roles of perceived irreplaceability, perceived credibility and compatibility, as these factors have never been examined before in the context of investigating customers' continued intention to use a technology. In this respect, this study is the first to consider perceived irreplaceability, perceived credibility and compatibility to enrich the theoretical knowledge in this domain, alongside the other commonly used factors, such as perceived usefulness, perceived ease of use and social influence. Such a study approach provides an excellent theoretical foundation for researchers to investigate

customers' continued intention to use a technology for different age groups, as well, by using the extended Technology Acceptance Model (TAM).

6.2. Implications for Practice

Besides its contribution to theory, the findings of this study can be utilized by digital health wearables developers, manufacturers, marketers and health practitioners in developing better strategies to increase the elderly diabetic patients' continuance intention to use this technology. Findings of this study related to the constructs of perceived credibility and compatibility will assist developers and manufacturers to become extra cautious about the elderly diabetic patients' privacy and sensitive health-related information and to ensure that their digital health wearables are compatible with users' other existing digital devices (e.g., smartphones or smartwatches). Marketers and health practitioners will be able to use the findings of this study, especially those relating to the construct of perceived irreplaceability, to benchmark the effectiveness of digital health wearables for elderly diabetic patients against other relevant healthcare technologies [12].

In previous studies, social influence was taken into account in terms of the customers' intention to use digital health wearables [1], but this study uniquely examined the relationship between social influence and elderly diabetic patients' continuance intention to use digital health wearables. From these findings, developers, manufacturers, marketers and health practitioners will be able to better utilise a variety of social forums, offline and online, to make elderly diabetic patients aware of the benefits of digital health wearables. These social forums would also serve the purpose of collecting constructive feedback about this technology. Last but not least, the findings of this study could be used by pharmaceutical companies as well, because digital health wearables are able to provide a variety of health-related data (e.g., heart rate and blood glucose level), which could be used for personalised and customised value-added service for elderly diabetic patients.

6.3. Limitations and Directions for Future Research

This study is not free from limitations, even though it has come up with some unique findings in the domain of digital health wearables for elderly diabetic patients. First of all, only age was taken into account when selecting elderly diabetic patients for data collection and, consequently, for the research findings. However, other variables such as gender, academic qualification and marital status could also have been considered for the proposed research model to provide a deeper understanding of this subject. Therefore, for future researchers, this study suggests taking these variables into consideration when developing the proposed research model and discussing the research findings. Secondly, data were collected only from Bangladesh, so the findings of this study cannot easily be generalised for other countries, due to the difference in their socioeconomic structure. Therefore, future research could be conducted based on cross-country data at different sociostructural levels.

Finally, this study took three unique constructs, namely, perceived irreplaceability, perceived credibility and compatibility, into account to investigate elderly diabetic patients' continued intention to use digital health wearables, whereas constructs like health literacy and health belief could also have been used to make the findings more impactful. Therefore, this study suggests that future researchers include these two constructs in their research.

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