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INVESTIGATING THE DETERMINANTS OF MOBILE HEALTH APPS ADOPTION AMONG ELDERLY CITIZENS IN BANGLADESH

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A B S T R A C T

In this modern era, healthcare services are provided through technology, one of which is m-health apps. As a developing country, Bangladesh pursues to offer healthcare facilities to its citizen by using modern technology. However, IT adoption is different among younger and older generations, and several factors impact the adoption intention. This research aims to investigate determinants influencing elderly citizens of Bangladesh to adopt m-health apps. This study applies PLS (Partial Least Squares) statistical technique based on Structural Equation Modeling (SEM) to achieve research objectives. A quantitative research methodology approach was adopted, and a structured questionnaire was disseminated to the 112 target respondents. Purposive random sampling technique was used in this study. The underpinning theory used in this research endeavor is the UTAUT model (Unified Theory on Acceptance and Use of Technology), incorporating several variables such as the quality of m-health apps, perceived risk, and cost. The findings demonstrate that social influence and app quality have a significant positive impact on older people's willingness to adopt m-health apps. In addition, the behavioral intention of users and actual usage behavior have a significant positive association. By extending the UTAUT model with some rationally related variables, this research has contributed to the ICT of the healthcare profession. M-health app providers need to consider improving the features of apps as the quality of apps is regarded as a critical criterion for users.

INTRODUCTION

Health information systems are becoming prominent in our daily life, and in the last few decades, it has grabbed the attention of scholars (Sam, 2017). Developed countries provide better healthcare services to their citizens. Educated citizens are needed, and healthy citizens are also necessary for economic development. The number of mobile phone users is increasing day by day in the world. The Internet population is becoming familiar with different app services. M-health services enable people to quickly get healthcare services at a low cost (Kallander et al., 2013).

Bangladesh is a developing country, and most people live in rural areas. Urban people get better health services instead of rural areas citizens. Moreover, older citizens are lagging in society. The digital divide still exists in developing countries. The government of Bangladesh develops IT infrastructure to provide modern facilities to all its citizens. During COVID-19, Bangladeshi citizens used m-health services and mobile health apps for registration to get the vaccine. Therefore, patients and healthcare service providers are now realizing the benefit of mobile health app services. In Bangladesh, numerous studies have assessed e-heath service adoption, m-health service adoption, and continuation intention. However, m-health app adoption among elderly citizens has not yet been addressed previously. As elderly citizens are more prone to illness, they frequently need healthcare services. Consequently, this study examines factors influencing older people to adopt m-health apps.

Usually, when new information technology is introduced, users are reluctant to accept it as they are familiar with legacy systems. Therefore, investigating crucial factors influencing adoption behavior is essential to establish an information

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system.

LITERATURE REVIEW

Mobile phone usage has increased in the past few decades; wireless technology to get health services has also enlarged. As a result, researchers have focused on these issues (Cameron et al., 2017). In addition, assessing the drivers influencing m-health app adoption with changing technology features has made this issue more attractive to researchers (Baabdullah et al., 2018).

Mobile Health Apps Services

The term m-health app services are provided through a mobile platform, encompassing health advice from professional physicians, medical registration, and geographical-based services (Zhang et al., 2017). In addition, m-health services are cost-effective and help assess health risks and positively modify patients' health habits (Brown-Connolly et al., 2014). Mobile health technologies have become popular because of the features of wireless technology, such as portability and ubiquitous (Akter et al., 2010). The benefits of the m-health app service were accessibility to qualified physicians at affordable cost at any time (Khatun et al., 2016).

Numerous research has been experimented to identify factors that impact m-health adoption. For example, Quaosar et al. (2018) found the significant drivers affecting the willingness of patients to accept m-health services: improved performance, social influence, anxiety about new technology, convenience, and resistance to change. Zhao et al. (2018) showed a meta-analysis in which they demonstrated that user intention was significantly influenced by observed usefulness, assumed convenience, perceived vulnerability, and perceived severity. Besides, Cajita et al. (2018) researched the USA using the TAM model to examine important facilitators and obstacles to adopting mobile health services. Their findings showed that user-friendly, adequate experience, training programs, and equipment support influenced m-health adoption behavior.

Moreover, Lee and Han (2015) demonstrated that users' age, gender, and earnings did not influence m-health adoption, while effectiveness, ease of accessibility, and economic values positively impact to use of mobile health services. Furthermore, Kaium et al. (2019) revealed that social influence, privacy issues (Hoque, 2016), monetary value, etc., impacted users' desire to use mobile health. Finally, Phichitchaisopa & Naenna (2013) asserted that the factors that significantly affect m-Health usage are performance improvement expectation, user-friendly expectation, facilitating settings, and behavioral willingness on technology adoption.

There are several established models for examining technology adoption, such as Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1977); Technology Acceptance Model (TAM) (Davis,1989) ; Technology Acceptance Model-2 (Venkatesh & Davis, 2000); Technology Acceptance Model-3 (Venkatesh & Bala, 2008); Theory of Planned Behavior (TPB) (Ajzen, 1991); Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Some similar constructs are identified among UTAUT, TRA, and TPB models (Kapoor et al., 2014).

Socio culture contexts are different in emerging countries compared to advanced countries; therefore, theories do not apply to all contexts. Identifying which factors are more influential in adopting technology in developing countries is challenging (Dwivedi et al., 2016). However, the user's adoption intention and external variables that impact the user's adoption willingness are being predicted more accurately using the TAM model compared to the TRA and TPB models (Zhang et al., 2017). Many scholars use the TAM model to identify the newest m-health technologies acceptance (Kang, 2014; Hoque, 2016; Sezgin et al., 2018; Cho et al., 2014; Byomire & Maiga, 2015; Chang et al., 2016).

Davis, Bagozzi, and Warshaw (1989) demonstrated that TAM explains why users accept or reject information systems based on the concept developed by Davis (1985). In the original TAM model, assumed effectiveness and perceived user-friendliness instigate an individual's intention to use technology. In 2008, Venkatesh and Bala presented TAM3 by incorporating different factors in perceived ease of use in the previous TAM2 model (Venkatesh & Davis 2000). The UTAUT model is a widely popular theory to examine IT adoption, and this study applied the UTAUT model (Hoque & Sorwar, 2017; Nunes et al., 2019). In addition, some new variables, such as app quality, perceived risk, and cost, are incorporated due to contextual demand. The following figure 1 represents the research model of this study.

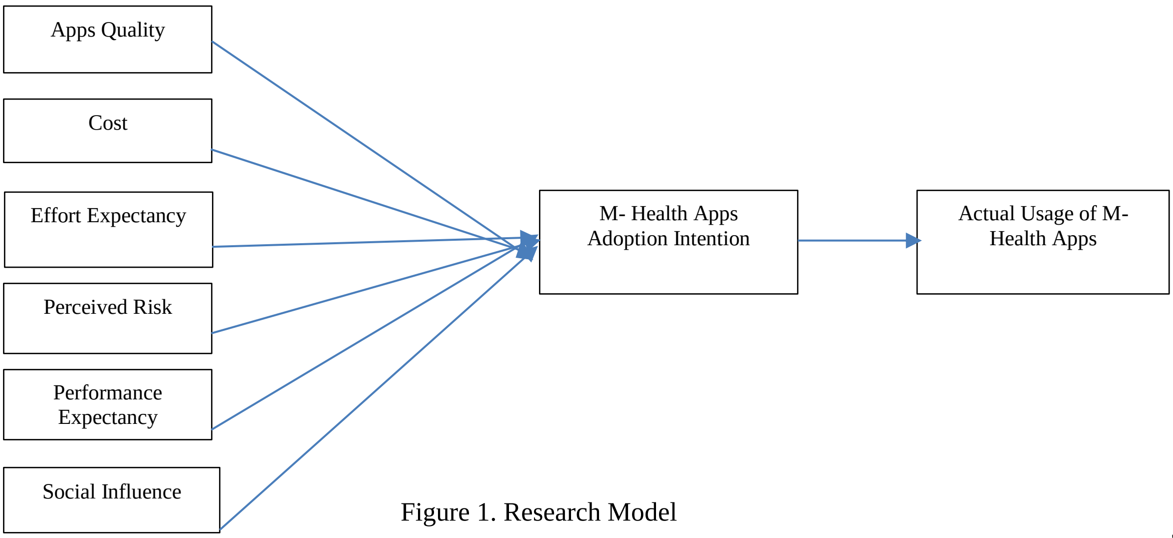

Figure 1. Research Model

MATERIALS AND METHODS

After investigating the previous study, several research constructs are developed to attain the purpose of this study. The hypotheses of this study are derived from prior studies. The operational definition of the research constructs of this study are discussed in the following section.

Quality of apps refers to the apps' features, display, and content. Users want updated content, attractive presentation, and informative features (Calisir et al., 2014). Therefore, when m-health apps do not meet users' expectations, users are not willing to accept m-health apps. Consequently, we propose the following hypothesis:

H1: App quality positively impacts the patients' intention to adopt m-health apps.

Another vital element is cost issues while adopting m-health apps. Users compare the cost and benefits when using any new IT (Lin et al., 2011). They prefer the lower cost and higher benefits of using IT. If the usage cost of m-health apps is within the benefits, they are willing to accept m-health apps. Thus, the following hypothesis is developed:

H2: Cost negatively impacts the patients' intention to adopt m-health apps.

Effort expectancy denotes the extent of ease of use of a system (Venkatesh et al., 2003). Users search for a system that is more convenient, easy to use, comfortable, and fulfills requirements. Therefore, end users' adoption of new technology is strongly influenced by effort expectancy. As a result, the following hypothesis is proposed:

*H3: Effort expectancy positively impacts the patients' intention to adopt m-health app*s.

Data theft, unauthorized access by thirst parties, and privacy violation have become significant issues for users as they share their personal information in the m-health app. Sometimes, different app installation on the mobile device requires access to personal information; consequently, users are unwilling to install apps. The more users perceive the risk of using m-health apps, the more they are reluctant to accept m-health apps (Laxman et al., 2015; Becker, 2016). Hence, we develop the following hypothesis:

H4: Perceived risk negatively impact the patients' intention to adopt m-health apps.

Performance expectancy refers to the individual's perception of the benefit they gain from using the systems. Performance expectancy is a vital determinant to influence adoption behavior among users, which is established by several previous studies (Cimperman et al., 2016; Hsu & Wu, 2017; Hoque & Sorwar, 2017). Based on prior studies the following hypothesis is developed:

H5: Performance expectancy positively impacts the patients' intention to adopt m-health apps.

Social influence represents that individuals are influenced by other members of society, especially the person whom they consider important (Venkatesh et al., 2003; Venkatesh et al., 2012). Social influence is another significant element that strongly effected users' intentional behavior in accepting digital technology and health information systems (Sun et al., 2013). This research proposes the following hypothesis:

H6: Social influence positively impacts the patients' intention to adopt m-health apps.

The association between behavioral intention (BI) and actual usage (AU) has been examined by scholars, and they asserted that there is a positive relationship between BI and AU (Sheppard, 1988; Venkatesh & Davis, 2000). In addition, in the health information systems discipline, similar findings were found in several studies (Kijsanayotin et al., 2009). Hence, the following proposition is made in this study:

H7: M- health apps adoption intention positively impacts the actual usage of m-health apps.

Measurement of the Research Constructs

The structured questionnaire was adapted after a rigorous studying previous literature. To confirm the questionnaire's clarity, accuracy, and readability, a pre-testing was conducted. The structured questionnaire of the study has two sections: demographic information of the respondents and user's acceptance of m-health apps services. A Likert five-point scale was used to assess the user's acceptance of m-health app services. The scale ranges from 1 to 5, where 1 = Strongly Disagree and 5= Strongly Agree. The measurement scale of the major research constructs of this study is given below:

Apps Quality (AQ)

The elements of mobile health apps quality are adapted from past studies, and these are: (1) M-health apps are very much organized; (2) M-health apps are updated regularly and available 24 hours; and (3) Looking m-health apps are attractive (Alaiad et al., 2019).

Cost (CT)
The indicators which measure the construct of cost are: (1) The cost of using m-health apps is expensive to me; (2) The benefit getting from using m-health apps is lower than the usage cost; and (3) Overall, I think cost factor is a barrier to me for adopting m-health apps (Alaiad et al., 2019).

Effort Expectancy (EE)
The effort expectancy construct is constituted of three elements such as (1) Using m-health apps is easy for me; (2) Learning how to use m-health apps is easy for me; and (3) Interaction with m-health apps is clear and understandable to me (Venkatesh et al., 2012; Johnston & Warkentin, 2010; Zhang et al., 2017; Alaiad et al., 2019).

Perceived Risk (PR)
Perceived risk is measured through three items such as (1) M-health apps would not keep my personal information confidential; (2) Information that I share with m-health apps may be attacked by hackers anytime; and (3) M- health apps are not trustworthy (Xue et al., 2012; Hoque & Sorwar, 2017; Alaiad et al., 2019).

Performance Expectancy (PE)
The items of performance expectancy are derived from previous studies, and these are (1) M-health apps help me to get better treatment quickly; (2) M-health apps enable me to manage my health problems more effectively; and (3) Overall, M-health apps are helpful to me (Venkatesh et al., 2003).

Social Influence (SI)
After studying prior literature, three items are adapted for measuring subjective norms, and these are (1) Individuals who are important to me think that I should use mobile health services; (2) Individuals whose opinions are valuable to me think that I use m-health services; and (3) People who are using m-health services have more high status in our social system (Venkatesh et al., 2012; Alam et al., 2020).

Adoption Intention (AI)
The construct of adoption intention is comprised of three items and these are (1) I intend to use mobile health service regularly in the future; (2) I plan to use mobile health services recurrently; and (3) I will always try to use mobile health services in my daily life(Zhang et al., 2017; Alam et al., 2020).

Actual Usage (AU)
For assessing actual usage construct, three components are adapted from previous literature, and these are (1) I actually use mobile health services to keep me healthy; (2) I use mobile health services often; and (3) Mobile health services provide me good experience (Moon & Kim, 2001; Alam et al., 2020).

Participant Characteristics
The following Table 1 demonstrates the demographic information of survey respondents. Among the respondents, male and female respondents were approximately 53% and 46%, respectively. As we considered only elderly citizens, the respondents' age was above 50 years. The majority of the participant completed their graduation and engaged in working. In terms of m-health app usage experience, nearly 70 percent of respondents have less than one year of experience. Moreover, thirty-four percent of the respondents stated that the frequency of m-health usage is once per month.

Table 1. Demographic information of respondents

Category	Frequency	Percentage (%)
Gender		
Male	60	53.57
Female	52	46.43
Age (Years)		
50 to 55	42	37.50
56 to 60	39	34.82
61 to 65	19	16.96
66 to 70	12	10.71
Educational Qualification		
Higher Secondary	19	16.96
Bachelor's degree	65	58.04
Master's degree	28	25.00
Employment Status		
Yes	58	51.79
No	54	48.21
Employment Nature		
Full Time	36	32.14
Self-employed	49	43.75
Part time	16	14.29
Others	11	9.82

M-Health Apps Usages Experiences		
Less than 1 years	79	70.54
1-3 years	16	14.29
4-6 years	11	9.82
More than 6 years	6	5.36
M-Health Apps Usage Frequency		
Once per week	34	30.36
Once per month	39	34.82
2-5 times per month	24	21.43
More than 5 times per month	15	13.39
Income Level		
Less than 15000 BDT	38	33.93
15001 to 30000 BDT	16	14.29
30001 to 45000 BDT	24	21.43
45001 to 60000 BDT	25	22.32
More than 60000	9	8.04

Sampling Procedures and Sample Size

The study's target population is users of m-health app services in Dhaka. Because of resource and time limitations, others cities in Bangladesh are not included in the study. A structured questionnaire was sent to the target population through Google and printed forms. Only completed questionnaires were used to conduct the analysis. Smart PLS (v3) was used to analyze the data. In PLS-SEM, the minimum sample size is one hundred to conduct an investigation (Reinartz et al., 2009). To attain the research objective purposive random sampling technique was used. The authors of this research paper used their judgment to select respondents with attributes to serve the survey purpose. This study used the G*power 3.1 software. The suggested sample size was 109, whereas this research has taken 112 respondents. The configuration was as follows: effect size $f^2 = 0.15$; α err prob= 0.05; power = 0.85; number of predictors= 6 have been used to identify sample size.

Research Design

A quantitative research approach is appropriate for this study, and a survey is used as a research technique. Furthermore, a structured questionnaire is used for conducting the survey. Participants were asked questions regarding some personal attributes and evaluated some statements related to m-health app services.

RESULTS

Common Method Variance (CMV)

This research uses SPSS software to conduct Harman's single-factor test to identify whether any common method bias exists (Podsakoff et al., 2003). The result of Harman's single factor is approximately 41% which is lower than the threshold value of 50%. Consequently, this study established there is no common method variance.

Measurement Model Analysis

The outer model analysis must be performed before evaluating the structural model. Therefore, it is suggested by Hair et al. (2019) to examine the loadings of the indicators for measuring measurement model. In addition, composite reliability and Average variance extracted also need to be measured to ensure convergent validity (Hair et al., 2010). The following Table 2 shows the outer model assessment result. All the indicator loadings values are greater than 0.70 and therefore meet the threshold value. Moreover, the CR and AVE values of the elements confirm the threshold values. As a result, the convergent validity of measurement has been established in this research.

Table 2. Validation of measurement model

Constructs	Indicators	Loadings	Composite Reliability (CR)	Average Variance Extracted (AVE)
AI	AI1	0.886	0.885	0.720
	AI2	0.802		
	AI3	0.855		
AQ	AQ1	0.819	0.840	0.638
	AQ2	0.844		
	AQ3	0.728		
AU	AU1	0.84	0.866	0.683
	AU2	0.782		
	AU3	0.855		
CT	CT1	0.549	0.769	0.535
	CT2	0.891		
	CT3	0.715		
EE	EE1	0.841	0.862	0.675
	EE2	0.86		
	EE3	0.761		
PE	PE1	0.604	0.789	0.560
	PE2	0.786		
	PE3	0.834		
PR	PR1	0.825	0.875	0.701
	PR2	0.85		

	PR3	0.835		
SI	SI1	0.783	0.875	0.700
	SI2	0.877		
	SI3	0.846		

Notes: AQ =Apps Quality; CT =Cost; EE= Effort Expectancy; PR =Perceived Risk; PE =Performance Expectancy; SI =Social Influence; AI =Adoption Intention; AU =Actual Usage

To ensure the discriminant validity of the research, the Fornell –Larcker criterion, HTMT$_{.90}$ criterion, and Cross Loadings are used, and these results are shown in Tables 3, 4, and 5. According to Fornell and Larcker (1981), to attain discriminant validity, the off-diagonal values should be lower than the diagonal value in the Fornell-Larcker criterion. Table 3 demonstrates that discriminant validity has been achieved using the Fornell-Larcker criterion. Another test result is HTMT$_{.90}$ criterion which is represented in Table 4, and all the values are below 0.90; thus, sufficient discriminant validity has been ensured (Henseler et al., 2015; Kline, 2015). Cross-loading is another criterion to establish discriminant validity. Table 5 depicts the cross-loading result, and it is seen that an indicator's loadings are greater than all of its cross-loadings, therefore, achieving discriminant validity (Hair et al., 2011).

Table 3. Assessing discriminant validity using Fornell –Larcker criterion

Constructs	**AU**	**AI**	**AQ**	**CT**	**EE**	**PR**	**PE**	**SI**
AU	0.826							
AI	0.745	0.849						
AQ	0.683	0.706	0.798					
CT	0.405	0.436	0.534	0.731				
EE	0.696	0.662	0.773	0.463	0.822			
PR	-0.621	-0.620	-0.649	-0.454	-0.680	0.837		
PE	0.629	0.556	0.637	0.405	0.507	-0.480	0.748	
SI	0.773	0.758	0.638	0.459	0.629	-0.602	0.621	0.837

Notes: AQ =Apps Quality; CT =Cost; EE= Effort Expectancy; PR =Perceived Risk; PE =Performance Expectancy; SI =Social Influence; AI =Adoption Intention; AU =Actual Usage

Table 4. Assessing discriminant validity using HTMT $_{.90}$ criterion

Constructs	**AU**	**AI**	**AQ**	**CT**	**EE**	**PR**	**PE**	**SI**
AU	-							
AI	0.891	-						
AQ	0.847	0.871	-					
CT	0.572	0.614	0.830	-				
EE	0.849	0.841	0.849	0.702	-			
PR	0.796	0.771	0.851	0.649	0.877	-		
PE	0.885	0.783	0.672	0.717	0.655	-		
SI	0.837	0.872	0.842	0.646	0.816	0.768	0.877	-

Notes: AQ =Apps Quality; CT =Cost; EE= Effort Expectancy; PR =Perceived Risk; PE =Performance Expectancy; SI =Social Influence; AI =Adoption Intention; AU =Actual Usage

Table 5. Cross Loadings

Constructs	AI	AQ	AU	CT	EE	PE	PR	SI
AI1	***0.886***	0.655	0.689	0.441	0.610	0.543	-0.600	0.690
AI2	***0.802***	0.549	0.610	0.263	0.461	0.396	-0.433	0.618
AI3	***0.855***	0.586	0.591	0.397	0.610	0.469	-0.536	0.617
AQ1	0.611	***0.819***	0.631	0.410	0.673	0.490	-0.616	0.552
AQ2	0.630	***0.844***	0.506	0.481	0.612	0.558	-0.485	0.519
AQ3	0.411	***0.728***	0.497	0.381	0.566	0.479	-0.442	0.450
AU1	0.651	0.644	***0.840***	0.382	0.649	0.547	-0.485	0.660
AU2	0.548	0.498	***0.782***	0.311	0.477	0.493	-0.482	0.599
AU3	0.640	0.543	***0.855***	0.309	0.586	0.518	-0.572	0.655
CT1	0.229	0.252	0.196	***0.549***	0.225	0.208	-0.202	0.247
CT2	0.430	0.459	0.427	***0.891***	0.405	0.395	-0.452	0.468
CT3	0.249	0.446	0.200	***0.715***	0.369	0.244	-0.284	0.230
EE1	0.557	0.684	0.634	0.393	***0.841***	0.439	-0.545	0.572
EE2	0.591	0.679	0.561	0.389	***0.860***	0.508	-0.615	0.514
EE3	0.478	0.532	0.518	0.358	***0.761***	0.283	-0.510	0.461
PE1	0.312	0.328	0.228	0.313	0.226	***0.604***	-0.153	0.291
PE2	0.429	0.549	0.538	0.213	0.462	***0.786***	-0.379	0.527
PE3	0.487	0.525	0.583	0.387	0.419	***0.834***	-0.486	0.537
PR1	-0.560	-0.575	-0.552	-0.356	-0.557	-0.456	***0.825***	-0.480
PR2	-0.500	-0.554	-0.495	-0.402	-0.571	-0.384	***0.850***	-0.484
PR3	-0.490	-0.495	-0.507	-0.383	-0.579	-0.356	***0.835***	-0.551
SI1	0.558	0.503	0.586	0.311	0.532	0.454	-0.492	***0.783***
SI2	0.680	0.569	0.677	0.436	0.531	0.506	-0.547	***0.877***
SI3	0.655	0.528	0.671	0.396	0.519	0.592	-0.473	***0.846***

Notes: AQ =Apps Quality; CT =Cost; EE= Effort Expectancy; PR =Perceived Risk; PE =Performance Expectancy; SI =Social Influence; AI =Adoption Intention; AU =Actual Usage

Structural Model Analysis

The first step of structural model analysis is confirming non-collinearity issues. Inner VIF (Variance Inflation Factor) should be lower than three to ensure non-collinearity matters, which Hair et al. (2019) recommend. All the inner VIF values are less than three, shown in Table 6. As a result, this study has no collinearity issues.

Hair et al. (2017) recommended that to examine hypotheses, some tests such as co-efficient, t-statistics, and p values need to be considered. Therefore, for hypotheses testing, bootstrapping with 5000 resamples has been executed, and the result is demonstrated in Table 6, and the graphical representation is shown in figure 2.

Table 6. Hypothesis Result

Hypothesis	Path	Std. Beta	Std. Error	*t* statistics	*p* values	Supported?	VIF	R^2	Q^2	f^2
H1	AQ -> AI	0.280	0.109	2.568	0.005	Yes	2.407	0.668	0.462	0.069
H2	CT -> AI	-0.016	0.073	0.220	0.413	Yes	1.468			0.001
H3	EE -> AI	0.089	0.114	0.782	0.217	Yes	2.995			0.008
H4	PR -> AI	-0.103	0.083	1.246	0.106	Yes	2.152			0.015
H5	PE -> AI	-0.001	0.090	0.015	0.494	No	1.950			0.000
H6	SI -> AI	0.469	0.094	4.968	0.000	Yes	2.248			0.295
H7	AI -> AU	0.745	0.042	17.643	0.000	Yes	1.000	0.554	0.370	1.244

Notes: AQ =Apps Quality; CT =Cost; EE= Effort Expectancy; PR =Perceived Risk; PE =Performance Expectancy; SI =Social Influence; AI =Adoption Intention; AU =Actual Usage

Participants' responses support all the hypotheses except H5. Apps quality (β = 0.280, t = 2.568, p < 0.01) and social influence (β = 0.469, t = 4.968, p < 0.001) have a significant positive impact on the adoption intention of the participants. Similarly, adoption intention has the most significant effect on the usage of the m-health app services (β = 0.745, t = 17.643, p < 0.001). However, performance expectancy is not considered a major driver for the participants to adopt m-health app services (β = -0.001, t = 0.015, p > 0.05). The f2 value of adoption intention is 1.244, which denotes a large effect size, whereas app quality (f^2= 0.069) has a small effect size. In addition, the f^2 value of social influence is 0.295, which is greater than 0.15 and thus has a medium effect (Cohen, 1988).

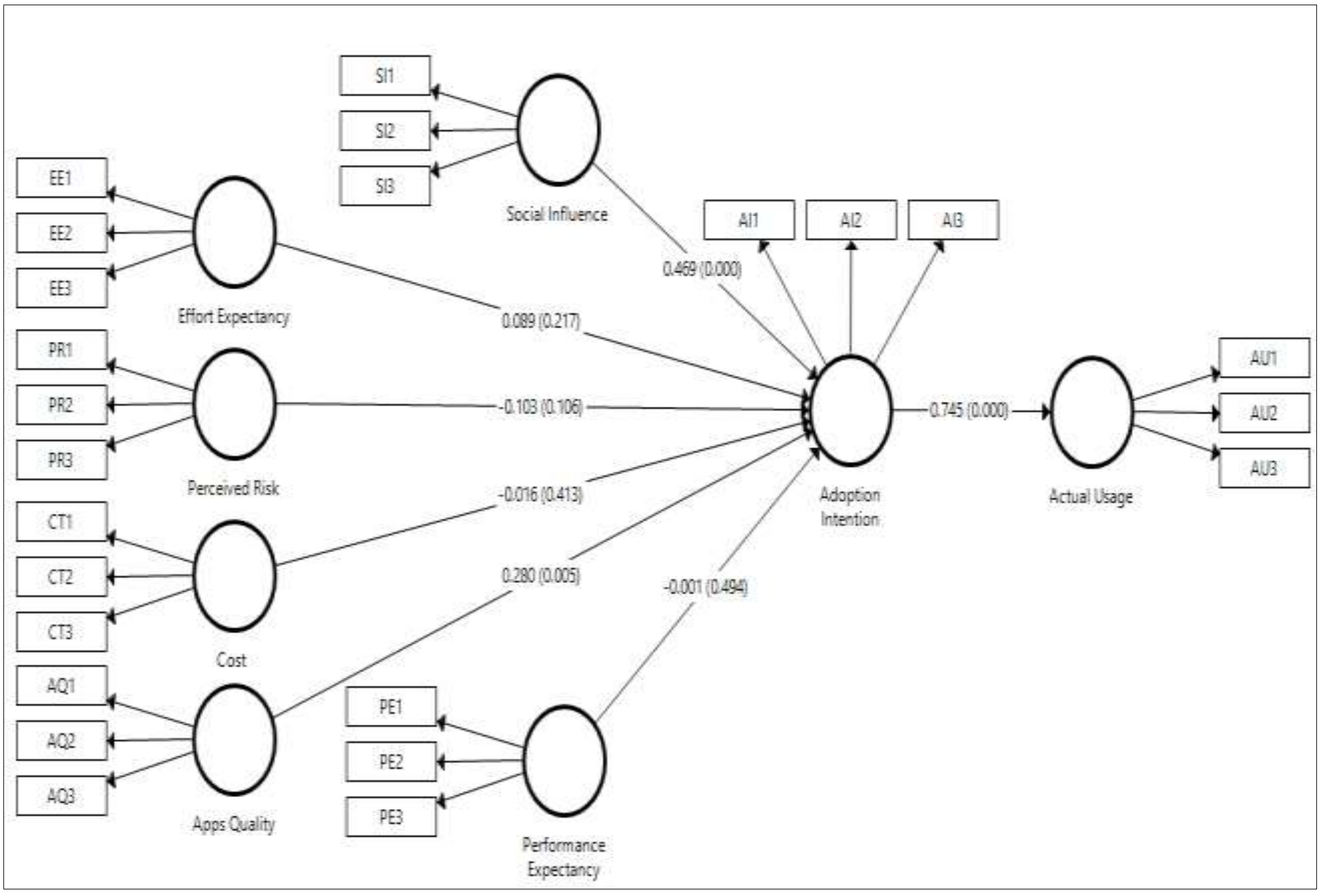

Figure 2. Structural model for m-health apps adoption by elderly citizens

Hair et al. (2017) advised that researchers should examine the value of R^2 for ensuring model predictive accuracy and Q^2 for establishing model predictive relevance. The value of R^2 in this research is 0.55, which indicates that this model explains around 55% variation of the actual usage of the m-health services. Furthermore, model relevance is examined through the Q^2 value, which should be more than zero. The Q^2 value of this study is 0.37, which is higher than zero; hence, model predictive relevance is acquired.

DISCUSSIONS

After performing hypotheses testing, social influence and quality of m-health apps are significant drivers that impact the users' intentional behavior. Besides, willingness to accept is also significantly positively associated with the actual course of action to use m-health apps. Social influence was found significant by Holtz and Krein (2011) as well as Hoque and Sorwar (2017), and this finding is consistent with our study.

The cost of using m-health apps influences the adoption intention is supported by collected data but not significantly. This may be due to the increased internet package cost because most m-health apps require an internet connection while using it. However, as the price of mobile devices is reasonable, the cost issue is treated as an insignificant barrier to the users. Alaiad et al. (2019) revealed that participants were not concerned about the cost of using m-health apps which is partially similar to the finding of this study.

Hoque and Sorwar (2017) and Nunes et al. (2019) demonstrated that performance expectancy was a major determinant of adopting m-health service. However, surprisingly our study reveals performance expectancy as a non-vital element, which is the opposite finding of prior studies (Hoque & Sorwar , 2017; Nunes et al., 2019). Furthermore, this study shows a negative association between perceived risk and older people's intention to use m-health apps. This finding is also reinforced by previous studies (Guo et al., 2013; Alaiad et al., 2019). In addition, this study established a positive relationship between effort expectancy and behavioral intention, which is also similar to prior research findings (Phichitchaisopa & Naenna, 2013; Dwivedi et al., 2016; Hoque & Sorwar ,2017; Alaiad et al.,2019). Finally, willingness to adopt technology and actual usage behavior has a significant association found in our study. Again, this is supported by prior research endeavors in the m-health discipline (Ifinedo, 2012; Hoque & Sorwar, 2017).

CONCLUSIONS

From the findings of this research, policymakers need to concentrate on the features, content, upgrade, accuracy, and quick response of the m-health apps. Developers of m-health apps need to consider several aspects, such as privacy, trust, and security risk issues. This study incorporates several variables rationally related to ICT in healthcare and thus contributes to the literature. However, some constraints limit the research findings from being generalized. At first, the sample size was insufficient, and only Dhaka metropolitan citizens were considered participants. In addition, a longitudinal study was not taken due to time and resource constraints. Several variables, such as the health condition of the participants, age, gender, social status, and education, can be considered moderating variables for future research in this sector.

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