Telemedicine acceptance during the COVID-19 pandemic: User satisfaction and strategic healthcare marketing considerations

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Abstract

A lot remains unexplored regarding the antecedents and outcomes of telemedicine acceptance from health service marketing perspective. This study addresses this gap by integrating the Health Belief Model and the Unified Theory of Acceptance and Use of Technology model in the context of generation Y and Z's response to the COVID-19 pandemic. Data collected from 293 respondents were analyzed using structural equation modeling. The results confirm theoretical rigor of integrating two models examining the antecedents and user satisfaction as an outcome of telemedicine acceptance. The findings also suggest marketing strategies for implementing telemedicine during pandemic. Future research directions are highlighted.

Keywords: Health Belief Model; health service marketing; telemedicine; user satisfaction; Unified Theory of Acceptance and Use of Technology Model

1. Introduction

The recent proliferation of chronic diseases and consumer consciousness of their health safety is accelerating the rise of retail healthcare industry. Hence, the mark between retail and healthcare is fading (Smith & Bernene, 2014). Retail health clinics, otherwise known as convenient care clinics, is gaining much acceptance as it can provide fast, cheap, and convenient health services (Hunter, Weber, Morreale, & Wall, 2009). As part of its innovation and expansion, telemedicine represents a major technology-driven health service, which is supplementing traditional and retail channel of healthcare delivery (Gaur, Sobhani, & Saxon, 2019). The outbreak of COVID-19 has accelerated the need for telemedicine as a safe and fast way to receiving health service from remote location by maintaining social distance and staying at home. Telemedicine is “the use of medical information exchanged from one site to another via electronic communications to improve patients’ health status” (American Telemedicine Association, 2020). Now this kind of technology-based health service is becoming more accessible, as more people now own mobile devices (García, Tomás, Parra, & Lloret, 2019). In the current study’s context, telemedicine is recognized as an actual medical consultation provided to individuals by healthcare providers using mobile phones.

It is also argued that healthcare’s future includes not only the conventional healthcare providers but also the intrusion of related technologies (e.g., telemedicine) and marketing (Anderson, Rayburn, & Sierra, 2019; Butt, Iqbal, & Zohaib, 2019). Moreover, conventional healthcare service is facing challenges with healthcare cost and long waiting time where telemedicine is retailing healthcare services with low cost and short waiting time (Wang, Zhang, Zhao, & Shi, 2019). Yet the use of telemedicine is sluggish than expected (Swan, Dahl, & Peltier, 2019), calling for further inquiry into consumer acceptance, especially in developing county context (Bagchi, Melamed, Yeniyurt, Holzemer, & Reyes, 2018).

Bangladesh as a developing country was one of the 57 countries with an imbalanced healthcare system (WHO, 2011). The country is now facing an acute shortage of skilled healthcare professionals (Alam, Hoque, Hu, & Barua, 2020). The COVID-19’s outbreak has made this situation even worse where telemedicine could be a feasible solution with easy access to regular healthcare services. This is also in line with the country’s initiatives to accomplish Digital Bangladesh Vision 2021 by engaging ICTs in different public services (Daily Sun, 2019), including healthcare. Besides, Bangladesh has a rising young generation with growing interests in health information technology (HIT) (Alam et al., 2020), making it appropriate to study telemedicine acceptance behavior for better designing technology-based health service retailing strategies targeting the promising younger generation.

With the emergence of health consumerism and increased market pressures, both the service providers and researchers are now acknowledging the importance of marketing concepts in healthcare industry (Anderson et al., 2019; Senot, Chandrasekaran, & Ward, 2016). Accordingly, healthcare industry is increasingly building around the requirements of the patient as a consumer (Gaur et al., 2019). This consequently prompts responding to challenges regarding the extent to which consumers are willing to accept the new form of healthcare delivery (Smith & Bernene, 2014). Responses to such challenges could include the exploration of factors motivating consumers to accept alternate, quick, cheap, convenient, and retail form of healthcare service through telemedicine. In this regard, former studies uncovered that analyzing consumers' intention and actual usage with emotional experience of using products and services (e.g., user satisfaction) help better understand consumer needs and formulate suitable marketing strategies (Konuk, 2018).

Within the extant literature on telemedicine (e.g., Kamal, Shafiq, & Kakria 2020; Sterling & LeRouge, 2019; Swan et al., 2019), some notable research gaps are still worth addressing. First, in the convergence of healthcare and technology (e.g., telemedicine), the predominant role of marketing is yet to be effusively explored (Anderson et al., 2019; Grewal, Hulland, Kopalle, & Karahanna, 2020). Indeed, there is a lack of studies outlining strategic and practical guidance for new entrants who are increasingly considering a viable business prospect with telemedicine service (Sterling & LeRouge, 2019). Second, user acceptance of telemedicine should be studied by combining relevant theories (Harst, Lantzsch, & Scheibe, 2019). Some former studies did so in HIT context (e.g., Dou et al., 2017; Kim & Park, 2012); yet such studies disregarded the

Health Belief Model (HBM) or the role of facilitating conditions (FC) and social influence (SI), which are critical to understanding users' acceptance of HIT (e.g., telemedicine) (Harst et al., 2019; Van Houwelingen, Ettema, Antonietti, & Kort, 2018). By overcoming those issues, an integration of HBM with the Unified Theory of Acceptance and Use of Technology (UTAUT) model could provide a holistic (i.e., technological, social, organizational, and individual) assessment of telemedicine acceptance behavior (Hastall, Dockweiler, & Mühlhaus, 2017), facilitating strategic healthcare marketing decisions regarding telemedicine. Third, most extant studies on HIT illustrated behavioral intention (e.g., Kamal et al., 2020) or actual usage (Alam et al., 2020; Dou et al., 2017) as a resultant variable. Theoretically, however, user satisfaction captures the success of implementing any information systems (IS) (e.g., telemedicine) (Isaac, Abdullah, Aldholay, & Ameen, 2019; Venkatesh, Morris, Davis, & Davis, 2003). Nonetheless, to date, the evaluation of user satisfaction as an outcome variable lacks in the existing telemedicine literature (Harst et al., 2019).

In addition to the abovementioned theoretical gaps, some relevant context-specific gaps require further attention. First, most existing literature has concentrated on telemedicine acceptance in rural context (e.g., Zobair, Sanzogni, & Sandhu, 2020) among elderly people (e.g., Sorwar, Rahamn, Uddin, & Hoque, 2016), overlooking the very promising urban young segment (Alam et al., 2020). Second, alongside general health emergencies, telemedicine is efficaciously managing several chronic diseases (e.g., diabetic, cancer) (Burki, 2020) during COVID-19. Nonetheless, it appears that no study has yet investigated the antecedents and satisfaction of telemedicine acceptance in a COVID-19 context.

This study addresses such research gaps by exploring the antecedents and user satisfaction as an outcome of telemedicine acceptance, making at least four key contributions to the extant literature. First, in response to the call made by earlier research (Dou et al., 2017; Harst et al., 2019), it integrates the UTAUT and HBM to understand the antecedents of telemedicine acceptance. UTAUT suggests that while performance expectancy (PE), effort expectancy (EE), SI, and FC directly predict behavioral intention (BI) to adopt the technology (e.g., telemedicine), FC and BI directly explain actual usage (Venkatesh et al., 2003). Besides, HBM recommends that many health-related behaviors are triggered by perceived health threats, along with perceived benefits and barriers of undertaking that behavior (Rosenstock, 1974). Second, the results would help policymakers and healthcare marketers better predict consumers' behavior relating to technology-based health service. Third, it enriches existing literature by empirically testing 'user satisfaction' as an outcome, contributing to the enhanced understanding of users' loyalty and continuance with HIT (Zobair et al., 2020). Fourth, with its focus on COVID-19, it allows a comprehensive exploration of the antecedents and outcomes of telemedicine acceptance among generation Y and Z in urban areas. By enabling service providers in making generalizations on particular age group, this study would therefore help improved strategy formulations regarding telemedicine usage during COVID-19 and post-COVID-19 period.

3. Literature and hypotheses

As discussed, this study has built its theoretical framework on six constructs from the UTAUT model (PE, EE, SI, FC, BI, and actual usage behavior – AUB), three constructs from the HBM (PE, perceived health threat and RC), as well as user satisfaction as an outcome of telemedicine acceptance.

3.1. Performance expectancy (PE)

PE refers to "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p. 447). In line with this, this study has defined PE as the degree that end-users believe telemedicine usage will result in fast and improved, low-cost healthcare services that overcame geographical barriers, especially during COVID-19 pandemic. PE has been recognized as a strong, positive determinant of intention to use other IT-related services such as m-banking (Baabdullah, Alalwan, Rana, Kizgin, & Patil, 2019). Several studies have also confirmed it is influential in predicting BI to use mhealth services (Alam et al., 2020; Hoque & Sorwar, 2017) and smartphone health technology (Dou et al., 2017). Drawing on these findings and recognizing telemedicine as efficient healthcare technology, it is surmised that if users' find it useful in meeting their healthcare needs within the current pandemic, they will illustrate more positive intentions. Thus, the following hypothesis was postulated:

H1. Performance expectancy positively influences behavioral intention to use telemedicine.

3.2. Effort expectancy (EE)

EE refers to "the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450), with extant studies recognizing it as having a significant influence on the end-user's intention to use e-health services (Boontarig, Chutimaskul, Chongsuphajaisiddhi, & Papasratorn, 2012) and electronic health record (EHR) (Hossain, Quaresma, & Rahman, 2019). In this context, telemedicine is argued to be an easy-to-use service with the use of such easily accessible devices as mobile phones (Suzuki et al., 2020). Besides, in a pandemic like COVID-19, users can easily get regular healthcare services remotely from their home by using telemedicine with minimal effort. Building on these arguments and past empirical evidence, the following hypothesis was put forward:

H2. Effort expectancy positively influences behavioral intention to use telemedicine.

3.3. Social influence (SI)

SI refers to “the degree to which an individual perceives that important others believe he or she should use the new system” (Venkatesh et al., 2003, p. 451). Porter and Ganong (2002) identified professional caregivers, children, and peers as those that most influence the acceptance of new technology. Social settings of developing countries like Bangladesh often make it obvious that people live in joint families and they primarily tend to be influenced by the behavior and opinion of other family members (e.g., elder brothers or sisters), relatives, or even neighbors. Evidence of such SI in telemedicine use (Kamal et al., 2020) would arguably be enhanced by further empirical examination in telemedicine acceptance. Accordingly, while several studies have reported the significant direct impact of SI on BI to use e-health (Boontarig et al., 2012), mhealth services (Alam et al., 2020), Harst et al. (2019) posited that further research is needed in the context of telemedicine. Thus, the following hypothesis was proposed:

H3. Social influence positively influences behavioral intention to use telemedicine.

3.4. Facilitating condition (FC)

FC refers to “the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system” (Venkatesh et al., 2003, p. 453). Boontarig et al. (2012) contended that FC positively influences the intention to use smartphones for e-health services. Likewise, telemedicine usage is predominantly triggered by related technical and organizational support services including the provision of specific hotline numbers (e.g., 333 in Bangladesh) and required guidelines facilitating users to instantaneously contact healthcare professionals upon experiencing any COVID-19 symptoms. This could foster the prompt adoption of telemedicine services among users. In this regard, while relevant studies have illustrated the positive, significant relationship between FC and both BI to use and AUB of EHR (Hossain et al., 2019) and mhealth (Alam et al., 2020), examining the influence of FC on BI to use and AUB of telemedicine with regard to generation Y and Z remains unexplored. Thus, the following hypotheses were proposed:

H4. Facilitating condition positively influences behavioral intention to use telemedicine.

H5. Facilitating condition positively influences actual usage behavior in telemedicine.

3.5. Perceived health threat (PHT)

PHT has been determined as end-users' awareness and concern for a personal health condition (Dou et al., 2017), identified as a direct determinant of BI to use HIT (Dou et al., 2017; Kim & Park, 2012). In other words, PHT is an individual's perception of the risk of facing a particular health condition (e.g., getting infected), including the likely clinical (e.g., death) or social outcomes (e.g., effects on family life) (Rosenstock, 1974). This is particularly relevant during COVID-19, because any such pandemic that triggers fear of being infected (Mamun & Griffiths, 2020) is likely to create the urge to adopt new systems. Being infected with COVID-19 might cause financial threats (e.g., cost of treatments) and social threats (e.g., being isolated in the society) (Mamun & Griffiths, 2020). Recognition of such threats might accelerate the uptake of preventive healthcare measures (e.g., avoiding crowds), leading people to use telemedicine services. In this regard, PHT has been confirmed as a direct determinant of BI to eating healthy (Deshpande, Basil, & Basil, 2009) or use HIT in the context of self-management of chronic disease (Dou et al., 2017; Kim & Park, 2012); yet it has not been explicitly tested in telemedicine literature. Hence, the following hypothesis was proposed:

H6. Perceived health threat positively influences behavioral intention to use telemedicine.

3.6. Resistance to change (RC)

Dou et al. (2017) recognized RC as an individual's effort to uphold their prior behaviors and existing habits when any change was required. The introduction of new technology within the existing setting might face confrontation from its common users. Such is the case of telemedicine implementation as it replaces conventional in-person patient visits with online consultation. People might start using telemedicine either forcibly or voluntarily; nonetheless, they would discontinue it in the longer run (Kamal et al., 2020). Consistent with this, former studies on healthcare technology, including smartphone health technology (Dou et al., 2017) and mhealth (Hoque & Sorwar, 2017), have demonstrated that RC has a significant, negative impact on BI to use. Yet in a pandemic situation like COVID-19, whether RC still has the same impact on BI to use an alternative, less threatening healthcare service (e.g., telemedicine) remains unexplored. Thus, the following hypothesis was put forward:

H7. Resistance to change has a significant negative influence on behavioral intention to use telemedicine.

3.7. Behavioral intention (BI)

BI has been conceptualized as an individual's willingness to perform a particular behavior (Ajzen, 1991). The UTAUT model exhibits a significant positive impact of BI on AUB (Venkatesh et al., 2003). Essentially, it is necessary to study BI's impact on actual usage behavior as BI does not always translate into AUB (Dou et al., 2017). In a healthcare context, recent studies on health technology (e.g., mhealth, EHR) affirms that BI to use is a significant determinant of AUB (Alam et al., 2020; Hossain et al., 2019). However, such an affirmation is yet to be investigated in the context of retail healthcare such as telemedicine; thus, drawing on core UTAUT logic and extant studies, this study hypothesizes that:

H8. Behavioral intention to use positively influences actual usage behavior of telemedicine.

3.8. AUB and user satisfaction (USF)

In line with Isaac et al. (2019), this study defines USF as the degree that end-users are satisfied with their decision to use telemedicine. AUB has been determined as the actual usage frequency of a system or service, with Venkatesh et al. (2003) recommending that user satisfaction be evaluated as a success factor of such usage. The important thing that matters to be with telemedicine service is the experiential outcome of AUB (e.g., satisfaction) (Kamal et al., 2020). Some former studies in IT system adoption have reported that AUB positively influences USF (e.g., Isaac et al., 2019); yet this area has been relatively unexplored in relation to telemedicine technology. In accordance with this discussion and amidst an unprecedented incident like COVID-19, we also speculated that AUB might hasten USF. Thus, it was posited that:

H9. Actual usage behavior positively influences user satisfaction.

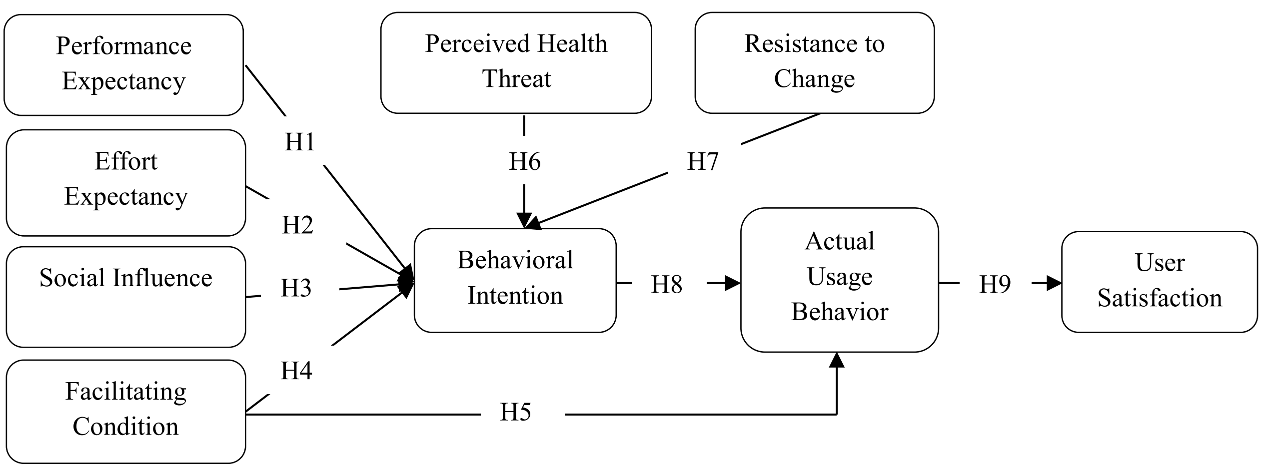

Figure 1: Proposed research model

4. Methodology

4.1. Measures

This study has adopted all but one previously validated measures for content validity (Hair Black, Babin, & Anderson, 2014). The COVID-19 infection affects people both physically and socially (Mamun & Griffiths, 2020), which influenced this study's development of a perceived health threat item (i.e., *I am concerned that getting infected with COVID-19 will cost me socially*) in consultation with HIT experts. Items for physical concern were adapted from other sources, as specified in Appendix 1. In line with previous studies (e.g., Hossain et al., 2019), a 5-point Likert scale was used, ranging from (1) strongly disagree to (5) strongly agree. To ensure appropriateness, two academics from the psychology and marketing departments and two HIT researchers reviewed and evaluated the questionnaire, which was then pre-tested among fifteen 19-25 year-old students that represented the target population. Final refinements were then made to ensure an acceptable range of criterion validity of the questionnaire. Appendix 1 presents the list of all measurement items and their sources.

4.2. Target population

The target population was generation Y and Z; those born between 1980 and 1995 and 1995 and 2010 respectively (Bencsik et al., 2016). It has been reported that a considerable amount in these generations have been infected with COVID-19 (IEDCR, 2020). They are also more technology prone, meaning they are more likely to influence a radical change in healthcare services (Alam et al., 2020). Moreover, youngers tend to use the internet more than the general people to search for health information (Erdem, 2008). The focus was also on urban generation Y and Z, based on identification of metropolitan areas as the epicenters of most countries' COVID-19 outbreaks (CNN, 2020; WHO, 2020), and Smith et al. (2020) noting that telemedicine is just as useful for patients in urban areas as it is for those in rural areas.

4.3. Sample and data collection

Employing a convenience sampling technique (Hossain et al., 2019), respondents were selected primarily from this researcher's social media network in Bangladesh (i.e., Facebook, Instagram). Three graduates contacted these 935 potential respondents via mobile phone, email, and messenger. After explaining the study’s rationale and nature, they were asked whether they were willing to participate, and if they had used a telemedicine service at least once. Moreover, participants were made aware of the option to quit participation at any phase during the survey. This generated 774 willing and relevant respondents who were then provided with the survey link via email or messenger, with two follow-ups occurring within seven-day periods. To prevent a participant from responding more than once, ‘Limit to 1 response’ option was checked in the setting of the Google Docs survey. Participants were not offered any incentives to avoid potential bias (Alam et al., 2020). The survey period was the first three weeks of April 2020, after COVID-19 had officially become a pandemic. This resulted in 301 responses with 39% response rate that is analogous to online survey response rates (Deutskens, De Ruyter, Wetzels, & Oosterveld, 2004). After checking for incompleteness, 293 completed responses were deemed usable.

5. Analysis and results

This study conducted principal component analysis (PCA) and structural equation modeling (SEM) with confirmatory factor analysis (CFA) using SPSS (V23) and AMOS (V23). Table 1 below presents the sample demographics.

Table 1: Sample demographics

		Frequency	**Percentage**
Age (years)	18-20	7	2.4
	21-25	88	30.0
	26-30	128	43.7
	31-35	51	17.4
	36-40	19	6.5
Educational qualification	Higher secondary	7	2.4
	Graduate	103	35.2
	Postgraduate	161	54.9
	Above Postgraduate	22	7.5
Gender	Female	142	48.5

		Frequency	Percentage
	Male	151	51.5
Telemedicine usage experience	Once in the last two months	171	58.4
	More than once in last two months	122	41.6

5.1. Principal component analysis (PCA)

PCA using varimax rotation resulted in a Kaiser-Meyer-Olkin (KMO) measure of 0.91 with significant Bartlett's Test of Sphericity (.000<0.05), which were both within the suggested threshold, indicating acceptable levels of sampling adequacy (Tabachnick & Fidell, 2014). The resultant nine factors with eigenvalues exceeding 1.0 explain 80.87% of the total variance. This study has used 0.70 as a threshold for factor loading, indicating distinct factor structure (Hair et al., 2014). Alpha values exceeding 0.70 suggest satisfactory internal consistency of the items. The result summary is reported in Table 2 below.

Table 2: Summary of constructs' reliability and convergent validity assessment

Constructs	Indicators	α	AVE	CR	PCA load	CFA load (λ*)
PE	PE1	0.91	0.71	0.91	0.77	0.82
	PE2				0.79	0.85
	PE3				0.77	0.86
	PE4				0.79	0.84
EE	EE1	0.91	0.71	0.91	0.78	0.83
	EE2				0.81	0.85
	EE3				0.81	0.87
	EE4				0.82	0.82
SI	SI1	0.90	0.74	0.89	0.87	0.84
	SI2				0.84	0.86
	SI3				0.85	0.88
FC	FC1	0.89	0.73	0.89	0.85	0.85
	FC2				0.84	0.89
	FC3				0.79	0.81
PHT	PHT1	0.89	0.72	0.88	0.84	0.87
	PHT2				0.83	0.87
	PHT3				0.76	0.81
RC	RC1	0.90	0.76	0.90	0.88	0.80
	RC2				0.93	0.90
	RC3				0.93	0.91
BI	BI1	0.88	0.71	0.87	0.78	0.82
	BI2				0.77	0.93
	BI3				0.76	0.78
AUB	AUB1	0.87	0.69	0.88	0.79	0.82
	AUB2				0.84	0.84

Constructs	Indicators	α	AVE	CR	PCA load	CFA load (λ*)
	AUB3				0.79	0.83
USF	USF1	0.86	0.67	0.86	0.78	0.77
	USF2				0.77	0.85
	USF3				0.80	0.83

*All factor loadings (λ) are significant at $p < 0.001$

Note: α=Cronbach's alpha; AVE=average variance extracted; CR=composite reliability; PCA=principal component analysis; CFA=confirmatory factor analysis

5.2. Measurement model

The overall goodness-of-fit indicators (i.e., $\chi^2_{(df=341)}$ =378.51, *p=0.079,* GFI=0.92, CFI=0.99, TLI=0.99, RMSEA=0.02, SRMR=0.03) indicate a satisfying acceptable fit for the measurement model (Doll, Xia, & Torkzadeh, 1994; Hu & Bentler, 1999). The analysis estimated 29 items across the nine constructs. As shown in the above table, the composite reliability (CR) and Cronbach's alpha of all estimated constructs were greater than 0.86, signifying adequate reliability (Fornell & Larcker, 1981). In addition, the CR ranges between 0.86 and 0.91, AVE between 0.67 and 0.76, and factor loadings (λ) between 0.77 and 0.93, were all higher than the suggested values and meet the requirements of the convergent validity of measurement scales (Fornell & Larcker, 1981; Hair et al., 2014).

As shown in Table 3 below, non-diagonal elements represent inter-correlation among the constructs, and diagonal elements are the square root of AVE. All diagonal elements were greater than the non-diagonal elements in the corresponding rows and columns, meeting the conditions for adequate discriminant validity, as recommended by Fornell and Larcker (1981). In addition, all inter-correlation elements were well below the threshold value of 0.85, indicating the analysis avoided multicollinearity (Kline, 2015).

Table 3: Correlation coefficients and square root of AVE (in bold on diagonal)

Constructs	BI	USF	AUB	PHT	FC	RC	SI	PE	EE
BI	**0.84**								
USF	0.55	**0.82**							

Constructs	BI	USF	AUB	PHT	FC	RC	SI	PE	EE
AUB	0.57	0.52	**0.83**						
PHT	0.56	0.55	0.47	**0.85**					
FC	0.54	0.47	0.44	0.46	**0.85**				
RC	-0.04	-0.04	0.04	0.01	-0.02	**0.87**			
SI	0.49	0.40	0.33	0.44	0.47	-0.08	**0.86**		
PE	0.60	0.58	0.53	0.52	0.48	0.02	0.47	**0.84**	
EE	0.54	0.55	0.51	0.50	0.44	-0.03	0.31	0.60	**0.84**

5.3. Structural model

The goodness-of-fit indicators (i.e., $\chi^2_{(df=353)}$ =477.32, *p=0.000,* GFI=0.91, CFI=0.98, TLI=0.98, RMSEA=0.04, SRMR=0.08) were within the recommended threshold, confirming acceptable fit for the structural model (Doll et al., 1994; Hu & Bentler, 1999).

Table 4: Results of hypothesis tests

Hypothesis	Structural path	Std. estimate (β)	SE	*t* value	*p* value	Results
H_1	PE → BI	0.24	0.074	3.214	0.001	Supported
H_2	EE → BI	0.19	0.066	2.815	0.005	Supported
H_3	SI → BI	0.15	0.047	2.371	0.018	Supported
H_4	FC→ BI	0.17	0.047	2.662	0.008	Supported
H_5	FC→ AUB	0.18	0.066	2.635	0.008	Supported
H_6	PHT→ BI	0.21	0.059	3.129	0.002	Supported
H_7	RC→ BI	-0.01	0.044	-0.282	0.778	Not supported
H_8	BI →AUB	0.53	0.098	7.140	0.000	Supported
H_9	AUB →USF	0.56	0.044	8.262	0.000	Supported

Table 4 shows that antecedents in the model explained 54% (r^2 =0.54) variations in BI. Among the antecedents, PE (β=*0.24, p<0.001*) was found to have a significant positive impact on the BI that is consequently followed by PHT (β=*0.21, p<0.01*), EE (β=*0.19, p<0.01*), FC (β=*0.17, p<0.01*) and SI (β=*0.15, p<0.05*). Accordingly, H1, H2, H3, H4, and H6 were supported. In contrast, the relationship between RC and BI (β=*-0.01, p>0.05*) was insignificant; thus, H7 was not supported. Furthermore, FC (β=*0.18, p<0.01*) and BI (β=*0.53, p<0.001*) had a positive and significant influence on AUB. Therefore, H5 and H8 were supported. Both FC and BI explain 41% (r^2 =0.41) variations in the AUB. Lastly, AUB had a significant and positive

(β=*0.56, p<0.001*) influence on user satisfaction, supporting H9 with 31% (r^2 =0.31) variations in user satisfaction.

6. Discussions

This study integrated the HBM and UTAUT model to explore the antecedents and user satisfaction of telemedicine acceptance among end-users. In line with past studies on HIT and HER (Hossain et al., 2019) and mhealth (Alam et al., 2020), our results suggest that PE is an important driver for the acceptance of telemedicine. The end-user's positive experience has been connected to technologies that are comfortable and easy to use (Alalwan et al., 2017), indicating that if telemedicine helps to improve the ability to manage healthcare efficiently, these younger generations would be more likely to use it. Generation Y and Z's regular use of smart applications, for an easier and faster way of life (Bencsik et al., 2016), aligns with this study's finding that EE has a positive influence on BI. This implies that if telemedicine usage is simple and justifiable, they will be more likely to use it.

Furthermore, result of H3 (SI is a determinant of BI) signifies these younger generations are more likely to be influenced by those close to them about accepting a new technology like telemedicine. In addition, our results highlight the positive impact of FC on end-users' telemedicine acceptance which is congruent with Alam et al. (2020). Thus, as with other technology-related services such as m-banking (Baabdullah et al., 2019), adequate organizational and technical infrastructure (e.g., trained staff, technology platform) may trigger intended and actual usage of telemedicine among generation Y and Z.

Furthermore, building on Dou et al.'s (2017) telemedicine study, our results show that PHT positively influences BI, suggesting that higher levels of awareness of health threats (e.g., COVID-19) will make generation Y and Z more likely to accept telemedicine. Our findings also suggest that RC does not have any significant negative influence on BI in adopting telemedicine, which is contrary to extant findings (e.g., Hoque & Sorwar, 2017). This indicates that generation Y and Z's enthusiasm toward technology drives their higher intention to use technologies like telemedicine, particularly during a pandemic like COVID-19 when social distancing is mandatory. Lastly, this study reports a positive association between AUB and USF in the context of telemedicine acceptance, which is a fresh finding, suggesting end-users are satisfied with such health technologies that provide prompt responses from specialized doctors.

7. Theoretical implications

This study's integration of the HBM and UTAUT model to explain end-users' telemedicine acceptance behavior is a fresh approach, especially in the context of technology-based retail health service. It empirically tested and confirmed the robustness of the combined model, which is an incremental contribution to existing telemedicine literature. For example, studies applying TAM (e.g., Dou et al., 2017; Kamal et al., 2020) disregarded HBM, or important outcome variables (e.g., satisfaction). Some studies also overlooked the potential role of SI in capturing users' HIT acceptance behavior. After taking these theoretical gaps into account, this study advances past works by exploring telemedicine acceptance among urban generation Y and Z, with a focus on COVID-19 pandemic. Accordingly, the current study enriches the telemedicine knowledge by deepening understanding of generations that are relatively untapped. Alongside technological characteristics, this study also analyzed HIT acceptance behavior with regard to users' individual, social, and organizational characteristics.

Moreover, by verifying the combined UTAUT and HBM in retail health service setting, this study unveiled a theoretical link between technology, health belief, and retail. This fresh link extended the findings relating to technology and health belief on retail health service. Further, by elucidating the impact of PE, EE, SI, and FC on telemedicine acceptance, this study extends on Boontarig et al. (2012) and Hoque and Sorwar (2017) who illustrated the impact of these constructs on comparable health-related technology (e.g., e-health, mhealth). Another important contribution is the recognized association between health-related behavior (i.e., PE, RC, and PHT) and technology acceptance, which builds on Rosenstock's (1974) work. Theoretically, such a finding is predominantly essential, providing a richer understanding of technology adoption behavior in relation to users' health-related concerns. That is, incorporation of HBM in our research model provides in-depth focus on characteristics relating to individuals (e.g., PHT); such an incorporation further exemplifies an improved explanatory power of the combined model (Harst et al., 2019). Thus, this study validates the HBM in comprehending HIT acceptance (i.e., telemedicine), offering a theoretical framework for future studies on technology enabled retail services (e.g., health care).

Overall, this study's validation of the path from cognitive process (e.g., PE, EE) to actual behavior to emotional reaction (i.e., USF) is in line with Bagozzi's (1992) disjointed concepts (cognitive, emotional, and behavioral). In this context, this study has gone a step further than simply exploring consumer acceptance by recognizing the impact of AUB on user satisfaction. From theoretical perspective, this is consistent with Isaac et al.'s (2019) finding, suggesting a link between telemedicine acceptance and its potential outcomes, which is largely unexplored in telemedicine literature. It consequently sets a theoretical foundation for further understanding of end-users' continuance intention with respect to health technologies like telemedicine.

8. Practical implications

While telemedicine offers a potential effective solution to healthcare services during COVID-19, challenges remain with consumers' acceptance of this service. This study's empirical findings have contributed to this issue by providing an extensive understanding of factors affecting young generation's acceptance of telemedicine as well as practical insights for health service delivery through telemedicine implementation as a supplement of traditional and retail healthcare, particularly post-COVID-19 pandemic. It highlights the positive influence of PE and EE on BI, suggesting that a nationwide campaign advocating the ease of its use could extend telemedicine acceptance. Policymakers and retail health service marketers should therefore promote it as an innovative, easy-to-use option for receiving healthcare services, particularly during pandemics like COVID-19. Together with awareness building, such as campaign could generate positive word-of-mouth and accelerate the role of SI. These findings also indicate that the younger generations often value opinions of important others (e.g. friends, peers, relatives) before initiating the use of technologies like telemedicine. Health service marketers should therefore focus on these influential others by publishing articles and creating social media content (e.g., Facebook, telemedicine user community) to spread positive word-of-mouth. Educating individuals about the expected health benefits of a new healthcare service is critical to such service be successful (Simons, Hampe, & Guldemond, 2014). Thus, policymakers should also ensure necessary resources are in place for telemedicine usage (e.g., trained medical staff, educational programs, well-equipped service facilities).

These findings also illustrate the positive impact of PHT on BI. In the context of the COVID-19 pandemic, young people concerned about the physical and social risks of infection primarily seek out healthcare services. Thus, a service or technology like telemedicine, which ensures privacy and minimizes the risk of infection, will trigger higher levels of acceptance. Furthermore, particularly in the context of COVID-19, the findings suggest that RC does not have any significant negative influence on generation Y and Z's acceptance of telemedicine.

This study has also added to existing telemedicine acceptance knowledge by empirically testing user satisfaction as an outcome of usage behavior, which is still in its infancy. It would appear that a positive influence of AUB on user satisfaction signifies a better prospect for a healthcare marketing setting. That means, the practical experiential outcome (i.e., satisfaction) obtained through a telemedicine service could create customer loyalty (Anabila, 2019; Clark, Wolosin, & Gavran, 2007) or might be extended to potential users via positive word-of-mouth. Furthermore, as many developing countries like Bangladesh are suffering from an acute shortage of healthcare professionals, this could be an important insight into the process of integrating telemedicine services into mainstream healthcare services.

9. Limitations and further research directions

This study acknowledges several limitations that might open up future research opportunities. First, it was limited to specific age cohorts (i.e., generation Y and Z) and periods (i.e., during COVID-19 pandemic) that might confine the generalization of these findings. Second, as the respondents all lived in metropolitan areas in Bangladesh, the results might not be an exact manifestation of the country's entire population. Future research could focus on both urban and rural population across different age groups to address these issues. It could also be interesting to examine whether the impact of the HBM and UTAUT factors differ across the demographics (e.g., age, gender, education). Third, this study applied cross-sectional data based on self-reported behavior, which could be enhanced by applying longitudinal data in the future. Furthermore, this research model could be applied in other developing country contexts, involving other potential telemedicine usage outcomes such as perceived quality and safety. Lastly, this study offers a conceptual framework for future studies intending to investigate continued intention to use telemedicine.

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