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Original Research

Factors influencing mHealth adoption and its impact on mental well-being during COVID-19 pandemic: A SEM-ANN approach

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ABSTRACT

The objectives of this study are to examine the factors affecting the intention and actual usage behavior on mHealth adoption, investigate the effect of actual usage behavior of mHealth on mental well-being of the end-users, and investigate the moderating role of self-quarantine on the intention–actual usage of mHealth under the coronavirus disease (COVID-19) pandemic situation. The required primary data were gathered from the end-users of mHealth in Bangladesh. Using the Unified Theory of Acceptance and Use of Technology (UTAUT2), this study has confirmed that performance expectancy, effort expectancy, social influence, hedonic motivation, and facilitating conditions have a positive influence on behavioral intention whereas health consciousness has an impact on both intention and actual usage behavior. mHealth usage behavior has an affirmative and meaningful effect on the mental well-being of the service users. Moreover, self-quarantine has strong influence on actual usage behavior but does not moderate the intention-behavior relationship. In addition, due to the existence of a non-linearity problem in the data set, the Artificial Neural Network (ANN) approach was engaged to sort out relatively significant predictors acquired from Structural Equation Modeling (SEM). However, this study contributes to the emergent mHealth literature by revealing how the use of the mHealth services elevates the quality of patients' mental well-being under this pandemic situation.

1. Introduction

Due to the scarcity of healthcare resources in developing countries, digital technologies are constantly evolving and finding new ways to deliver healthcare services through digital transformation. It provides many opportunities for strengthening healthcare systems; particularly, it could be vital resources during any public healthcare emergency [43]. For instance, during the recent outbreak of COVID-19, where physical distancing and self-quarantine are required, digitalization of healthcare sector has emerged to play a vital role in delivering healthcare services to the individuals. In such situation, where the individuals avoid going outside of their homes and keep themselves in self-quarantine due to the fear of infection, mHealth (mobile health) can be a powerful technology to help people connect with their physician [13].

In fact, at present, the diffusion rate of digital technology in the healthcare sector has rapidly increased and has more advanced features and added values [36,53]. mHealth, for example, is empowered with Artificial Intelligence (AI) technologies which have achieved primary impact in combating the emerging threat of this virus globally [25]. Due to the rapid penetration of mobile phone worldwide, huge potentials exist for mHealth system to enhance the accessibility to specialist clinical diagnostics and treatment advice [57]. mHealth provides a range of programs and facilitates ease of access to the healthcare sectors for individuals, especially for females, the elderly, and the poor via their smartphones [32].

Though there are many studies exploring factors that affect mHealth adoption in the context of both developed and developing countries [6,21,48], a lack of study exists to investigate the consequence of using mHealth services. In this regard, the authors believe that adopting mHealth services can play an important role in the user's mental well-being as a consequence. Mental well-being has been defined as individual realization on his/her own abilities to cope with stress of life,

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work productively, and contribute to their community [58]. According to scholars, health technology has appeared as the appropriate solution to ensure the individuals' mental well-being [65]. Specifically, during this pandemic situation where people are in self-quarantine, it can facilitate individuals to uplift their mental well-being status [41]. Recent study suggests that self-quarantine situation is largely having negative effect on the mental health of the individuals [74]. However, theoretically it is not clear yet, to what extent mHealth brings less mental pressure for the patients and its adoption can enhance the mental well-being of the individuals, particularly during this pandemic.

Therefore, the current study applies Unified Theory of Acceptance and Use of Technology (UTUAT2) model [68] and attempts to explore factors affecting on the adoption of mHealth technology which leads to mental well-being of patient considering the role of self-quarantine and the effect of health consciousness. The objectives of this study are to; examine the factors affecting the intention and actual usage behavior in mHealth adoption; investigate the effect of actual usage behavior of mHealth on mental well-being of the end-users; examine the moderating role of self-quarantine on the intention–actual usage behavior of mHealth. The context of this study is Bangladesh. In this country, for a long time, the mobile phone was ignored as a powerful tool to diminish the digital divide in the healthcare sector. But in the last decade, compared to other developing countries, mHealth has rapidly been evolved in Bangladesh. During this pandemic situation, like other countries in the world, the government of Bangladesh has imposed restriction on peoples' movements and required them to practice self-quarantine [24]. Therefore, mHealth services have been the most preferable and vital option to interact individuals with their physician.

Methodologically, due to the complicated nature of consumer decision-making process, examining the objectives of this study solely with linear models might be oversimplified. Hence, we utilized a SEM-ANN (Structural Equation Modeling – Artificial Neural Network) approach which can deal with non-compensatory and non-linear relationships. The application of SEM-ANN in the complex situation of consumer decision-making process is evident in several scholarly works (e.g. [7,29,39]). In the next section, this paper presents the conceptual framework and development of research hypotheses. Then, it presents the research methodology and analysis of data, and finally, discussions, contributions, conclusions, limitations, as well as directions for future research.

2. Theoretical framework and hypotheses development

This study is grounded on the UTAUT2 model as a theoretical basis due to its high relevancy and predictive capacity in the consumer context. As recommended by Venkatesh et al. [68], an extension of UTAUT2 model through revision or modification is expected for the adoption of new IT applications. Therefore, this empirical study incorporates two additional predictors to the original UTAUT2 model pertinent to the COVID-19 pandemic situation – namely, self-quarantine and health consciousness. As stated by Xiao et al. [72], individuals having a high sense of health consciousness are in high demand for better health information with a hope to engage themselves in promoting health services. Moreover, Hong [31] also affirmed that the health consciousness of an individual is required to be re-conceptualized from the psychological standpoint rather than from the behavioral viewpoint alone, with an aim to better comprehend the orientation of individuals regarding their health concerns. Existing research in mHealth has not explained yet the complex relationship between self-quarantine, health consciousness, behavioral intention as well as actual usage behavior. Further, this study has advanced the existing mHealth research by considering mental well-being as a consequence of actual mHealth use. However, we have excluded the original moderating variables (age, gender, experience, and education) from the proposed. The reason is that in the current literature it has extensively been studied the moderating role of users' demographics using UTAUT2 model in the context of eHealth or mHealth services. In this connection, further exploration might not be an interesting investigation for the greater readership. The extended proposed model is shown in Fig. 1. In this model performance expectancy, effort expectancy, social influence, hedonic motivation, price value, facilitating condition, habit, and health consciousness influence on behavioral intention. Behavioral intention, facilitating condition, habit, health consciousness, self-quarantine influence on actual usage behavior (USE). USE effects on mental well-being. In addition, self-quarantine is the moderating variable in this model.

Performance expectancy is conceptualized as the extent to which an individual realizes that utilizing the information system will assist the person to attain the certain performance [67]. In the extant literature of mobile services, performance expectancy has been appeared as the significant influencer of behavioral intention [15]. People have more inclination to accept the new technology given that such technology is easily accessible and convenient to operate [23]. If the mHealth service is easy to use, it is expected that users will have the intention to use the services. Social influence is conceptualized as to what extent an individual perceives the beliefs of others as important that he or she should adopt the innovative system [67]. In fact, the acceptance of technology impressively depends not only on an individual's thought but also on social influence [73]. Thus, if the users are well influenced by the acquaintances to use mHealth services, it will create the intention to adopt such technology. Besides, scholars have demonstrated that facilitating conditions significantly affect behavioral intention to adopt tech-oriented services [1]. In the milieu of Apps-driven healthcare services, facilitating condition has proven as one of the vital factors influencing the behavioral intention and use of mHealth services [7]. Hedonic motivation refers to the fun or pleasure that an individual gathers from using an innovative technology [68]. Upon realizing the presence of pleasure, entertainment, comfort, fun, and enjoyment when using an innovative technology, people are more likely to accept that technology [10]. Several recent studies have revealed that hedonic motivation positively and significantly affects the intention to accept/use a given tech-based services [3,9]. Price value means suitable price ranges and the best value for the money sacrificed [61]. Users of a given technology have the tendency to compare the benefits that they might receive from using the technology and the foregone monetary cost that they have made for having the technology [10]. Compare to typical in-hospital healthcare services, mHealth is a less costly channel to deliver the healthcare services due to reduction in physical trips to doctors' chambers, hospitals, and emergency centers [42]. Dhiman et al. [19] demonstrated that price value is the most prominent determinant behind technology adoption intention. Habit refers to the reflexive performance of the peoples' behaviors due to their experiences [71]. It is sensible to state that upon the engagement of a customer in health

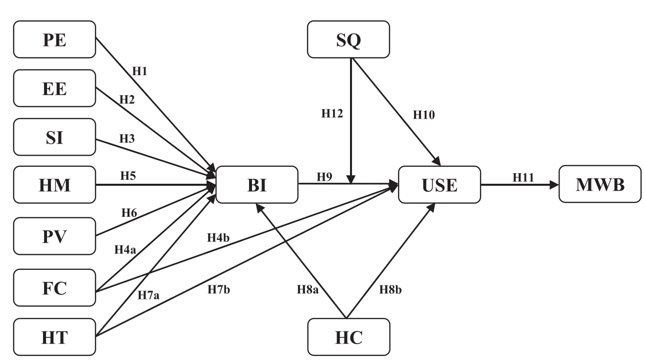

Fig. 1. Conceptual framework of the study. Note: PE=Performance Expectancy; EE=Effort Expectancy; SI=Social Influence; HM=Hedonic Motivation; PV=Price Value; FC=Facilitating Condition; HT=Habit; HC=Health Consciousness; BI=Behavioral Intention; SQ=Self-Quarantine; MWB=Mental Wellbeing.

behavior, the early intention to use will be re-enforced, which will lead to use recurrently [17]. In fact, surfing the Internet on mobile and using various apps are possibly compulsive, which in turn leads to a strong habit and exemplifies the behavioral intention and use of tech-based services despite other external influences [15]. Thus, we posit the below hypotheses:

H1: Performance expectancy has positive influence on the intention to use mHealth services.
H2: Effort expectancy has positive influence on the intention to use mHealth services.
H3: Social influence has positive influence on the intention to use mHealth services.
H4a: Facilitating condition has positive influence on the intention to use mHealth services.
H4b: Facilitating condition has positive influence on the actual use of mHealth services.
H5: Hedonic motivation has positive effect on the behavioral intention to use mHealth services.
H6: Price value has positive influence on the intention to use mHealth services.
H7a: Habit positively affects behavioral intention to use mHealth services.
H7b: Habit positively affects actual use of mHealth services.

In line with Lee [37], this study conceptualizes health consciousness as a cognitive inclination regarding the significance of health rather than actual behavior. People have the tendency to involve themselves in demonstrating more protective health-related behaviors if they are very much health conscious [46]. Thus, having more consciousness regarding their health, people are expected more to have intention and be engaged in using mHealth services to endure and/or heighten their health situations To et al. [64]. Behavioral intention has more frequently been used as an instantaneous predictor of true usage behavior and represented the conviction/readiness of an individual to accomplish a particular behaviour [63]. It is more likely that an individual's conative stage (behavioral intention) is frequently and positively transformed into his/her action stage (actual behavior) [49]. It has been observed in the literature that behavioral intention is the key predictor of usage behavior in the domain of app-oriented services [4,54]. Since December 2019, a new infectious disease, namely COVID-19, has been spreading throughout the world and as one of the preventive techniques, governments and health authorities call for self-quarantine [75]. Self-quarantine refers to the "restriction of persons who are presumed to have been exposed to a contagious disease but are not ill, either because they did not become infected or because they are still in the incubation period" [70]. Self-quarantine and isolation are associated with depression, anger and chronic stress [44]. As a result, the quarantine people are in demand to have healthcare services and in this connection, mHealth services possibly suitable solutions and can mitigate their demand. Moreover, during the COVID-19 pandemic situation where people are in self-quarantine, all over the world, the use of mobile apps and Internet has been substantially increased [12]. Considering the above discussion, we propose:

H8a: Health consciousness significantly influences the behavioral intention of mHealth services.
H8b: Health consciousness significantly influences the actual usage behavior of mHealth services.
H9: Behavioral intention has positive influence on the actual usage behavioral of mHealth services.
H10: Self-quarantine has positive effects on the actual use of mHealth

In the population health literature, the mental well-being has appeared as one of the key constructs and closely revolved around psychological and functional wellbeing [45]. When confidence is instilled within an individual to cope up with the problematic situation, then the individual is said to have a mental well-being. During the COVID-19 pandemic situation, people are required to be confined at home in terms of self-quarantine, which make their life more stressful. In such a situation, individuals try to build trust and confidence among themselves to overcome the situation. In this connection, health technology (such as mHealth and Telehealth) has appeared as the appropriate solution to ensure the mental wellbeing [65]. In the study of Rahman et al. [54], it has been empirically proved that the use of technology significantly enhances the subjective wellbeing of the technology users. Moreover, mental health education through various apps during COVID-19 pandemic situation facilitates the individuals to uplift their mental wellbeing status [41]. Dick and Basu [20] asserted that there is no assurance that an individual's behavioral intention will surely be converted to his/her actual practices. They also argued that several situational factors might intensify the peoples' behavioral intention to be translated into real actions (i.e. use or purchase). People with self-quarantine situations are in need of health services, particularly as they are passing time with psychological stresses like depression and anxiety [14]. In this connection, mHealth services are to be considered as a suitable solution to prevent the outbreak of infections and also benefit, as quarantine people are getting their necessary health services on demand. Thus, considering the situational impact of self-quarantine, it is expected that people with intention to use mHealth services will exhibit more actual usage behavior in a pandemic situation like COVID-19. Therefore, we hypothesize:

H11: mHealth usage positively enhances the mental well-being of the users.
H12: Self-quarantine moderates the association between BI and actual use of mHealth services.

3. Methodology

3.1. Measures and survey instrument development

This study has developed a structured survey instrument (see Appendix A) adapting the measurement items from the current scholarship to best suit this study context. Particularly, four items of performance expectancy, effort expectancy, facilitating condition, and habit, and three items of social influence, hedonic motivation, price value, and behavioral intention were sourced from Venkatesh et al. [68] with minor changes. Five items of health consciousness and three items for self-quarantine were adapted from Dutta-Bergman [22] and Van et al. [66] respectively. Five measurement items for mHealth USE were sourced from Akter and Ray [2] and Alam et al. [8] and seven items of mental well-being were adapted from Melendez-Torres et al. [45]. For each measurement item, the opinion of the respondents was captured by using 5-point Likert scale starting from 1 ("strongly disagree") to 5 ("strongly agree"). Back to back translation of the survey instrument was completed. Pre-testing was conducted with a pool of three industry experts, two academicians, and five actual users of mHealth services to confirm content validity. A few adjustments were made based on their suggestions. In addition, a pilot testing comprising of 45 actual mHealth users was administered to check and ensure the reliability of the study constructs.

3.2. Sample and data collection

In Bangladesh, numerous types of mhealth apps services are in operation under different categories. For example, *Patient Aid* under general healthcare information category, *Gym Now* under body fitness category, *DoctorsBD* under doctors' information category, *Aponjon* under mother and child category, *DiaHealth* under diseases specific category, *Pusti Kotha* under food and nutrition category, *Herbal Medicine Bangla* under herbology category, *Homeopathic Quick References* under homeopathic category, etc. [33,34]. The target population of this study was mHealth users of any kind in Bangladesh who were in self-quarantine during COVID-19 pandemic. Owing to the non-availability of any directory where mHealth users are enlisted, this study employed non-probability techniques (self-selection and snowball) to approach the respondents. In the tech-oriented study, the use of non-probability sampling in the absence of a sampling frame is evident in several scholarly works (e.g. [30,38]). Following Merhi et al. [47], an online version of the structured research instrument was disseminated in the numerous social media platforms and various WhatsApp and Messenger groups where people were connected. In fact, the data were collected during the COVID-19 pandemic situation in Bangladesh where most of the people kept themselves in self-quarantine mode, and thus, reaching the sample through an online platform was more viable. However, an initial filtering question was asked to the participants to confirm their belongingness to the mHealth user group. In this connection, respondents with at least one time experience with any mHealth services during the COVID-19 pandemic were only asked to continue the survey. Initially, the questionnaire link was disseminated to potential 600 respondents in the above said platforms. Finally, a total of 434 responses were received who had the experiences in using mhealth services at least once during the COVID-19 pandemic. The details of the sample profile are shown in Table 1.

4. Analysis and results

To identify the presence of possible nonresponse bias, the authors scrutinized the dissimilarities between mean scores of early and late respondents in relation to all study constructs. Linking to this, following Rahman et al. [54], the initial 10% responses of the data set were defined as early responses and the last 10% were categorized as late responses. All the mean differences were appeared statistically insignificant ($p > 0.05$), indicating that collected data are free from the issue of nonresponse bias.

Since the data were gathered from the same respondent using the same measurement scale, there might be an issue of common method variance (CMV). According to Richardson et al. [56], CMV can be defined as the "systematic error variance shared among variables measured with and introduced as a function of the same method and/or source" (p. 763). This study utilized both procedural and statistical remedies to ensure the non-issue of CMV. From the procedural stance, we assured the respondents regarding their secrecy of participation and informed them just to be honest and feel free to provide their responses as there is no accurate or inaccurate answer. From statistical standpoint, we inspected the Harman's test for sole factor following the guidance by Podsakoff and Organ [51]. The analysis outputs reveal that the highest variance explained by a sole factor is 29.63%, which is below than the recommended 50%. Besides, the aggregated variance explained by all the extracted factors is 70.94%, which is above the recommended threshold level of 50%. Hence, CMV is a non-issue for the data set as evident in many latest studies [5,55].

Before moving for further multivariate analyses, we have checked the various multivariate assumptions with respect to normality, linearity, and multicollinearity. For detecting distribution normality, we employed non-parametric one sample Kolmogorov-Smirnov (K-S) test. The distributions of all the study variables are not normal as all K-S statistics are significant. Following Alam et al. [7], Analysis of Variance (ANOVA) test was conducted (see Appendix B) to identify the linearity in the relationships between the assumed exogenous and endogenous variables. Social influence is only linearly associated, and habit is only non-linearly associated with behavioral intention. The rest of the predictors of behavioral intention (performance expectancy, effort expectancy, facilitating condition, price value, health consciousness, and hedonic motivation) are both linearly and non-linearly associated. Moreover, habit has only non-linear relationship with mHealth usage. The remaining predictors of mHealth usage (self-quarantine, health consciousness, facilitating condition, and behavioral intention) are non-linearly as well as linearly associated. In this study, we examined the multicollinearity issue by calculating variance inflation factor (VIF) as suggested by Hair et al. [26]. The outputs show that all the VIF values (1.013 and 1.925 as minimum and maximum respectively) are within the recommended threshold of 3.3 (see Table 4) following Kock and Lynn [35]. Thus, the issue of multicollinearity has become immaterial for this study.

Due to model complexity (>6 constructs) and non-normality of distribution, Partial Least Squares Structural Equation Modeling (PLS-SEM) is mostly fitted to our data analysis. Unlike SEM, ANN is mostly capable of dealing with non-linear as well as non-compensatory associations which makes it unique in predicting the relationships [50]. However, despite of its robustness against the ruins of different multivariate assumptions, ANN is unable to test the hypothesis [7]. The hybrid PLS-SEM-ANN is supportive of each other in generating outputs because PLS-SEM can test the hypothesis of linear kind but cannot deal with non-linear associations while ANN is stronger in capturing non-linear relationships but incapable of testing hypothesis due to the "black-box" mechanism with artificial algorithm [39]. Since the relationships of the predictors with the endogenous variables are the mixture of both linear and non-linear in our study, SEM-ANN is the perfect approach to be utilized in predicting the model.

Table 1
Sample profile.

Variables	Frequency	Percent	Variables	Frequency	Percent
Gender			*Age (years)*		
Male	271	62.4	18 to 24	202	46.5
Female	163	37.6	25 to 34	127	29.3
Mobile phone usage experience			35 to 44	54	12.4
1 to 5 years	153	35.3	45 to 54	32	7.4
6 to 10 years	223	51.4	55 and above	19	4.4
11 to 15 years	49	11.3			
15 + years	9	2.0			
mHealth usage experience			*Education*		
< 1 year	39	8.9	SSC	24	5.5
1 to 3 years	224	51.6	HSC	103	23.8
4 to 6 years	131	30.2	Bachelor	238	54.8
7 to 10 years	32	7.3	Masters	56	12.9
> 10 years	8	1.8	Mphil/ PhD	13	3.0

Note: SSC = Secondary School Certificate; HSC = Higher Secondary Certificate.

4.1. Measurement model

To ensure the reliability as well as validity aspects of the study constructs, the measurement model was evaluated by means of convergent validity and discriminant validity. According to the cut-off value, the item loading (0.70), Cronbach's Alpha (0.70), CR (0.70), and AVE (0.50) all (Table 2) were above the threshold which confirm the item reliability, construct reliability, internal consistency reliability, and convergent validity of the constructs respectively [26]. Following Henseler et al. [28], Heterotrait-Monotrait (HTMT) ratio of correlations grounded on Multitrait-Multimethod approach was calculated and found that all the HTMT ratio values are within the recommended threshold of 0.85 which confirm the discriminant validity (Table 3).

4.2. Structural model

By following the bootstrapping procedure with 5000 resample technique in SmartPLS, we tested the significance of the assumed relationships. Table 4 reports the details of the path analysis. Performance expectancy ($\beta = 0.223$, $p < 0.001$), effort expectancy ($\beta = 0.141$, $p <$

Table 2
Reliability and convergent validity.

Variable	Item	Loading	α	CR	AVE	Variable	Item	Loading	α	CR	AVE
PE	PE1	0.864	0.864	0.907	0.709	EE	EE1	0.826	0.856	0.902	0.698
	PE2	0.857					EE2	0.860			
	PE3	0.844					EE3	0.837			
	PE4	0.802					EE4	0.819			
SI	SI1	0.836	0.803	0.884	0.718	PV	PV1	0.877	0.874	0.922	0.798
	SI2	0.865					PV2	0.916			
	SI3	0.840					PV3	0.887			
FC	FC1	0.880	0.916	0.941	0.799	HT	HT1	0.756	0.778	0.855	0.596
	FC2	0.903					HT2	0.761			
	FC3	0.891					HT3	0.780			
	FC4	0.901					HT4	0.789			
HM	HM1	0.899	0.865	0.918	0.788	BI	BI1	0.881	0.838	0.903	0.756
	HM2	0.897					BI2	0.855			
	HM3	0.866					BI3	0.872			
HC	HC1	0.765	0.844	0.889	0.616	SQ	SQ1	0.838	0.818	0.891	0.733
	HC2	0.829					SQ2	0.867			
	HC3	0.792					SQ3	0.863			
	HC4	0.780				MWB	MWB1	0.793	0.889	0.913	0.599
	HC5	0.757					MWB2	0.803			
USE	USE1	0.864	0.872	0.907	0.662		MWB3	0.794			
	USE2	0.825					MWB4	0.790			
	USE3	0.817					MWB5	0.756			
	USE4	0.786					MWB6	0.769			
	USE5	0.772					MWB7	0.713			

Note: α = Cronbach's Alpha, CR = Composite Reliability, AVE = Average Variance Extracted, PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Condition, HM = Hedonic Motivation, HT = Habit, PV = Price Value, HC = Health Consciousness, BI = Behavioral Intention, USE = Actual Usage Behavior, SQ = Self Quarantine, MWB = Mental Well-Being.

Table 3
Discriminant validity (HTMT criterion).

	PE	EE	SI	FC	HM	HT	PV	HC	BI	SQ	USE	MWB
PE												
EE	0.182											
SI	0.556	0.171										
FC	0.336	0.148	0.467									
HM	0.340	0.183	0.369	0.586								
HT	0.068	0.320	0.102	0.096	0.087							
PV	0.258	0.121	0.328	0.403	0.357	0.100						
HC	0.491	0.254	0.496	0.473	0.492	0.086	0.394					
BI	0.555	0.316	0.509	0.543	0.544	0.067	0.372	0.604				
SQ	0.482	0.211	0.490	0.438	0.444	0.046	0.308	0.574	0.538			
USE	0.470	0.189	0.609	0.500	0.554	0.090	0.312	0.634	0.591	0.627		
MWB	0.603	0.179	0.498	0.427	0.504	0.072	0.333	0.690	0.700	0.590	0.597	

Note: PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Condition, HM = Hedonic Motivation, HT = Habit, PV = Price Value, HC = Health Consciousness, BI = Behavioral Intention, USE = Actual Usage Behavior, SQ = Self Quarantine, MWB = Mental Well-Being.

Table 4
Outputs of path analysis.

Hs	Relationship	Beta	SE	t-value	Supported	R^2	f^2	Q^2	VIF
H1	Performance Expectancy -> Behavioral Intention	0.223	0.050	4.444**	Yes	0.453	0.065	0.309	1.401
H2	Effort Expectancy -> Behavioral Intention	0.141	0.037	3.780**	Yes		0.032		1.132
H3	Social Influence -> Behavioral Intention	0.087	0.052	1.673*	Yes		0.009		1.462
H4a	Facilitating Condition -> Behavioral Intention	0.176	0.049	3.625**	Yes		0.035		1.607
H5	Hedonic Motivation -> Behavioral Intention	0.164	0.053	3.105**	Yes		0.033		1.504
H7a	Habit -> Behavioral Intention	−0.058	0.050	1.145	No		0.006		1.078
H6	Price Value -> Behavioral Intention	0.055	0.043	1.290	No		0.004		1.235
H8a	Health Consciousness -> Behavioral Intention	0.191	0.047	4.039**	Yes		0.043		1.546
H4b	Facilitating Condition -> Actual Usage Behavior	0.158	0.049	3.223**	Yes	0.455	0.033	0.274	1.411
H7b	Habit -> Actual Usage Behavior	0.033	0.040	0.812	No		0.002		1.013
H8b	Health Consciousness -> Actual Usage Behavior	0.259	0.053	4.857**	Yes		0.079		1.561
H9	Behavioral Intention -> Actual Usage Behavior	0.170	0.049	3.441**	Yes		0.027		1.925
***H*10**	Self-Quarantine -> Actual Usage Behavior	0.267	0.054	4.895**	Yes		0.088		1.477
***H*11**	Actual Usage Behavior -> Mental Well-Being	0.532	0.046	11.69**	Yes	0.283	0.396	0.156	1.000
Moderation Analysis									
H12	Behavioral Intention * Self-Quarantine -> Actual Usage Behavior	−0.02	0.041	0.483	No				

** $p < 0.01$, * $p < 0.05$.

0.001), social influence (β = 0.087, $p < 0.05$), facilitating condition (β = 0.176, $p < 0.001$), hedonic motivation (β = 0.164, $p < 0.01$), and health consciousness (β = 0.191, $p < 0.001$) have significant effects on behavioral intention. Thus, H1, H2, H3, H4a, H5, and H8a are supported. However, in explaining the variation of behavioral intention, habit (β = -0.058, $p > 0.05$) and price value (β = 0.055, $p > 0.05$) have no significant influence. Therefore, H7a and H6 are not supported.

In determining mHealth usage, facilitating condition (β = 0.158, $p < 0.01$), health consciousness (β = 0.259, $p < 0.001$), behavioral intention (β = 0.170, $p < 0.001$), and self-quarantine (β = 0.267, $p < 0.001$) have positive and significant effect. Hence, H4b, H8b, H9, and H10 are supported. As not expected, habit (β = 0.033, $p > 0.05$) has no significant power in explaining the variation of mHealth usage. Thus, H7b is not accepted. Moreover, the significant effect of mHealth usage (β = 0.532, $p < 0.001$) on mental well-being indicates that H11 is also statistically supported. Surprisingly, the moderation effect of self-quarantine (β = -0.020, $p > 0.05$) on the behavioral intention - mHealth usage path has appeared insignificant, discarding H12.

We also calculated the R^2 for every endogenous variable. Table 4 illustrates that the R^2 value for behavioral intention, mHealth usage, and mental well-being is 0.453, 0.455, and 0.283 respectively. Hence, the explanatory power of the predictors of each criterion variable is substantial as guided by Cohen [18]. To see the effect of the predictors, we calculated the f^2 value as guided by Cohen [18]. Table 4 displays that the effect size of mHealth usage on mental well-being is large and the rest of the predictors have trivial effect on their respective endogenous variable. Finally, we also investigated the predictive relevancy (Q^2) of the model by exploiting the blindfolding procedure (see Table 4). Results indicate that predictive relevancy of behavioral intention (0.309), mHealth usage (0.274), and mental well-being (0.156) are medium which is $Q^2 > 0$ [26].

4.3. Artificial Neural Network (ANN)

As defined by Haykin [27], ANN is "a massively parallel distributed processor made up of simple processing units which have a neural propensity for storing experimental knowledge and making it available for use". The simple processing units of ANN are referred to as neurons or nodes. The gathered knowledge from the environment is being stored in the weights of the inter-connected neurons, which is widely familiar as synaptic weights [7]. The widely used feed-forward-back-propagation (FFBP) with multi-layer perception model was utilized in this empirical

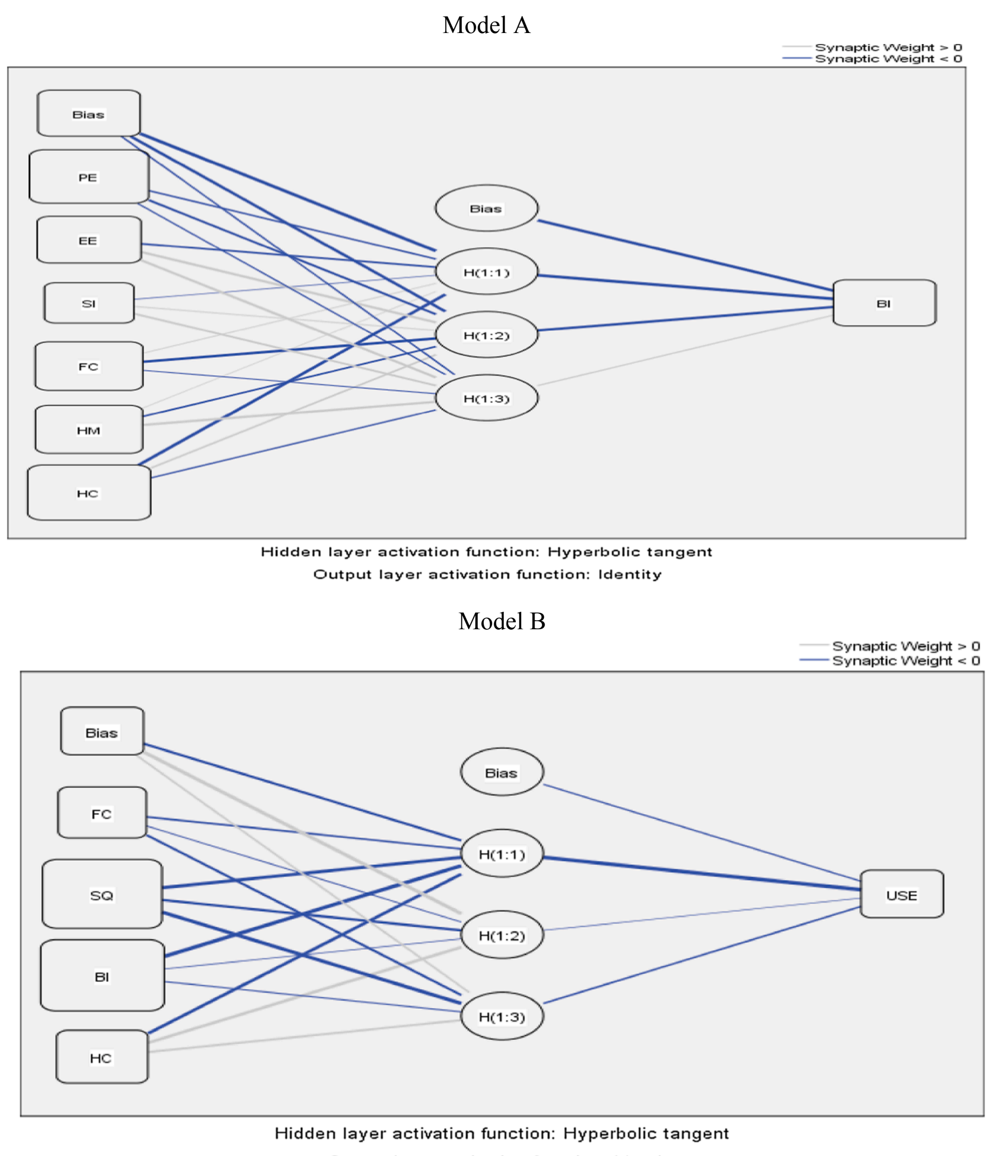

Fig. 2. Example of two random ANN networks.

study for both learning (training) and testing stages. Typically, the FFBP model consists of three consecutive layers (input, hidden, and output). The neurons of all these layers relate to synaptic weights. Under the FFBP method, data are being conceived by the neurons of the input layer, which feed the neurons of the output layer through the neurons of the hidden layer in the forward fashion and consequently, the generated errors are feed reversely back to the neurons of input layer via the training process [38]. However, to confirm the prediction accuracy of the model, the generated errors can be kept minimize through a series of training.

4.3.1. Outputs of neural network analysis

We utilized the Statistical Package for Social Science (SPSS) software version 24 to investigate the ANN model for this study. The significant predictors of the PLS-SEM analysis were considered as input neurons in the model. As we have two endogenous variables (output neurons) in the investigated model, two separate ANN models were developed. For BI, there are six significant influencing factors (PE, EE, SI, FC, HM, and HC) whereas for USE, this number is four (FC, HC, BI, and SQ) as shown in Fig. 2. The number of neurons in the hidden layer (hidden neurons) is generated automatically by the software. However, in the current scholarship, determining an accurate number of neurons in the hidden layer is still an imminent challenge [69].

To avoid the possible over-fitting problem in the ANN model, a ten-fold cross-validation process was applied. In this connection, 90% of the responses were considered for learning and the remaining 10% were for prediction [39]. Table 5 shows the mean and standard deviation of Root Mean Squared Error (RMSE) values for both training (learning) and testing (predicting). The possible lower limit of RMSE is zero (0) with unlimited upper boundary. However, the closer the RMSE value to zero (0) indicates the better predicting capacity of the ANN model [52]. The results reveal that the RMSE mean value for training and testing in model A is 0.5092 and 0.4696 whereas for model B, the values are 0.5279 and 0.5329 respectively, indicating that the ANN models are appeared as sturdily reliable in sensing the linear-nonlinear associations [39]. Since the mean RMSE values are sensibly small with negligible standard deviations in both learning and prediction stages, the ANN models are to be considered with a higher level of accuracy in predicting the relationships [40].

4.3.2. The sensitivity analysis

In addition, the sensitivity analysis was done to order the predictors based on their normalized relative importance (NRI) headed to the dependent variable. The NRI of each predictor for a certain output neuron was worked out by dividing the mean importance of each predictor by the predictor with maximum importance mean. Table 6 illustrates that in predicting the behavioral intention of mHealth services, health consciousness is the highest in order of importance followed by performance expectancy, facilitating condition, hedonic motivation, effort expectancy, and social influence. On the other hand, self-quarantine is the most important predictor of mHealth usage followed by health consciousness, behavioral intention, and facilitating condition. In Fig. 2, it is shown that the thickness of the connecting line from the health consciousness (input neuron) to behavioral intention (output neuron) through hidden neuron is the highest in Model A and from the self-quarantine (input neuron) to mHealth usage (output neuron) through hidden neuron is the highest in Model B, indicating their influencing strength.

Table 5
RMSE values for training and testing of ANN.

Network	Model A		Model B	
	Inputs: PE, EE, SI, FC, HM, and HC Output: BI		Inputs: FC, BI, SQ, and HC Output: USE	
	Training	Testing	Training	Testing
ANN1	0.4951689	0.5196272	0.5290318	0.5389482
ANN2	0.5006765	0.5387064	0.5077443	0.4873579
ANN3	0.5465257	0.3730799	0.5320994	0.5267711
ANN4	0.5034659	0.4500339	0.5215877	0.5570269
ANN5	0.4942711	0.5065489	0.5456025	0.3875329
ANN6	0.5342424	0.4315543	0.5261824	0.6084475
ANN7	0.4817356	0.4809712	0.5398639	0.5036024
ANN8	0.4817356	0.4717472	0.5150101	0.5758844
ANN9	0.5463458	0.3588075	0.5497673	0.6546063
ANN10	0.5075573	0.5651745	0.5130052	0.4889925
Mean	0.5091725	0.4696251	0.5279895	0.5329170
SD	0.0245780	0.0677688	0.0141051	0.0737983

Note: PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Condition, HM = Hedonic Motivation, HC = Health Consciousness, BI = Behavioral Intention, USE = Actual Usage Behavior, SQ = Self Quarantine, SD = Standard Deviation.

5. Discussion

Drawing on the modified UTAUT2 model, this study examined the determining factors of behavioral intention and use of mHealth services in the context of Bangladesh during the COVID-19 pandemic situation. In addition to the original UTAUT2 constructs, we have examined additional two constructs pertinent to the pandemic situation, namely health consciousness and self-quarantine, in predicting the use of the mHealth services. Moreover, this study investigated the impact of mHealth services usage in shaping the mental well-being of the users. By utilizing an innovative hybrid SEM-ANN technique, this study has introduced a novel methodological approach in ascertaining the influencing factors of intention and use of mHealth services. The empirical findings of our study reveal that performance expectancy, effort expectancy, social influence, facilitating condition, hedonic motivation, and health consciousness are the significant determinants of behavioral intention towards the adoption of mHealth services, whereas, facilitating condition, health consciousness, behavioral intention, and self-quarantine are the influencing factors in foreseeing the use of these services.

As per expectation, performance expectancy was appeared as significant in affecting behavioral intention toward mHealth usage. This finding justifies the earlier claims of several scholars in various contexts [54,63]. Having a positive perception regarding the usefulness of the healthcare delivery services through mobile channels, people tend to form a favorable intention to pursue the mHealth services. The effect of effort expectancy on behavioral intention was also found to be significant, meaning that easiness in dealing with mHealth technology in terms of interface design and navigation system allures the intention of the individuals to adopt such tech services which is similar to the previous studies [4,19]. Consistent with Alam et al. [6], social influence in predicting behavioral intention was found significant in the context of mHealth services. It is apparent that individuals with insufficient experience regarding technology usage are more inspired by social influence [32]. Since mHealth services are relatively new in Bangladesh, people are less oriented and experienced with such tech-related services that might motivate them to take suggestions from their well-wishers.

In shaping both the intention and use behavior of mHealth services, facilitating condition also played a significant role. Several supportive tools (e.g. smart phones) are said to be essential to confirm the use of apps oriented services [11]. Hence, to accelerate the usage of mHealth services, facilitating condition plays a vital role which is strongly supported by the study of Venkatesh et al. [68]. Hedonic motivation also appeared as a significant determining factor of behavioral intention which is in the same line with Duarte and Pinho [21] in the context of mHealth services. In fact, in the situation like COVID-19 pandemic, people's movement has been restricted through legislative order. Consequently, spending more time with hedonism became obvious.

Interestingly, the outcomes of Artificial Neural Network analysis reveal that health consciousness is the most important driver of behavioral intention and the second most predicting factor of mHealth

Table 6
Sensitivity analysis: standardized importance of constructs for both Model A and B.

Model A			Model B		
Variables	Average Importance	Normalized Importance	Variables	Average Importance	Normalized Importance
PE	0.214	81.368	SQ	0.310	100.000
EE	0.133	50.570	BI	0.216	69.677
SI	0.097	36.882	HC	0.298	96.129
FC	0.156	59.315	FC	0.176	56.774
HM	0.138	52.472	–	–	–
HC	0.263	100.000	–	–	–

Note: PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Condition, HM = Hedonic Motivation, HC = Health Consciousness, BI = Behavioral Intention, SQ = Self Quarantine.

usage. During the COVID-19 pandemic situation, people have become more cognizant about their health-related issues. Such consciousness expedited the people to take mHealth services. Moreover, Meng et al. [46] opined that people with a high level of health consciousness are more deterministic to exhibit precautionary health behaviors. This outcome is supported by the study of Xiao et al. [72].

Surprisingly, price value was found insignificant towards behavioral intention to pursue mHealth services. This result contradicts the study of Shaw and Sergueeva [59] but consistent with the findings of many researchers in the milieu of mobile technology [21,62]. The conceivable explanation of such finding might be based on the socio-economic situation of the country and the availability of mHealth apps with minimum or free of cost. In a similar fashion, in shaping both behavioral intention and use of mHealth services, habit was not significant. Though these empirical outcomes are contradictory to the classic findings of Venkatesh et al. [68], they are similar to and supported by many scholarly works in the mobile tech context [54,59]. The reasonable explication is that most of the mobile apps are designed in a user-friendly way with smart navigation systems where least trial is demanded. Since consistency prevails in the operation of smartphones and the downloading and installing process of different apps are quite similar, a very negligible effort is expected in using health-related apps.

The most interesting finding of this study is the significant association between self-quarantine and mHealth usage. In fact, the Artificial Neural Network outputs reveal that self-quarantine contains the highest importance in explaining mHealth usage behavior. In fact, during their stay at home in the quarantine situation, people in Bangladesh tend to use more mobile applications and spend a longer time surfing the net. As expected, this study found BI as an important determinant for mHealth services usage.

Another notable finding from this research is a meaningful consequence of mHealth usage in shaping the mental well-being of the service users. In the recent literature, Shaw [60] states that people are passing a very stressful life due to the COVID-19 out-breaks which ultimately may affect their mental well-being. Like other countries, in Bangladesh, by the directives of the government, people are encouraged to stay at home to prevent the spread of the novel coronavirus. Hence, mHealth services perhaps uplift the confidence among them which consequently enrich their mental well-being. In fact, in Bangladesh, there are several mHealth apps specifically tailored to combat the COVID-19 diseases through which doctors are connected 24/7 round the clock. Therefore, the users of these apps are having/developing sense of confidence and comfort.

5.1. Theoretical contributions

The current study has tested and validated the significant effect of both self-quarantine and health consciousness, along with other UTAUT2 constructs, on the actual use of mHealth services, particularly in the context of a developing country, like Bangladesh. Regarding the mHealth literature, this study has several theoretical contributions. Firstly, unlike other previous studies pertinent to mHealth that examined the effect of health consciousness on perceived usefulness [16], behavioral intention [64], routine use intention [46], the current study has scrutinized the predicting power of health consciousness in explaining the actual usage of mHealth services which possibly could be claimed as novice attempt.

Secondly, the current study has also tested and confirmed the causal effect of self-quarantine, as a relevant construct during pandemic situation, on the actual mHealth usage. This contribution will enhance better insights into mHealth adoption behavior particularly in crisis or pandemic conditions. Integrating this construct with the original UTAUT2 model in explaining the adoption/use behavior in the arena of mHealth services is one of the novel theoretical contributions of this study.

Thirdly, among UTAUT2 constructs, performance expectancy, effort expectancy, social influence, facilitating condition, hedonic motivation have been identified as the significant determinant of mHealth usage intention; and facilitating condition and behavioral intention have been recognized as the meaningful predictors of actual mHealth services usage. This outcome will give a fresh insight regarding the explanatory power of the UTAUT2 model in a pandemic situation like COVID-19.

Fourthly, unlike other mHealth studies that mainly focused on ascertaining the predictors of mHealth usage intention or actual usage behaviour [6,21,32], this study has moved further to inspect the consequence of the adoption/use of mHealth services. In this line, the current scholarship has examined and validated the positive consequence of mHealth services usage in shaping the mental well-being of the users, especially in the current contextual situation where people have a stressful life and mental well-being is the expectation from the individuals.

Finally, we have dealt with both the linear as well as non-linear associations between the predictors and intention as well as actual use in mHealth. In fact, it is a step forward from the typical regression-based linear models (Logistic Regression, Structural Equation Modeling etc.) and an exemplar modification in the ground of mHealth literature.

5.2. Practical implications

This study's outcomes can be taken up by mHealth apps providers and health-related institutions in Bangladesh and other countries to encourage a greater fervent acceptance and use of mHealth apps among the general population. It can be implemented by capitalizing the operative variables from the model (performance expectancy, effort expectancy, social influence, hedonic motivation, facilitating condition, and health consciousness) which proved to be the salient predictors of behavioral intention for using mHealth apps during the COVID-19 pandemic situation. Thus, mobile health app designers and public health-related institutions should ponder the roles of performance expectancy, effort expectancy, social influence, hedonic motivation, facilitating condition, and health consciousness in enhancing the level of intention to use the mobile health services among the people in the society. Further, once the intention has been formed to use the mHealth services, these institutions should also focus more on facilitating condition, health consciousness, self-quarantine, and obviously behavioral intention to increase the usage of mHealth services during a pandemic or any other unusual situation, where people should opt for self-quarantine. To advance the perception of performance expectancy, health-related institutions must position mHealth services as an effective health and hygiene tool. In this connection, health-related institutions require increasing their public communications to expedite the awareness regarding the benefits of using mHealth services. mHealth service developers also require devoting resources in designing and creating apps to excel in people experience. It is evident from the findings that people will remain to use mHealth services given that they have the basic skills to operate along with infrastructural and institutional supports. Thus, the marketers of mHealth services should be concerned about the necessary support that general people need to use the mHealth apps effectively. Providers of mHealth services should also concentrate on the features that can be managed easily, such as improving the communication with physicians, nurses, few minor health check-ups. Some supplementary features such as an option to call emergency ambulance, video streaming regarding different diseases and preventive measures should be included. mHealth service providers can create an option with smart navigation system to generate information regarding diseases and pandemics which will help the users to get a comprehensive picture of the situation.

Most importantly, this study suggests that usage of the mHealth apps will enhance the mental well-being of individuals who are in self-quarantine. Being a novel outcome, this has a managerial implication in the IS and mHealth research. As the usage of mHealth apps apparently improves the mental well-being, the mHealth service providers can promote this information among the current and prospective users to build their confidence and positive impression regarding such services, respectively. Pharmaceuticals companies can also create strategic alliances with the mHealth apps provider for their products and services. As mental well-being is particularly important during the self-quarantine, government agencies can encourage people to enhance the usage of health care services through mobile devices to ensure the well-being of their citizens.

6. Limitations, and future research directions

Despite several important contributions in the mHealth literature, this study bears a few limitations. Firstly, the study was conducted in the COVID-19 pandemic situation which might limit the generalizability of the outcomes for the normal situation. However, the objective of the study was to examine the model during the pandemic situation, which can be contextualized in the future in a similar situation. Secondly, the study is cross-sectional in nature. Human behavior during stress and after stress situations might be different. Hence, longitudinal study design will be more suitable to capture better insights regarding the mHealth adoption. Thirdly, the data were gathered in an online platform on a convenience and referral basis, which might not be the proper representation of the entire population of mHealth users. Future studies should focus on finding a suitable sampling frame to have the details of the mHealth users. Future studies can further investigate the plausible positive consequences of mHealth usage (i.e. quality of health life, users' psychological well-being, user satisfaction and loyalty, etc.) along with other antecedents like lifestyle, perceived security, etc. Besides, variables that might have a negative influence on users' mental well-being can be investigated simultaneously with the positive influencing factors. Moreover, as a future endeavor, studies can focus on the perceptions of a generational cohort, particularly Generation Y or Z, as they are more technology prone.

CRediT authorship contribution statement

Mirza Mohammad Didarul Alam: Conceptualization, Supervision, Visualization, Software, Formal analysis, Writing - original draft, Writing - review & editing. **Mohammad Zahedul Alam:** Methodology, Writing - original draft, Data curation. **Syed Abidur Rahman:** Methodology, Supervision, Visualization, Writing - original draft. **Seyedeh Khadijeh Taghizadeh:** Supervision, Visualization, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Measurement items

Construct	Item	Source
PE	I find mHealth services useful in my life.	Venkatesh et al. [68]
	Using mHealth services increases the chances of meeting my healthcare needs.	
	Using mHealth services helps me managing my daily healthcare issues more quickly	
	Using mHealth services increases my productive capability to manage my health	
EE	Learning how to use mHealth services is easy for me	Venkatesh et al. [68]
	My interaction with mHealth services is clear and understandable.	
	I find mHealth services easy to use.	
	It is easy for me to become skillful at using mHealth services.	
SI	People who are important to me think that I should use mHealth services	Venkatesh et al. [68]
	People who influence my behavior think that I should use mHealth services	
	People whose opinions that I value prefer that I should use mHealth services	
FC	I have the necessary resources to use mHealth services	Venkatesh et al. [68]
	I have the knowledge and skills necessary to use mHealth services	
	Using mHealth services is compatible with other technologies that I used to.	
	I can get help from others when I encounter difficulties using mHealth services	
HM	Using mHealth services is fun	Venkatesh et al. [68]
	Using mHealth services is enjoyable	
	Using mHealth services is entertaining	
HT	The use of mHealth services has become a habit for me	Venkatesh et al. [68]
	I am addicted to using mHealth services	
	Using mHealth services would be a regular activities for me	
	Using mHealth services has become natural to me	
PV	The fees of mHealth services are reasonable.	Venkatesh et al. [68]

(continued on next page)

(*continued*)

Construct	Item	Source
	Usually mHealth services are a good value for the money	
	At the current price, mHealth services provide a good value	
HC	Living life in the best possible health is very important to me	Dutta-Bergman [22]
	Eating right, exercising, and taking preventive measures will keep me healthy	
	My health depends on how well I take care of myself	
	I actively try to prevent disease and illness	
	I do everything I can to stay healthy	
BI	I intend to continue using mHealth services in the future	Venkatesh et al. [68]
	I will always try to use mHealth services in my daily life	
	I plan to continue to use mHealth services frequently	
USE	Diagnostic and treatment support services	Akhter and Ray [2]; Alam et al. [8]
	Health education and awareness services	
	Data collection and disease surveillance services	
	Health information systems (HIS) and point of care services	
	Emergency medical services	
SQ	I try to keep safe distance from friends, relatives during this pandemic	Van et al. [66]
	I have confined myself in home during this pandemic	
	I am avoiding busy public places (e.g. shopping areas, cinemas, restaurants) during this pandemic	
MWB	Using mHealth services ……..	Melendez-Torres et al. [45]
	I have been feeling optimistic about the future	
	I have been feeling useful	
	I have been feeling relaxed	
	I have been dealing with problems well	
	I have been thinking clearly	
	I have been feeling close to other people	
	I have been able to make up my own mind about things	

Note: PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Condition, HM = Hedonic Motivation, HT = Habit, PV = Price Value, HC = Health Consciousness, BI = Behavioral Intention, USE = Actual Usage Behavior, SQ = Self Quarantine, MWB = Mental Well-Being.

Appendix B. Linearity test

[1] ANOVA for Behavioral Intention

			Sum of squares	df	Mean square	F	Sig.
BI*PE	Between groups	(Combined)	82.174	11	7.470	14.071	0.000
		Linearity	68.301	1	68.301	128.653	0.000
		Deviation from Linearity	13.873	10	1.387	2.613	0.004
	Within groups		224.038	422	0.531		
BI*EE	Between groups	(Combined)	25.171	11	2.288	4.848	0.000
		Linearity	15.949	1	15.949	33.786	0.000
		Deviation from Linearity	9.222	10	0.922	1.954	0.037
	Within groups		199.203	422	0.472		
BI*SI	Between groups	(Combined)	38.670	11	3.515	9.980	0.000
		Linearity	32.390	1	32.390	91.952	0.000
		Deviation from Linearity	6.280	10	0.628	1.783	0.062
	Within groups		148.647	422	0.352		
BI*FC	Between groups	(Combined)	78.280	11	7.116	14.162	0.000
		Linearity	65.691	1	65.691	130.730	0.000
		Deviation from Linearity	12.588	10	1.259	2.505	0.006
	Within groups		212.054	422	0.502		
BI*HM	Between groups	(Combined)	69.754	11	6.341	14.430	0.000
		Linearity	54.755	1	54.755	124.598	0.000
		Deviation from Linearity	14.999	10	1.500	3.413	0.000
	Within groups		185.450	422	0.439		
BI*HT	Between groups	(Combined)	4.326	11	0.393	0.847	0.593
		Linearity	0.163	1	0.163	0.351	0.554
		Deviation from Linearity	4.163	10	0.416	0.897	0.536
	Within groups		195.878	422	0.464		
BI*PV	Between groups	(Combined)	56.811	11	5.165	7.370	0.000
		Linearity	35.212	1	35.212	50.248	0.000
		Deviation from Linearity	21.599	10	2.160	3.082	0.001
	Within groups		295.721	422	0.701		
BI*HC	Between groups	(Combined)	59.638	11	5.422	18.734	0.000
		Linearity	46.807	1	46.807	161.735	0.000
		Deviation from Linearity	12.832	10	1.283	4.434	0.000

Note: BI = Behavioral Intention, PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Condition, HM = Hedonic Motivation, HT = Habit, PV = Price Value, HC = Health Consciousness.

[2] ANOVA for USE

			Sum of squares	df	Mean square	F	Sig.
USE*FC	Between groups	(Combined)	84.393	19	4.442	8.929	0.000
		Linearity	58.244	1	58.244	117.088	0.000
		Deviation from Linearity	26.148	18	1.453	2.920	0.000
	Within groups		205.941	414	0.497		
USE*HT	Between groups	(Combined)	11.309	19	0.595	1.305	0.175
		Linearity	0.961	1	0.961	2.107	0.147
		Deviation from Linearity	10.348	18	0.575	1.260	0.210
	Within groups		188.895	414	0.456		
USE*SQ	Between groups	(Combined)	93.226	19	4.907	11.663	0.000
		Linearity	74.366	1	74.366	176.769	0.000
		Deviation from Linearity	18.860	18	1.048	2.491	0.001
	Within groups		174.169	414	0.421		
USE*HC	Between groups	(Combined)	78.095	19	4.110	16.414	0.000
		Linearity	53.888	1	53.888	215.194	0.000
		Deviation from Linearity	24.207	18	1.345	5.370	0.000
	Within groups		103.672	414	0.250		
USE*BI	Between groups	(Combined)	89.870	19	4.730	14.259	0.000
		Linearity	58.367	1	58.367	175.948	0.000
		Deviation from Linearity	31.503	18	1.750	5.276	0.000
	Within groups		137.334	414	0.332		

Note: USE = Actual Usage Behavior, FC = Facilitating Condition, HT = Habit, HC = Health Consciousness, BI = Behavioral Intention, SQ = Self Quarantine.

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