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Modeling the predictors of mobile health adoption by Rohingya Refugees in Bangladesh: An extension of UTAUT2 using combined SEM-Neural network approach

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ABSTRACT

While the healthcare facilities for the people is questionable in Bangladesh, Rohingya refugees is a burning issue for both Bangladesh and global community. Integrating Rohingya refugees into the framework of mHealth could be beneficial for both Bangladesh and Rohingya refugees in general, and in specific situation like COVID-19 outbreak. However, no research has been found on what motivates Rohingya refugees to accept mHealth in Bangladesh. Drawing on the UTAUT2 model, this study investigates the predictors of acceptance of mHealth services technologies among Rohingya refugees. The study also seeks to clarify the roles of mHealth developers, the Bangladesh government, and non-governmental organizations working with the 1.1 million Rohingya refugees in Bangladesh. Quantitative data were collected from refugee camps with the permission of the Refugee Relief and Repatriation Commissioner (RRRC). The data were analyzed in two stages using a mixed approach that combines PLS-SEM and Artificial Neural Network (ANN). This study revealed that Effort expectancy (EE, with $t = 5.629$, $\beta = 0.313$) and facilitating conditions (FC with $t = 4.442$, $\beta = 0.269$) in PLS-SEM, and FC (with 100 percent importance) and Health consciousness (HC, with 94.88 percent importance) in ANN analysis were found to be the most substantial predictors of mHealth adoption. The study also revealed that EE and FC are more important for low education group, while PE and Situational Constraint (SC) are more important for the high education group of refugees. In addition to providing insights for mHealth developers, this study particularly focuses on the role of government institutions and non-governmental social workers in working with the subjects to increase FC and HC among Rohingya refugees and bring them under mHealth services.

Introduction

Bangladesh is currently providing shelter to over 1.1 million Rohingya refugees, making it one of the largest host countries for this displaced population (The Conversation, 2020). The Rohingya refugees, who constitute the largest group of homeless individuals (Riley et al., 2017), sought refuge in Bangladesh, where they primarily reside in confined areas or camps located in the Southwest region of the country (UNHCR, 2021). Unfortunately, in close proximity to these camps, thousands of vulnerable Bangladeshis also live, further exacerbating the challenges faced by both communities. This densely populated environment puts all inhabitants at a heightened risk of health complications during a pandemic, such as the ongoing COVID-19 crisis (Guglielmi et al., 2020; Islam and Yunus, 2020; Khan et al., 2020). Given these circumstances, it is crucial to address the pressing needs of these communities, particularly in terms of basic services such as shelter, nutrition, education, medication, and healthcare. In situations requiring urgent physical and nutritional interventions, healthcare providers prioritize the provision of counseling services based on comprehensive documented reports of the refugees' conditions (Al Masud et al., 2017). By addressing these immediate needs, the well-being and resilience of both the Rohingya refugees and vulnerable Bangladeshis can be improved, allowing for a more sustainable and inclusive approach to their overall health and social integration.

Research shows that Rohingya refugees in Bangladesh suffer from multiple health problems (Al Masud et al., 2017). However, the current healthcare services provided for these refugees are insufficient, lacking an adequate number of physicians, a consistent medicine supply, and

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timely referrals to other organizations. They require supplies of adequate medicine, available physician and nurse facilities, health information, and modernized treatment, childcare facilities and increased awareness of life-threatening diseases (Al Masud et al., 2017). The congested and unsanitary living conditions in the refugee camps further exacerbate the already severe health risks, posing a significant challenge for service providers attempting to address the health needs of this vulnerable population (Inter Sector Coordination Group, 2017). Additionally, mental health conditions are prevalent among the refugees due to prolonged exposure to violence and atrocities, forced migration leaving behind the ancestral lands and relatives, insolvency, disruption of social networks, harsh living conditions and insecurity (Kirmayer et al., 2011; Silove et al., 2017).

On the other hand, Bangladesh, the hosting country, faces challenges in the health sector due to limited access to care, uneven development, lower quality service, and high costs (Berry and Bendapudi, 2007; Porter and Teisberg, 2006). According to Bangladesh Health Watch, there is a shortage of healthcare professionals, with only three physicians and two nurses per 10,000 population (Islam, 2014). The Rohingya influx exacerbates the problem as they lack timely access to adequate health services. Delays in services occur due to difficulties in adjusting to government regulations, camp hospital systems, and bureaucratic processes. Typically, they are referred to hospitals only when services cannot be provided within the camps, resulting in prolonged suffering. Implementing mHealth services for Rohingya refugees can address these challenges by providing better healthcare facilities. mHealth, defined by WHO (2011), utilizes portable devices such as smartphones, patient monitoring devices, sensors, and wireless networks to deliver medical and public health practices. mHealth utilizes mobile health applications in mobile devices, such as a cellphone or a tablet, to support healthcare practices. On the other, eHealth encompasses a wider scope of healthcare services, whereas eHealth specifically refers to digital health records, patient management systems, laboratory systems, and other types of data that cannot be stored in mobile health applications. Nevertheless, this study only considered mHealth for further study. However, copious benefits of mHealth produce a great potential for improving health care that could fundamentally alter the health care facilities for Rohingya Refugees. For instance, Saleh et al. (2018) noted that mHealth is helpful in addressing non-communicable diseases (NCDs) by health education and self- management, improving prevention and treatment strategies.

As Bangladeshi consumers are becoming passionate in ICT adoption (Barua et al., 2018; Sagib and Zapan, 2014), a recent study reported that, currently, there are 26 mHealth projects run by public or private institutions in Bangladesh with the aim of providing health services and/or managing health information (Ahmed et al., 2014). Ministry of Health established mHealth to offer medical advice 24/7, particularly to impoverished individuals (Ahmed et al., 2014). However, as refugees are living under the poverty line so the mHealth intervention would lead better health outcome. Though mHealth is considered as a promising technique to deliver the healthcare services to both healthcare professionals and patients, its adoption by Rohingya Refugee is severely low. There could be several barriers for adopting mHealth by refugees, as they undergo cultural differences, language differences, mental health pressure, lack of quality education, scarce resource facilities, etc. Literature shows no single study to investigate the issue reflecting this huge number of refugees in Bangladesh as well as other parts of the world. The unique characteristics of refugees, such as cultural and educational differences from the host community, warrant a separate study on mHealth adoption. Nonetheless, the implementation of mHealth could be a powerful solution for remote treatment of refugees who live in confined or restricted areas, as well as during emergencies like the COVID-19 pandemic. Given this context, this study aims to identify the determinants that influence Rohingya refugees in adopting mHealth services.

Literature review and development of research framework

In the last decade, mHealth technologies adoption has received tremendous attention among the researchers from both developed and developing countries. It is because the extensive use of mHealth services which has altered the health service delivery system as well as improved the effectiveness and efficiency of health care services (Sadegh et al., 2018). However, the research on the acceptance and use behavior of mHealth services are copious and has mainly been formulated using some leading established theoretical models. More specifically, while the field is dominated by technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT), the role of other like the Diffusion of Innovation-DOI Theory, Theory of Planned Behavior-TPB, Theory of Reasoned Action-TRA, Delone and McLean (2003) Theory of Information System Success are also significant. Tao et al. (2020), in a meta-analysis regarding user acceptance of consumer-oriented health information technologies, reported that out of 68 studies 44 studies used TAM individually and 14 studies used TAM combining theory of planned behavior (TPB), health belief model (HBM), Uses and Gratifications theory, and other, while 11 studies used UTAUT and UTAUT2 (Venkatesh et al., 2012).

The UTAUT2, an extension of UTAUT by incorporating three additional variables namely, hedonic motivation, PV, and habit, has been used widely in the technology research for identifying factors contribute to adoption and use behavior of consumer. The superior benefits of UTAUT framework are- it was developed extensively investigating and combining several the then prevailing theory like TAM, TPB, TRA, DOI and the motivational model (Duarte and Pinho, 2019), which ultimately demonstrated in the UTAUT2 too, first. According to Venkatesh et al. (2003), the UTAUT model surpassed all eight models that utilized the same data, accounting for approximately 70% of the differences observed in behavioral intention. Additionally, in another study by Venkatesh et al. (2012), the UTAUT model explained approximately 50% of the variations in technology use. Further, the models such as TRA, TAM, TPB explained between 17% and 53% variance in user intentions to use technology (Venkatesh et al., 2003). Second, the UTAUT2 is better than the UTAUT in the variance explained in a model of behavioral intention and technology use (Jang et al., 2016). However, UTAUT2 has proved its validity in the field of technology adoption research, in general, and mHealth and eHealth adoption research, in particular. For instance, Huang & Yang (2020) used UTAUT2 for exploring factors accountable to use an artificial intelligence-powered mobile application for weight loss and health management, and Alalwan et al. (2018) used for investigating key factors influence the Jordanian customers' intentions and adoption of Internet banking.

The current study considered the UTAUT2 for modeling the predictors of mHealth acceptance and use by Rohingya Refugee in Bangladesh. The UTAUT2 model was proposed to measure the technology adoption in the individual consumer use context (Huang and Yang, 2020). However, prevailing technology acceptance models have extensively been investigated incorporating additional constructs for direct relationship with behavioral intention and use behavior as well as mediating and moderating variables in the models (Alam et al., 2020). Consequently, considering the situation how Rohingya Refugees are living in Bangladesh (in a confined area from where they are not allowed to go outside without respective authorities' permission), the current study model removed hedonic motivation and habit from the model because the use of mHealth still in its fancy stage not even in the Rohingya camp but also in the whole country, therefore, they are not considered as habituated in regular use of health technology. Further, hedonic value, which is conceptualized as perceived enjoyment (Venkatesh et al., 2012), is irrelevant with the subjects since the health facilities provided to them as essential needs, and not for as enjoyment. Besides, habit is reflected as prior behavior and distinguished as the extent to which a person tends to perform behaviours spontaneously (Venkatesh et al., 2012).

On the other hand, the study combined the UTAUT2 with SC and HC. Agarwal (2000) advocated that consideration of factors such as individual difference, situational influence, could produce better understanding of individual acceptance of information technologies, and Otto & Harst (2019) suggested that health status should be included as socio-demographic predictors in the UTAUT2 for adequately explaining the health technology use. Further, Dou et al. (2017) proposed that perceived health status of the individual should be added for greater understanding of the acceptance of telemedicine technology. Consequently, SC and HC are incorporated in the model. The subjects of this study are living in a confined area from where they are not allowed to go outside without permission and their movement are under the surveillance of respective authorities. The restriction imposed upon the Rohingya Refugees resulted in their limitation to travel different places in the country. In this study, therefore, the SC is defined as the limitations of the consumers that they cannot do whatever they want due to social surroundings. The social surroundings can momentarily change customers' likings, attitudes, or intentions, thus, have an influence on transforming the behaviours of customer (Simon and Usunier, 2007). Subsequently, the stated constraint can influence the Rohingya to adopt and use the mHealth services. Besides, the Rohingya refugees lives in a congested area where there is big potentiality to be sick easily. Hence, the subjects who are conscious about their health might be inclined with adoption and use mHealth to reduce their health risk. Further, this study will investigate the influences of educational differences on the relationships proposed in the research model. A reason behind it is that the respondents of the study are facilitated with limited education. For instance, they cannot enroll in any college or university in Bangladesh. Instead, they receive their education through some non-governmental organization (NGO). However, the proposed research model is depicted in the Fig. 1.

Hypotheses development

UTAUT2 constructs

PE is theorized as the degree to which a consumer believes that operating the system or technology will assist him or her to achieve gains in job performance (Venkatesh et al., 2003). Venkatesh et al. (2003) demonstrated that PE plays the biggest role to influence the consumer to adopt the technology. Research in mHealth noted that PE is significant predictors of mHealth adoption in Bangladesh (Alam et al., 2020; Barua and Barua, 2021). Thus, we hypothesized that:

H_1: PE has a positive effect on Rohingya refugees' adoption intention of mHealth services.

EE, also known as perceived ease of use in TAM, demonstrates the extent of the ease coupled with individuals' use of new technology (Venkatesh et al., 2012). deVeer et al. (2015), regarding the intention to use e-Health by community dwelling older people, revealed that 64.5 percent respondents think that EE is imperative to adopt e-Health. Thus, we theorized that:

H_2: EE has a positive effect on Rohingya refugees' adoption intention of mHealth services.

SI is outlined as the level to which a person perceives that other

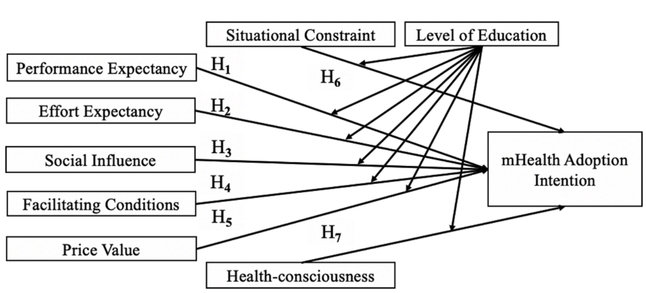

Fig. 1. Extended UATUT2 model.

believe he or she should use a technology (Venkatesh et al., 2003; Venkatesh et al., 2012). SI strongly affects the behavioral intention regarding use of technology when the technology is in the initial stages of development with absence of information about how to use them properly (Adapa et al., 2018). Thus, formulated that:

H_3: SI has a positive effect on Rohingya refugees' adoption intention of mHealth services.

FC is described as the degree of organizational and technical facilities available to an individual to use a technology (Venkatesh et al., 2012). The variable suggests that the use of technology will increase if technological and/or organizational environmental barriers are removed (Baudier et al., 2020). Regarding mHealth adoption by general consumers, Alam et al. (2020) found significant influence of FC on BI. We also framed that:

H_4: FC has a positive effect on Rohingya refugees' adoption intention of mHealth services.

PV is theorized as the consumers' rational trade-off between the expected benefits of the technology applications and the expected cost for using applications (Venkatesh et al., 2012). PV is crucial in the acceptance of technology because consumers often bear the cost of using the technology (Verkijika, 2018). Further, it can be more important for Rohingya refugees who lives with no income sources. Thus, we speculated the following hypothesis:

H_5: PV has a positive effect on Rohingya refugees' adoption intention of mHealth services.

Situational constraint (SC)

Situational variables have been theorized as circumstances linked to the physical and social surroundings of consumers (Belk, 1975). The physical and social surroundings of consumers can play a role to predict their behavior. Gehrt & Yan (2004) noted that customers demonstrate diminutive cross situational consistency and their ultimate behavior is situationally determined. Therefore, the subjects of this study could choice mHealth services instead of physically visiting hospital or physician. However, in different context such as retail environment evaluations, media choice, and shopping patterns, situational factors have a significant effect on customer's activities, intentions, and evaluations (Collier et al., 2015). A recent study by Barua and Barua (2021) noted that SC has a significant contribution on mHealth adoption in Bangladesh. Similarly, the following hypothesis was formulated:

Hypothesis, H6: SC has a positive effect on Rohingya refugees' intention to adopt mHealth services.

Health consciousness (HC)

HC indicates to the degree to which a person tends to engage in health-related actions (Becker et al., 1977). Health-conscious people tends to be self-awareness about their health and engage themselves for improving their health behavior (Gould, 1988, 1990). Espinosa & Kadić-Maglajlić (2018) advocated that HC play a critical role for promoting health and well-being. Health-seeking behavior is influenced by HC (Ahadzadeh et al., 2015). Consequently, Barua and Barua (2021) empirically showed HC has a significant influence on mHealth adoption. Considering so, this study also posited the following hypothesis:

Hypothesis, H7: HC has a positive effect on Rohingya refugees' intention to adopt mHealth services. Fig. 1

Education as moderating variable

In a systematic review of literature, Kavandi & Jaana (2020) noted that there is inconsistency of the effects of socio-demographic factors such as age, gender, and education on the adoption of health information technology. However, researchers noted that education has been considered as a crucial factor particularly in the acceptance of new information technologies (Baker et al., 2007). Based on the findings that citizens with a lower level of education had less intention of using e-Health, deVeer et al. (2015) suggested that attention to institutional less educated people to improve their education could enhance the acceptance new technology. In a study, Vroman et al. (2015) noted that majority of the participants (40%) with some school high education were non-users of ICT, while merely 8% of them were greatest users. On the other hand, the same authors revealed that a majority of participants (63.4%) with college education were maximal users and only a small 2.4% were non-users. Therefore, level of education influences the consumer to use information technology (Vroman et al., 2015). Zacharopoulou et al. (2019), using a logistic regression model, argued that a higher educational level was correlated to the use of ICT and their devices. The greater the level of education, the greater the possibility that a consumer would use health care services (Zacharopoulou et al., 2019). Zaccarelli et al. (2013) demonstrated that patients with tertiary education could learn easily how to use ICT devices. However, we are not aware of research recommending that PE, EE, SI, FC, PV, SI, and HC should interact with level of education on adoption intentions of mHealth, but we hypothesized as follows:

Hypothesis, MH: There will be significant differences on the relationships between exogenous and endogenous variables for high education and low education groups of Rohingya refugees.

Methods

This study adopted an empirical survey for predicting variables accountable for mHealth acceptance by Rohingya refugees. The research model was tested by using both SmartPLS 3.0 for measurement model, structural model, and moderation effect, and SPSS 23 for identifying relevant significance of the variables in the model using Artificial Neural Network.

Survey instrument and measures

The instrument of the study was adapted from previously validated research for most of the variables of the UTAUT2. For instance, PE, EE and PV were measured using the scale of Venkatesh et al. (2012). Four items SI-scale was adapted from Venkatesh et al. (2003). Scale for FC was adapted from Venkatesh et al. (2012) and Zhou et al. (2010). HC construct was measured using the scale developed by Chen (2011) and Ophuis (1989). Barua & Barua (2021) developed SC scale following the methodology portrayed by Peters et al. (1980), that scale was used to examine the situational constraint. Finally, adoption intention was measured by the scale proposed by Saheb (2020); Venkatesh et al. (2012); and Venkatesh et al. (2003). All the scales were anchored at "1 = strongly disagree" to "2 = strongly agree". After developing a well-structured questionnaire in English, it was translated in Bengali. An expert in health care technology research with good command in both completed the task to ensure the same meaning and originality in both versions, because proper translation is important to ensure maximum precision when the original instrument's language and respondent's language are different (Deng et al., 2014). However, final instrument was translated in native language Bengali and back-to-back translation was followed to. The Rohingya refugees can easily understand Bengali because they use Bengali frequently in their daily lives.

Procedure and participants

The study was carried out in Bangladesh, particularly in Cox's Bazar district where the Rohingya refugees are living now. The participants were only the Rohingya who are living in the designated area, designated by the Government of Bangladesh. Data were collected physically visiting the camp with the permission of RRRC of Bangladesh. Before handing over the self-administered questionnaire, a brief description was given to individual respondent about mHealth. 220 questionnaires were distributed and received too. Eleven questionnaires were discarded due to inconsistency in the responses. The demographic profiles of the respondents are detailed in Table 1.

Analysis and results (Part 1)

Analysis strategy

A combined approach for information system research is recommended by Venkatesh et al. (2013) to produce meaningful insights into complex information system problems as there is scarcity of that kind of research. Consequently, two methods, namely- SEM and Artificial Neural Network, were followed to evaluate the current model. For partial least square-structural equation modeling (PLS-SEM), in the first method, SmartPLS 3.0 software were used to evaluate the measurement and structural models. In some cases, SPSS 23 was also used, for instance, for checking common method bias (CMB) of the data. For neural network model, in the second method, SPSS 23 was used to verify the findings of the first method, and for determining the comparative importance of each factor to the acceptance of mHealth.

As SEM technique, PLS was selected as a variance-based technique. PLS is widely used in new in business and social sciences, new technology research (Henseler et al., 2016), and in information systems research (Marcoulides and Saunders, 2006; Henseler et al., 2016). For its robustness, PLS is known as "most fully developed and general system" (McDonald, 1996) and a "silver bullet" (Hair et al., 2011). Further, this study's objective is prediction, and when the objective is prediction, the PLS-SEM is more appropriate (Hair et al., 2011). However, PLS path modeling outcomes can be measured globally (the overall model) and locally (for the measurement models and the structural model) (Henseler et al., 2016). Moreover, compare to covariance-based SEM approach, multivariate normality in dataset is not essential in PLS (Jain et al., 2012). Further, PLS can be used with small sample sizes (Barua and Barua, 2021; Kallweit et al., 2014).

Measurement model specification

The internal reliability, convergent and discriminant validity are widely used for evaluating the measurement model (Ketchen, 2013). For measuring internal reliability, the Cronbach's alpha (α) and composite reliability were checked, and found that Cronbach's alpha ranged from 0.707 to 0.853 and composite reliability (also called Dillon-Goldstein's ρ, factor reliability) ranged from 0.820 to 0.900 where the level of 0.70 and higher are suggested adequate internal consistency (Henseler et al., 2009). Convergent validity was checked by using average variance extracted (AVE) and item loadings. Table 2 shows that the values of AVE

Table 1
Participants' psychometric properties.

Variables/dimensions		Frequency	Percentage	Variables/ dimensions	Frequency	Percentage
Gender	Female	108	51.67	**Education**		
	Male	101	48.33	Primary School	114	54.54
Age	18–30	113	54.06	Highschool	95	45.46
	31–40	65	31.11	**Experience in Using Mobile Phone**		
	41–50	21	10.04	< 3 years	47	22.49
	50–60	10	4.87	> 3years	162	77.51

Table 2
Construct reliability and validity.

Constructs	Items	Loadings	Cronbach's alpha	CR	AVE
Performance Expectancy	PE1	0.769	0.784	0.860	0.607
	PE2	0.836			
	PE3	0.766			
	PE4	0.743			
Effort Expectancy	EE1	0.841	0.853	0.900	0.693
	EE2	0.845			
	EE3	0.832			
	EE4	0.811			
Facilitating Condition	FC1	0.729	0.824	0.876	0.587
	FC2	0.803			
	FC3	0.784			
	FC4	0.759			
	FC5	0.752			
Social Influence	SI1	0.711	0.757	0.845	0.578
	SI2	0.751			
	SI3	0.823			
	SI4	0.751			
Price Value	PV1	0.883	0.793	0.876	0.701
	PV2	0.837			
	PV3	0.790			
Situational Constraint	SC1	0.822	0.795	0.880	0.709
	SC2	0.853			
	SC3	0.851			
Health Consciousness	HC1	0.743	0.707	0.820	0.532
	HC2	0.710			
	HC3	0.736			
	HC4	0.728			
Adoption Intention	AdoIn1	0.804	0.841	0.883	0.558
	AdoIn2	0.751			
	AdoIn3	0.736			
	AdoIn4	0.702			
	AdoIn5	0.711			
	AdoIn6	0.771			

are above the recommended values of 0.50 (Fornell and Larcker 1981). Items' loadings are presented in Table 2, where we can see all the items loadings are 0.702 and higher. Further, we checked the discriminant validity. The diagonal value in bold in Table 3 shows that all constructs are discriminately valid since the square root of the AVE for each facto is higher than intercorrelated values (Gaskin, 2012). Additionally, the correlations among all constructs are below 0.85, which is a sign of multicollinearity (Kline, 2015). Moreover, Table 4 demonstrates that the values of HTMT (Henseler et al., 2015) ratios are less than 1.0 (Henseler et al., 2016). The presented evidences, therefore, confirmed the measures convergent and discriminant validity.

Common method bias (CMB)

CMB can be experienced if the data are self-reported. CMB is an occurrence that is produced by the measurement method used in an SEM study (Kock, 2015). For checking the CMB, we implemented two methods, namely- Harman's single factor test, and correlation matrix suggested by Bagozzi et al. (1991). In Herman single factor test using principal axis factoring with unrotated factor, we revealed that a single factor was accountable for 29.64%, which is much smaller than the suggested 50% (Podsakoff et al., 2003). While followed the suggestion of Bagozzi et al. (1991), we found that there was no correlation greater than 0.90 (Table 3). Further, inner variance inflation factor (VIF) was examined for validating the study is out pf CMB. However, this study revealed that VIFs for individual dependent factor ranged from 1.078 to 2.880 which are much smaller than the value 0f 3.3 recommended by (Kock, and Gaskins, 2014). The analysis of Harman's single factor test and correlation matrix, therefore, confirmed that the CMB is not an issue in this study.

Test of linearity

Following the studies of Alam et al. (2021) and Leong et al. (2019), this study employed Analysis of Variance (ANOVA) to test the linearity in the relationships between the anticipated exogenous and endogenous variables. Results (See Appendix A) indicate that PE, SI, and SC are the predictors that associated linearly with adoption intention. The remaining constructs (EE, FC, PV, HC) have both linear and non-linear relationships with adoption intention

Structural model and hypotheses testing

The bootstrapping method in SmartPLS 3.0, with a resample size 5000 (suggested by Hair et al., 2011), was implemented to test the hypothesized relationships at a significance level of 0.05 ($p < 0.05$) (Efron and Tibshirani, 1994). The results reveal substantial influence of factors such as EE ($t = 5.629$, $\beta = 0.313$, $p < 0.00$), H2; FC ($t = 4.442$, $\beta = 0.269$, $p < 0.00$), H3; SC ($t = 3.096$, $\beta = 0.134$, $p < 0.05$), H6; HC ($t = 3.062$, $\beta = 0.202$, $p < 0.05$), H7; SI ($t = 2.301$, $\beta = 0.103$, $p < 0.05$), H4; and PE ($t = 2.112$, $\beta = 0.126$, $p < 0.05$), H1; on mHealth adoption intention. Thus, H1, H2, H3, H4, H6 & H7 were supported. On the other hand, PV was not statistically significant ($t = 1.777$, $\beta = 0.069$, $p > 0.05$). Thus, H5 was rejected.

Goodness of fit: R^2 and predictive relevance (Q^2)

The predictive power of the structural model was assessed. Chin (1998) recommended that R^2 value of the endogenous construct indicates a good measure for predictive power. According to Chin (1998) R^2 values of 0.19, 0.33, and 0.67 are the indexes for weak, moderate, and strong predictive power respectively. Result shows that the model predicted a large and strong portion of the variance in the adoption intention with a R^2 value of 0.74. As the value of R^2 is much greater than 30%, it indicates a satisfactory model (Falk and Miller 1992).

Additionally, we used the Stone-Geisser's Q^2 to re-validate the predictive relevance of the model. According to Henseler et al. (2009), Q^2 value of 0.02, 0.15, and 0.35 are considered as a small, medium, or large predictive relevance of the endogenous variable. Using the blindfolding technique in the SmartPLS and after calculation we reveal that the Q^2 value is 0.405 of endogenous construct adoption intention. The R^2 and Q^2 both have shown strong predictive relevance; thus, the model is substantive.

Table 3
Fornell-Larcker Criterion for Discriminant Validity.

	VIF	EE	FC	HC	PE	PV	SC	SI	AI
Effort Expectancy (EE)	1.735	0.832							
Facilitating Condition (FC)	2.068	0.626	0.766						
Health Consciousness (HC)	1.790	0.437	0.508	0.729					
Performance Expectancy (PE)	1.665	0.379	0.486	0.565	0.779				
Price Value (PV)	1.078	0.163	0.248	0.148	0.144	0.838			
Situational Constraint (SC)	1.242	0.308	0.378	0.303	0.325	0.026	0.842		
Social Influence (SI)	1.363	0.337	0.319	0.452	0.402	0.032	0.287	0.760	
Adoption Intention (AI)	2.880	0.705	0.729	0.643	0.585	0.242	0.467	0.477	0.747

Table 4
Heterotrait-Monotrait Ratio (HTMT) for Discriminant Validity.

	EE	FC	HC	PE	PV	SC	SI	AI
Effort Expectancy (EE)	0							
Facilitating Condition (FC)	0.736	0.000						
Health Consciousness (HC)	0.552	0.666	0.000					
Performance Expectancy (PE)	0.456	0.602	0.750	0.000				
Price Value (PV)	0.180	0.298	0.182	0.167	0.000			
Situational Constraint (SC)	0.372	0.465	0.395	0.410	0.088	0.000		
Social Influence (SI)	0.416	0.411	0.617	0.514	0.110	0.365	0.000	
Adoption Intention (AI)	0.822	0.861	0.816	0.708	0.281	0.565	0.589	0.000

Measurement invariance analysis across groups

Prior to testing the moderating effect, we conducted an evaluation to determine if there were any potential concerns regarding measurement invariance. This assessment was based on the measurement invariance of composite models (MICOM) procedure, as outlined by Hair et al. (2016) and Sinkovics et al. (2016).

According to Hair et al. (2016), conducting a multigroup analysis involves establishing two types of invariance: configural invariance, which ensures equal parameterization and estimation methods, and compositional invariance, which ensures equal indicator weights. In SmartPLS 3, configural invariance is automatically set up, while compositional invariance is assessed using a permutation algorithm option (Hair et al., 2018, p. 222). In our study, both the path model and data treatment were identical for the education group, meeting the necessary requirement for establishing configural invariance (Sinkovics et al., 2016). Additionally, since our group-specific model estimations utilized the same algorithm settings, configural invariance was established (Sinkovics et al., 2016).

To establish compositional invariance, we examined the correlation values of the calculated scores, comparing them to the 5% quantile of the empirical distribution. Appendix B shows that the original correlation between the composite scores exceeded the 5% quantile of the empirical distribution, providing sufficient evidence for compositional invariance (Hair et al., 2018). Overall, measurement invariance was confirmed across the two groups (education-low vs education-high).

Moderating effect of education level

To evaluate the moderating effect of level of education, we further divided the data into two subgroups namely, education-low and education-high. As a conservative approach for testing significant differences, PLS-Multigroup Analysis were than implemented (Sarstedt et al., 2011) using SmartPLS software. This method in PLS-MGA is a parametric significant test. However, after running the model with two different groups, the results revealed that the path coefficients for the relationship between EE and mHealth adoption intention ($\beta = 0.240$ education low VS education high $\beta = -0.037$, $t = 1.992$, $p < 0.05$), FC and mHealth adoption intention ($\beta = 0.363$ education low VS education high $\beta = 060$, $t = 2.597$, $p < 0.05$), and HC and mHealth adoption intention ($\beta = 0.114$ education low VS education high $\beta = 0.496$, $t = 2.881$, $p < 0.05$) were found significant. More specifically, for low education level EE ($\beta = 0.240$, $t = 3.420$, $p < 0.05$), FC ($\beta = 0.363$, $t = 5.098$, $p < 0.05$) were stronger than education high. On the other hand, PE ($\beta = 0.247$, $t = 3219$, $p < 0.05$), HC ($\beta = 0.496$, $t = 5.418$, $p < 0.05$), SC ($\beta = 0.237$, $t = 3.939$, $p < 0.05$) were stronger for the high education group than low education group.

Analysis and results (Part 2)

Artificial neural network (ANN)

Though there are plenty of studies used SEM individually for investigating hypothesized causal relationships, the combination of SEM with other systematic approach such as ANN are scant (Chong, 2013). SEM alone may not be suitable for technology adoption decisions because it only measure linear relationship (Priyadarshinee et al., 2017). Consequently, researchers suggested that some weakness of SEM, like its ability to examine only linear relationships which sometime overgeneralize the intricacies involved in the human decision-making processes, could be overcome by using ANN combinedly with SEM (Leong et al., 2015). However, ANN is defined as "a massively parallel distributed processor made up of simple processing units, which has a normal inclination for loading experiential knowledge and building it available for use." (Haykin, 1999, p. 24).

Palmer et al., (2006) noted that ANN is built up with a substantial number of simple processing elements known as nodes or neurons. As an artificial intelligence technique and machine learning approach, ANN is competent in ensuring both linear and nonlinear associations with high predictive accuracy compared with traditional linear models such as SEM (Chong, 2013; Leong et al., 2013; Sharma et al., 2016). Chan and Chong (2012) demonstrated that neural networks assist to evaluate the convoluted linear and non-linear relationships between predictors and the acceptance decision. Further, it helps to identify the critical factors according to their relative importance (Chan and Chong, 2012). Another important advantage of ANN is it does not require multivariate assumptions like normality, homoscedasticity as prerequisites statistical analysis (Lee et al., 2013; Leong et al., 2013). However, ANN is not appropriate for testing the hypothesis of causal relationships due to its "black-box'' operational nature (Lee et al., 2013). Fig. 2

Validations of neural networks

SPSS 23.0 software was used for concluding neural networks analysis. Following the recommendation of Sim et al. (2013), a ten-fold cross-validation was employed with partitioning the data 90% for training and the rest for testing purpose in order to avoid the over-fitting. Further, the current research implemented one hidden layer as it is suggested that a continuous function can be symbolized adequately by one hidden layer (Sharma et al., 2016). Further, we set the Sigmoid function as the activation function for hidden and output layers which takes real-valued arguments and converts them to the range (0, 1). We did not set the number of hidden neurons; hence, it was automatically generated. The precision of the model was assessed based on the root mean square of error (RMSE) values of the 10 networks. Table 5 shows that the cross-validated RMSE values for training ranged from 0.0111 to 0.1206 and for testing were 0.0145 to 0.1230. These RMSE values denote that the ANN models are fairly consistent in generating the numerical relationships between predictors and outputs.

Sensitivity analysis

Sensitivity analysis was performed for obtaining the relative importance of the predictors. In the sensitivity analysis, normalized relative importance of each predictor variable was calculated by dividing the relative importance of each predictor by the maximum important predictor and the result is converted into percentage form presented in the Table 6. Table 6 shows that FC is the strongest predictor

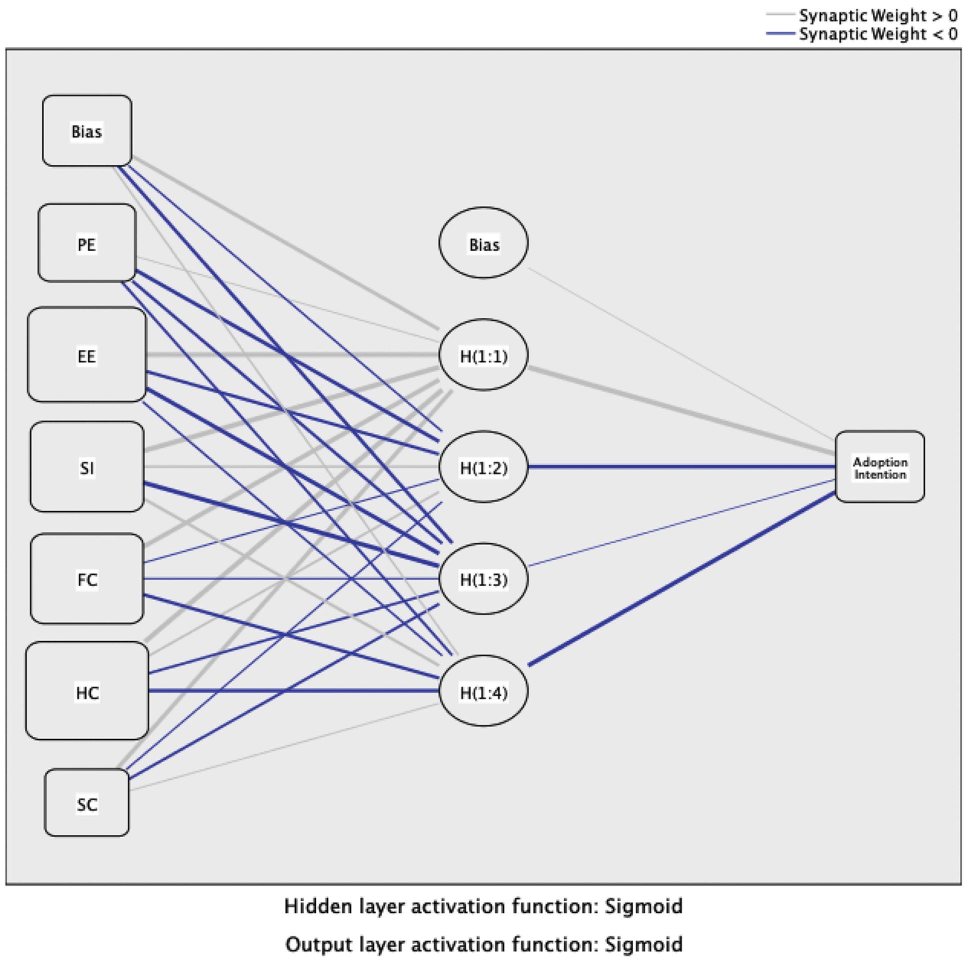

Fig. 2. Example of a random ANN.

Table 5
RMSE values for training and testing of ANN.

Network	Training	Testing
ANN1	0.1206	0.0951
ANN2	0.1089	0.0941
ANN3	0.0854	0.0892
ANN4	0.0909	0.0986
ANN5	0.0917	0.1079
ANN6	0.0965	0.0955
ANN7	0.0915	0.0685
ANN8	0.0886	0.1230
ANN9	0.0901	0.0940
ANN10	0.0868	0.0803
Average	0.0951	0.0946
St. Deviation	0.0111	0.0145

Table 6
Independent Variable Importance.

Rank	Variables	Average Importance	Normalized Importance
1	FC	0.213	100.00
2	HC	0.202	94.88
3	EE	0.179	84.13
4	SI	0.148	69.62
5	SC	0.118	55.54
6	PE	0.108	50.75

of Rohingya refugee's adoption intention of mHealth services technologies followed by EE, SI, HC, PE, and SC.

Discussion

Being a resource-limited nation, Bangladesh developed an advantageous ICT policy to implement mHealth services for the protection of healthcare services for its citizens (Alam et al., 2020). This study aimed to explore ways to extend mHealth services to a greater number of Rohingya refugees, considering both Bangladesh's overall healthcare system and the healthcare provisions for the refugees. The introduction of mHealth services for Rohingya refugees will undoubtedly improve their current healthcare situation, as they reside in a confined area with inadequate access to healthcare facilities.

This study vigorously tried to comprehend the mHealth technology use behavior and acceptance by Rohingya refugees in Bangladesh. Considering the subject of this study, we incorporated SC and HC in the UTAUT2 and excluded hedonic motivation and habit, since mHealth is at its fancy stage for Rohingya refugees in Bangladesh and their experience with it is not advanced enough to derive pleasure from using technology to transform their lifestyle. This study also explored the differential effect of refugees' education level in the model. The R^2 value of adoption intention indicates the modified UTAUT2 model is well suited to explain factors that influence refugees' behavioral intention to adopt mHealth technology.

According to the structural model, six factors (PE, EE, SI, FC, SC, and HC) from the seven have shown significant influence on mHealth adoption intention, similar to the findings of previous research in different context (Barua and Barua, 2021; Alam et al., 2020; Baudier et al., 2020; Beh et al., 2019). However, the study found that PV had no significant impact on refugees' intention to adopt mHealth. This finding is consistent with previous research, despite the existence of contradictory evidence in support of it. For instance, Alam et al. (2020) and Alam et al. (2018) also discovered the same result regarding mHealth adoption in the Bangladesh context, whereas Yuan et al. (2015) explored that PV significantly influence health apps adoption in the United State context.

Regarding the effects of education level of the Rohingya refugee, this study unveiled that the category of respondents with education level low exhibited greater path loading t-values for EE and FC on the adoption. These findings for EE and FC are similar to the findings of Kwateng et al. (2019) who showed in the case of mobile banking adoption. However, the category of participants with higher education level indicated greater path loading t-values for PE, SC, and HC on mHealth adoption. Though the finding for PE is also corroborated by Kwateng et al. (2019), findings for SC and HC are newly established in this study.

This study also employed ANN analysis to circumvent the limitation of PLS-SEM. Together, they produced comprehensive and valuable results. For instance, ANN displayed that FC is the most important predictor for Rohingya refugees followed by HC, EE, SI, SC, and PE. On the other, PLS-SEM exhibited that EE is the most influential factor followed by FC SC, HC, SI, and PE. Though the findings are distinctive in two different analyses, previous studies also reported the same in other contexts. For instance, in investigating the predictors of m-learning adoption, Shukla (2021) revealed that FC is the most important predictor in SEM, whereas EE is most important in ANN analysis.

Contribution to theory

This study aims to investigate the factors influencing the adoption of mHealth among Rohingya refugees in Bangladesh and potentially among other vulnerable stateless refugees worldwide. We excluded two variables from UTAUT2 model namely- hedonic motivation & habit which are not considerable for refugees since the use of mHealth is significantly low by the subject. Supplementarily, considering the subject and their residing area, we incorporated SC and HC and the findings on SC and HC in the UTAUT2 are significant for the literature of health technology adoption as well as for refugees' health study. Though some findings are similar to the findings of Barua and Barua (2021), the incorporation of SC and HC have shown significant association with mHealth adoption by refugees.

This study employed PLS-SEM & ANN analyses to validate our modified model and testing the hypotheses. We find some prioritize factors that put greater importance on adoption behavior toward mHealth apps and differences in the ranking of antecedents of mHealth apps adoption by Rohingya refugees in PLS-SEM and ANN. For instance, PLS-SEM reported that EE is the most significant predictor whereas ANN revealed FC. But if we consider the participants and their current condition, both findings are important to accelerate the adoption of mHealth. Therefore, the combined approach of analysis would have impact on the literature of refugees' health technology study.

Though education as moderating variable is suggested in the original UTAUT2 by Venkatesh et al. (2012), the empirical study regarding this is scant in mHealth research domain. This study explored the differential effects of education on the UTAUT2. The investigation of differential effects of education is substantial contribution for both the participants as well as mHealth research.

Implications for practice

This study provides valuable theoretical insights into techno-health services and refugee health studies. Additionally, the results offer crucial information for relevant authorities involved in the implementation of mHealth services, particularly for marginalized groups such as Rohingya refugees. App developers, telecommunication operators, government policy makers, and non-governmental organizations (NGOs) can utilize this information to redefine guidelines and expand the range of services available to refugees and rural populations.

As revealed in this study, FC is the most influential variable in ANN analysis (second most important in PLS-SEM analysis) for refugees living in confined area where government has imposed restriction on their movement. It is government's responsibility to subdue the violence in the camp area and vicinity, thus the government intentionally keep bandwidth of internet connection slow. Rohingya refugees cannot afford to buy smart phone since they are fully dependent on the donation of NGOs and others, thus suffer resource scarcity. Further, internet connection is also expensive for them. Therefore, respective authorities like NGOs and government should ensure better internet connection, available devices at least one for each family to optimize mHealth adoption as well as to ensure better health of Rohingya refugees. Like the study of Beh et al. (2019), the current study also considered the essential resources like internet accessibility, use of compatible mobile devices, and necessary knowledge as the FC to participate in mHealth services adoption.

On the other hand, PLS-SEM indicates that EE is a crucial predictor of mHealth adoption. However, participants have limited experience using multiple apps, including mHealth. Therefore, having an easy-to-use navigation system for health apps is crucial to encourage their adoption. Primarily, social workers working in the camp area can contribute in this regard by arranging training session for Rohingya refugee on how to use health apps, making them feel more comfortable with adoption. In addition, incorporation of video streaming in local dialect in the apps would assist the users. Further, instant voice messaging system in the apps in local dialect would increase the performance of mHealth technology, which in turn increase the use of mHealth services. In this regard, the incorporation of latest medical chatbot would further facilitate the adoption of mHealth apps.

ANN results indicate that HC is the second most valuable predictor. Consequently, Apps developer need to arrange promotional campaign collaborating with government telecommunication provider, NGOs, and front-line users to build health-consciousness as well as to educate them in order to build trust on techno-based apps for health purpose which in turn increase adoption. Respective authorities in the camps need to consider the education and consciousness level of refugees since the differential effects of education shows that participants with a lower education are reluctant to use mHealth concerning the factors FC and EE.

SI is considered another most influential variable. People generally convinced mostly when their relatives, neighbors and reliable persons advise them. Consequently, respective authorities and apps providers need to convince frontline workers such as doctors, nurses, social workers to convince refugee in adopting mHealth technology. Advertisement on mass communication channel, social media to spread the benefits of mHealth could induce more and more users.

Limitations and anticipated research directions

While this study stipulates valuable insights in terms of extending health technology acceptance literature as well as implications for apps designers and respective authorities, it also not out of some limitations. In the first instance, the data was collected from only one Rohingya camp though there are several camps as permission was given by RRRC. Second, this study did not consider the culture in the model though there are cultural differences between Rohingya refugee and people of Bangladesh. Third, generalizability of the findings is limited since the sample size of this study is comparatively small. Fourth, though the factors in the model have been incorporated considering the participants conditions and they are a good number, still other factors such as refugees' innovativeness, mobile interactivity, etc. could be investigated in future study.

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.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmh.2023.100201.

Appendix A: Test of Linearity

			SoS	df	MS	F	Sig.
AI*PE	Between groups	(Combined)	74.657	16	4.666	7.164	0.000
		Linearity	65.678	1	65.678	100.843	0.000
		Deviation from Linearity	8.979	15	0.599	0.919	0.544
	Within groups		122.442	188	0.651		
AI*EE	Between groups	(Combined)	111.487	15	7.432	16.408	0.000
		Linearity	95.991	1	95.991	211.911	0.000
		Deviation from Linearity	15.496	14	1.107	2.444	0.003
	Within groups		85.612	189	0.453		
AI*SI	Between groups	(Combined)	59.569	14	4.255	5.878	0.000
		Linearity	43.705	1	43.705	60.379	0.000
		Deviation from Linearity	15.865	13	1.220	1.686	0.067
	Within groups		137.530	190	0.724		
AI*FC	Between groups	(Combined)	116.279	19	6.120	14.009	0.000
		Linearity	102.195	1	102.195	233.927	0.000
		Deviation from Linearity	14.084	18	0.782	1.791	0.029
	Within groups		80.820	185	0.437		
AI*PV	Between groups	(Combined)	43.043	11	3.913	4.902	0.000
		Linearity	10.382	1	10.382	13.006	0.000
		Deviation from Linearity	32.661	10	3.266	4.092	0.000
	Within groups		154.057	193	0.798		
AI*HC	Between groups	(Combined)	96.068	15	6.405	11.981	0.000
		Linearity	78.740	1	78.740	147.299	0.000
		Deviation from Linearity	17.328	14	1.238	2.315	0.006
	Within groups		101.032	189			
AI*SC	Between groups	(Combined)	55.409	12	4.617	6.257	0.000
		Linearity	42.375	1	42.375	57.421	0.000
		Deviation from Linearity	13.034	11	1.185	1.606	0.100
	Within groups		141.691	192	0.738		

Note: SoS→ Sum of Squares, MS→ Mean Square, AI→ Adoption Intention, PE → performance expectancy, EE → effort expectancy, SI → social influence, PV → price value, FC → facilitating conditions, HC → Health-consciousness, SC → situational constraint.

Appendix B

MICOM Step1-> Configural Invariance: Established
MICOM Step 2-> Compositional Invariance: Education-low vs Education-high

Construct	Correlations among construct scores ($H_0 = 1$)	5% Quantile of Empirical Distribution of C_u	P Value	Compositional Invariance?
Performance Expectancy	1.000	0.998	0.705	Yes
Effort Expectancy	1.000	1.000	0.965	Yes
Facilitating Condition	1.000	1.000	0.567	Yes
Social influence	1.000	1.000	0.407	Yes
Price value	1.000	0.996	0.886	Yes
Situational Constraint	1.000	0.999	0.809	Yes
Health Consciousness	1.000	1.000	0.088	Yes
Adoption Intention	1.000	0.998	0.375	Yes

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