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A two-stage structural equation modeling-neural network approach for understanding and predicting the determinants of m-government service adoption

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Abstract

Purpose – Despite the widespread use of mobile government (m-government) services in developed countries, the adoption and acceptance of m-government services among citizens in developing countries is relatively low. The purpose of this study is to explore the most critical determinants of acceptance and use of m-government services in a developing country context.

Design/methodology/approach – The unified theory of acceptance and use of technology (UTAUT) extended with perceived mobility and mobile communication services (MCS) was used as the theoretical framework. Data was collected from 216 m-government users across Bangladesh and analyzed in two stages. First, structural equation modeling (SEM) was used to identify significant determinants affecting users' acceptance of m-government services. In the second stage, a neural network model was used to validate SEM results and determine the relative importance of the determinants of acceptance of m-government services.

Findings – The results show that facilitating conditions and performance expectancy are the two important precedents of behavioral intention to use m-government services, and performance expectancy mediates the relationship between MCS, mobility and the intention to use m-government services.

Research limitations/implications – Academically, this study extended and validated the underlying concept of UTAUT to capture the adoption behavior of individuals in a different cultural context. In particular, MCS might be the most critical antecedent towards mobile application studies. From a practical perspective, this study may provide valuable guidelines to government policymakers and system developers towards the development and effective implementation of m-government systems.

Originality/value – This study has contributed to the existing, but limited, literature on m-government service adoption in the context of a developing country. The predictive modeling approach is an innovative approach in the field of technology adoption.

Keywords Mobile government, Technology adoption, UTAUT, Developing countries, Structural equation modeling, Neural network, Bangladesh

Paper type Research paper

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1. Introduction

Mobile technologies are being widely adopted by governments around the world for the delivery of various services to citizens, employees, businesses, and other organizations; this concept is generally known as *mobile government* (m-government) (Ahmad and Khalid, 2017). The widespread use of m-government services is not surprising, given that approximately seven billion people (97 per cent of the global population) currently live under the mobile-cellular network coverage (ITU, 2016). Globally, the total mobile-broadband penetration exceeds 3.6 billion (47 per cent of the global population), more than the coverage of PC-based internet (3.2 billion) (ITU, 2016). In this context, there is a growing need to understand the effectiveness of the acceptance of services provided through m-government (Rana and Dwivedi, 2015).

Despite the growing mobile penetration, improved design and usability, and increased government support, the adoption of m-government services in developing countries has not yet achieved its objectives, and studies have shown similar e-government projects have either failed or experienced a slow adoption process (Gao *et al.*, 2014; Alshibly and Chiong, 2015; Sharma *et al.*, 2018). For instance, in the context of developing countries, only 15 per cent of e-government projects were successfully implemented, 50 per cent were partially completed, and 35 per cent of e-government projects failed to be implemented (Napitupulu and Sensuse, 2014). Therefore, a key challenge for m-government systems, to date, has not necessarily been their design, but their utilization (Almarashdeh and Alsmadi, 2017). However, the utilization or adoption behaviour of users of m-government systems has not been adequately addressed in the relevant literature, and there is room for more research in this area (Saxena, 2018; Sharma *et al.*, 2018).

Although some recent studies have explored the adoption of m-government services (Ahmad and Khalid, 2017; Gao *et al.*, 2014; Saxena, 2018; Wang, 2014), they do not include context-specific predictors such as quality of mobile communication services (MCS) and perceived mobility. For example, in a developing country context, m-government is still considered a disruptive technology (Chen *et al.*, 2016); and the importance of MCS might be the most critical factor in m-government service adoption (Sultan and Steve, 2015). MCS, therefore, need to be considered in the study of m-government service adoption. This study attempts to bridge this gap in the literature by adding contextual predictors to the unified theory of acceptance and use of technology (UTAUT) model and by observing the effect of some additional contextual constructs, namely quality MCS and mobility, on the adoption of m-government services. It should be noted that, in this study, in order to facilitate the understanding of the topic, m-government is considered as an overall concept, rather than focusing on any one particular service, and Bangladesh – a developing country with a large population – has been selected as the target for this study.

A large majority of prior studies in this field have employed conventional statistical methods such as multiple regression analysis and structural equation modeling (SEM) as their methodological approach. These techniques, however, might not be adequate in explaining complex interaction effects among multiple predictors, since relationships between predictors and system usage behaviors could be asymmetric, and conventional regression techniques are incompatible with asymmetric relationships (Liu *et al.*, 2017). This limitation lends credibility to predictive modeling techniques, such as neural networks, as an alternative approach for exploring information systems (IS) usage behavior (Raymond *et al.*, 2010; Liu *et al.*, 2017; Woodside, 2013). A neural network offers an alternate avenue for deducing causal relationships between the antecedents and outcome of IS adoption behavior by taking into account interdependencies among the former. Therefore, we address the limitation discussed above by employing a two-stage predictive modeling approach suggested by Chong (2013), whereby SEM is used to examine the causal relationships between predictors of m-government service adoption, and a neural network model is used to validate SEM results and rank the independent predictors. This multi-analytical statistical approach provides a fine-grained understanding of the topic, and the two approaches generally offset each other's weaknesses (Scott and Walczak, 2009).

The rest of this paper is organized as follows. In Section 2, we discuss the research model and develop hypotheses to be tested in this study. We then discuss the research methodology in Section 3. After that, we provide the results and analyze them in Section 4, and discuss their theoretical and practical implications in Section 5. Finally, we conclude the paper in Section 6.

2. Research model and hypotheses development

2.1 The unified theory of acceptance and use of technology model

The UTAUT is a unified model that comprises eight theoretical models of technology adoption (Venkatesh *et al.*, 2003). It consists of four major constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions, which can be used to determine user acceptance and user behavior of any innovative and complex technology (Venkatesh *et al.*, 2003). In contrast to other models, UTAUT is known to explain about 70 per cent of the variance in the behavioral intention to use and accept a technology (Venkatesh *et al.*, 2003).

M-government has been treated as a "technology" because of its inherent dependence on an information technology (IT) platform where information exchange happens between the government (supplier of m-government services) and the citizens (users of m-government services) via mobile technologies. The rationale behind using the UTAUT framework is that it helps to examine social and other facilitating factors that influence the IT linked with m-government systems. Social factors, such as the behavior of m-government users and the influence of others on them, are important for the acceptance and use of m-government services (Zuiderwijk *et al.*, 2015). The importance of examining social factors in technology adoption is well recognized (Gwebu and Wang, 2011), particularly in countries with collectivist culture, such as Bangladesh (Srite and Karahanna, 2006). There are also a number of facilitating conditions (e.g. support, training, infrastructure) that impact the actual use and acceptance of a technology (Sykes *et al.*, 2009). These facilitating conditions are included in the theoretical framework proposed in this study.

Moreover, Venkatesh *et al.* (2012) argued that there is a need to assess the magnitude, direction, and significance of the relationships among variables; such relationships might also vary according to the context. The UTAUT model is appropriate for capturing end user behavioral intention for complex and sensitive ICT-related services where contextual differences exist (Dwivedi *et al.*, 2016). Therefore, the UTAUT model is employed as the theoretical framework to explore m-government service adoption in the context of Bangladesh.

The UTAUT model is widely used along with additional contextual constructs incorporating specific elements of a required field (Venkatesh *et al.*, 2012). Introduction of additional contextual predictors demonstrates a clearer understanding of consumers' acceptance of domain-specific technology (Cimperman *et al.*, 2016; Jeong *et al.*, 2017; Venkatesh *et al.*, 2011). Based on previous research and the m-government context, two contextual variables, namely quality of MCS and mobility were added to the existing model. The extended model is shown in Figure 1. As shown in the figure, performance expectancy, effort expectancy, social influence and facilitating conditions are taken as direct antecedents of behavioral intention, while MCS and mobility are used as antecedent of performance

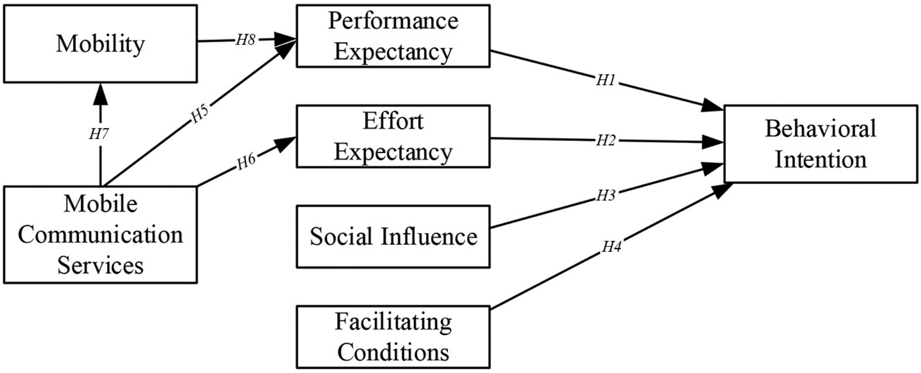

Figure 1.
Research model

expectancy and effort expectancy, respectively. Behavioral intention is taken as the dependent variable in this study. Behavioral intention is defined as an individual's intention, plan, or prediction to use m-government services in the future. The development of hypotheses based on these antecedents is discussed in the following section.

2.2 Hypothesis development

2.2.1 Performance expectancy. Performance expectancy is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh *et al.*, 2003). We assert that the availability of m-government services, such as m-government platforms, application, tools, and interfaces, increases an individual's expectancy to perform better. Thus, consistent with the theoretical arguments underlying UTAUT, we anticipate a direct and positive impact of performance expectancy on the intention to use and accept m-government services.

2.2.2 Effort expectancy. Effort expectancy is related to the degree of ease associated with the use of a technology (Venkatesh *et al.*, 2003) and the degree to which a person believes that the use of the technology will be free of effort (Gwebu and Wang, 2011). We define effort expectancy as the extent to which a person believes that using m-government services will be free of effort and easy to learn. In the context of this study, we assert that people analyze their expectations of the degree to which m-government services are easy or difficult to use, and that this perceived ease of use influences their intention to use m-government services.

2.2.3 Social influence. Social influence is defined as a change in an individual's thoughts, feelings, attitudes, or behaviors that results from communicating with another individual or a group (Rashotte, 2007). Social influence may come from friends, family and other people who influence a person's behavior or are important to this person (Talukder *et al.*, 2019). Almuraqab *et al.* (2017), Yfantis *et al.* (2013) and Sultana and Ahlan (2014) have shown that social influence has a significant impact on the behavioral intention to use m-government services. In contrast, Alshehri *et al.* (2012) showed that social influence has no positive impact on behavioral intention in Saudi Arabia. Such differences may be the reflection of contextual difference in Saudi Arabia, such as culture and demographic variables. However, in this study, we argue that it is possible that the influence of colleagues, peers, family members, supervisors and others could determine an individual's usage of m-government services.

2.2.4 Facilitating conditions. Facilitating conditions can be defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh *et al.*, 2003). Although prior research has shown that facilitating conditions are not the best predictors for the behavioral intention to use technology (Alshibly *et al.*, 2016), we expect that facilitating conditions influence the intention to adopt m-government services. If facilitating conditions such as mobile networks, connection to the internet, sufficient and appropriate m-government infrastructure are available, the intention to use m-government will be higher.

Based on the above arguments, we propose the folowing hypotheses:

H1. Performance expectancy has a positive impact on behavioral intention to use m-government services.

H2. Effort expectancy has a positive impact on behavioral intention to use m-government services.

H3. Social influence has a positive impact on behavioral intention to use m-government services.

H4. Facilitating conditions have a positive impact on behavioral intention to use m-government services.

2.2.5 Mobile communication services. In rural Bangladesh, mobile network coverage is not yet widely available, and high-speed data transmission (i.e. 3G, 4G) coverage is unavailable even in many cities. As a consequence, it is difficult to access and use government services by using mobile technologies, anytime and anywhere. Mobile communication characteristics, such as rich content, real-time content update and availability, personalization, comprehensive customer service, service accessibility, network coverage, transmission speed, and signal quality are pre-requisities for any m-government service to be used with less effort and while in motion (Shieh *et al.*, 2014). Widespread and reliable mobile communication facilities allow users to access and use m-government systems from anywhere and anytime (Al-Hubaishi *et al.*, 2017). Previous research has found MCS to be an essential factor for citizens' acceptance of mobile-based services (Chen *et al.*, 2016; Hung *et al.*, 2013; Shieh *et al.*, 2014; Wu *et al.*, 2009). Strong and sound telecommunication facilities improve the convenience, and usefulness of m-government systems for the citizens (Shieh *et al.*, 2014) along with providing safer and faster access to m-government services. Therefore, it is believed that MCS will make m-government systems more useful, accessible with minimal effort, and able to support myriad needs of the users. Thus, the following hypotheses are proposed:

H5. Mobile communication service has a positive impact on performance expectancy towards the use of m-government services.

H6. Mobile communication service has a positive impact on effort expectancy towards the use of m-government services.

H7. Mobile communication service has a positive impact on mobility towards the use of m-government services.

2.2.6 Perceived mobility. Perceived mobility is defined as the level of user awareness towards the value of mobile technologies (Huang *et al.*, 2007). In a mobile communication environment, mobility refers to the characteristics of mobile devices to handle ubiquitous use, and access information, communication and business transactions in a state of motion via wireless networks (Yuan *et al.*, 2010). Perceived mobility is one of the crucial determinants of perceived usefulness in m-government service adoption (Alotaibi and Roussinov, 2016; Wang, 2014), in using mobile learning services (Huang *et al.*, 2007), and mobile communication networks (Siau and Shen, 2003). Gunawardana and Ekanayaka (2009) suggested that perceived mobility significantly impacts effectiveness of mobile systems and service quality. Perceived mobility is assumed as an antecedent to performance expectancy because mobility is an essential characteristic of any wireless network service. Thus, we propose the following hypothesis:

H8. Mobility has a positive effect on performance expectancy of m-government systems.

3. Research methodology

3.1 Measurement development

All constructs of the research model were adapted from previous research and modified for this study. The number and sources of items used to measure each construct are summarized in Appendix 1. A structured questionnaire was initially developed in English and then translated into the local language (Bangla) by a professional translator. Next, another professional translator translated the questionnaire back into English. Based on this double translation process (Hoque and Sorwar, 2017), slight corrections were made to the questionnaire to ensure that the meaning of all items remained the same during translation. Two experts were asked to review the questionnaire in both languages to ensure clarity of instructions, content validity, and consistency. In the questionnaire, a five-point Likert scale was used to gather data for the constructs, where 5 indicates "Strongly agree" and 1 indicates, "Strongly disagree". The survey questionnaire comprises two parts. The first part consists of 23 items related to the nine constructs of the proposed research model. The second part consists of five questions about demographic information of the respondents, including gender, age, education, and experience in using mobile technologies. Prior to data collection, the questionnaire was refined via limited pre-testing with 20 MBA students from University of Dhaka, Bangladesh.

3.2 Data collection

A cross-sectional study was conducted. The data was collected over a period of five months, from October 2017 to February 2018. Non-probability convenience sampling was undertaken due to time, cost and workforce constraints (Sekaran, 2006). In particular, we focused on university students, professionals in government and private sectors, people in business, and retirees from various public places of Dhaka city such as university campuses, parks, playgrounds, and community centers.

Printed questionnaires were personally distributed among the potential participants in the targeted places. Although home and location-based surveys are more time consuming, they provide a higher response rate compared to other instruments such as, telephone or online surveys (Malhotra, 2008). We sought the respondents' verbal informed consent and confirmed the privacy of their information. Participants were also advised of their right to withdraw from the study at any time without incurring any negative consequences. In total, 230 survey questionnaires were distributed and since it was a self-administered survey, the response rate was 100 per cent. 14 questionnaires with missing data was excluded from further analysis (Joseph *et al.*, 2010) and, thus, 216 valid responses were used for further analysis.

4. Data analysis and results

Data was analyzed using SPSS 23.0 and SmartPLS 3.2.8 version software. In the first stage, SEM was applied to determine the reliability and validity of the constructs, and to evaluate the predictive relevance of the model and the total variance explained (Chin, 1998). In the final stage, neural network analysis was conducted to validate the SEM results and to rank the key predictors of m-government service adoption.

4.1 Demographic information

The demographic characteristics of respondents presented in Appendix 2 show that males and females constituted 62 per cent and 38 per cent of the participants, respectively. A large majority of respondents (89 per cent) were between 20 and 40 years old. Most of the participants (89 per cent) were university students and professionals, with 57 per cent of them having more than 3 years of mobile phone usage experience.

4.2 Measurement model

The measurement model was assessed by examining the internal reliability, convergent validity, and discriminant validity (Hair *et al.*, 2013), and the results are shown in Tables 1 and 2. Table I shows that the composite reliability values range from 0.86 to 0.90, and Cronbach's alpha values range from 0.75 to 0.86. These indicate strong internal reliability, as all the values are above the acceptable 0.7 threshold (Hair *et al.*, 1998). Next, we can see in Table I that the average variance extracted (AVE) ranges (0.61 to 0.75) and the estimated loading ranges (0.72 to 0.89), are greater than the recommended threshold of 0.50, indicating convergent validity (Anderson and Gerbing, 1988). Therefore, the conditions of internal

Constructs	Items	Loadings	CR	AVE	Cronbach's alpha
Behavioral Intension	BI1	0.839	0.892	0.734	0.819
	BI2	0.858			
	BI3	0.873			
Effort Expectancy	EE1	0.774	0.862	0.61	0.788
	EE2	0.721			
	EE3	0.813			
	EE4	0.813			
Facilitating Conditions	FC1	0.829	0.864	0.679	0.764
	FC2	0.864			
	FC3	0.778			
Mobile Communications Services	MCS1	0.829	0.859	0.671	0.754
	MCS2	0.855			
	MCS3	0.772			
Performance Expectancy	PE1	0.849	0.893	0.676	0.839
	PE2	0.759			
	PE3	0.842			
	PE4	0.835			
Perceived Mobility	PM1	0.873	0.902	0.754	0.837
	PM2	0.863			
	PM3	0.87			
Social Influence	SI1	0.886	0.869	0.69	0.774
	SI2	0.844			
	SI3	0.757			

Notes: AVE = Average variance extracted; CR = Composite reliability

Table I.
Measurement model

reliability and convergent validity of the measurement instruments were satisfied in this study.

In addition, since the square root of AVE (shown in the diagonal of the factor correlations in Table II) for each latent variable was greater than the correlation of that variable with other latent variables, the Fornell–Larcker criterion was satisfied (Fornell and Larcker, 1981); thus indicating good discriminant validity (Henseler *et al.*, 2015).

4.3 Structural model

The structural model was constructed to identify the path relationships among the constructs in the research model. The bootstrapping method was used to test the hypotheses at a significance level of 0.05 ($p < 0.05$) and the path coefficients. The relationship between dependent and independent variables was tested by path coefficient (β) and *t-statistics* value above 1.96 at 5 per cent level of significance (Hair *et al.*, 2012). The R square value was used to calculate the percentage of the variance explained by the independent variables in the structural model (Klarner *et al.*, 2013). The research model accounts for behavioral intention (BI) $R^2 = 59$ per cent of the variance in response to m-government service adoption in Bangladesh.

The results from the research model show that all the antecedents of behavioral intention were found statistically significant, except for social influence. More specifically, performance expectancy (PE: $t = 4.239$, $\beta = 0.286$), effort expectancy (EE: $t = 3.953$, $\beta = 0.210$), and facilitating conditions (FC: $t = 3.965$, $\beta = 0.213$) were found to have significant effect on behavioral intention to use m-government services, whereas social influence (SI: $t = 0.801$, $\beta = 0.050$) was found to not have a significant effect. Results also indicate that mobile communications services (MCS: $t = 10.394$, $\beta = 0.571$), (MCS: $t = 3.162$, $\beta = 0.275$), and (MCS: $t = 6.428$, $\beta = 0.464$) have significant and direct effect on effort expectancy, performance expectancy and perceived mobility, respectively. Additionally, perceived mobility (PM: $t = 4.823$, $\beta = 0.433$) has a significant positive effect on performance expectancy towards behavioral intention to use m-government services. In contrast, social influence (SI: $t = 0.801$, $\beta = -0.050$) was found to have a non-significant effect on behavioral intention. Therefore, among the hypotheses, *H1*, *H2*, *H4*, *H5*, *H6*, *H7*, and *H8* were supported, and *H3* was not supported. The detailed results are shown in Table III.

The study also supports the previous findings using Q^2 predictive relevance measure (Stone, 1974). The obtained Q^2 values, after running the blindfolding procedure (Chin, 1998) with an omission distance D = 7, were 0.23 for performance expectancy, 0.18 for effort expectancy, 0.15 for perceived mobility, and 0.42 for behavioral intention. All of the Q^2 values are well above zero; indicating the predictive relevance of the PLS path model.

Constructs	BI	EE	FC	MCS	PE	PM	SI
BI	*0.857*						
EE	0.567	*0.781*					
FC	0.576	0.428	*0.824*				
MCS	0.488	0.568	0.377	*0.819*			
PE	0.624	0.465	0.438	0.478	*0.822*		
PM	0.677	0.543	0.465	0.461	0.559	*0.869*	
SI	0.430	0.417	0.385	0.407	0.552	0.403	*0.831*

Notes: BI = Behavioral intention; PE = Performance expectancy; EE= Effort expectancy; SI = Social influence; FC = Facilitating conditions; MCS = Mobile communication services; PM = Perceived mobility

Table II.
Correlation matrix and square root of the AVE

Finally, the f^2 values (i.e. effect size) for performance expectancy, effort expectancy, and perceived mobility were measured. As shown in Table IV, according to the standard of Aiken *et al.* (1991), the effect size for performance expectancy on behavioral intention is medium, effort expectancy on behavioral intention is small, and perceived mobility on performance expectancy is also medium.

4.4 Neural network modeling

While SEM provides us an excellent understanding of the relationships among the constructs in the model, it is often not enough to understand the complexity of decision-making in forming the behavioral intention to use m-government services (Al-Shihi *et al.*, 2018; Sharma and Sharma, 2019). Therefore, in addition to SEM, we have employed an innovative hybrid SEM and neural network approach to help us develop a more fine-grained understanding of the relationships among the various constructs in the research model. Employing a neural network allows the detection of both linear and nonlinear relationships among decision variables (Sharma *et al.*, 2018). Furthermore, an artificial neural network model does not need to test requirements of any data distribution such as linearity, normality and independence (Chong, 2013).

4.4.1 Validations of neural networks. The back propagation multilayer perceptron neural network model was used to describe the neural networks and the variables that the user can control during training of a neural network (Poulton, 2001). To avoid overfitting of the model, a ten-fold cross validation approach was used. In this study, we have divided data into 10 equal groups, where 90 per cent of the data was used to train the neural network and the remaining 10 per cent were used to test the prediction accuracy of the trained network.

The accuracy of the neural network model was measured using Root Mean Square Error (RMSE) values. The two significant constructs, namely quality of MCS and mobility, were used as input layer and performance expectancy (Figure 2). In the second model, performance expectancy, effort expectancy, and facilitating conditions were used as input

SL no.	Path	Coefficient (β)	*t*-statistics	Comments
H1	PE -> BI	0.286	4.239	Supported
H2	EE -> BI	0.265	4.153	Supported
H3	SI -> BI	0.050	0.801	Not Supported
H4	FC -> BI	0.203	3.765	Supported
H5	MCS -> PE	0.275	3.162	Supported
H6	MCS -> EE	0.571	10.394	Supported
H7	MCS -> PM	0.464	6.428	Supported
H8	PM -> PE	0.433	4.823	Supported

Notes: R^2 for BI = 0.594; Significant at $p < 0.05$

Table III. Structural model

Endogenous latent variables	R^2	Q^2	F^2
PE	0.374	0.229	0.117
EE	0.323	0.180	0.079
PM	0.212	0.150	0.234
BI	0.616	0.418	–

Table IV. Results of R^2, Q^2 and f^2

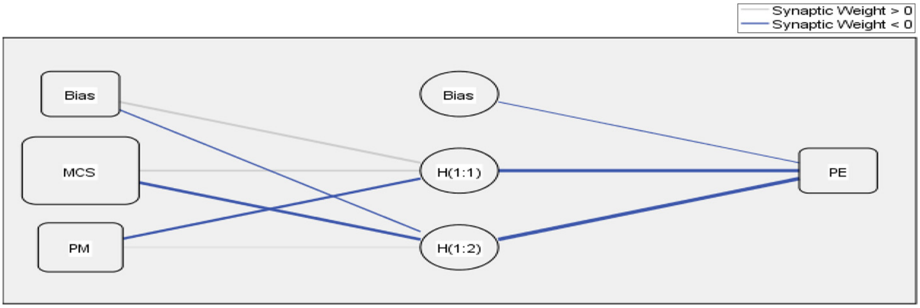

Figure 2. Neural network Model 1

Notes: Hidden layer activation function: Hyperbolic tangent, Output layer activation function: Identity

layer and behavioral intention was used as the output layer (Figure 3). From Table V, we can see that the average cross-validated RMSE for the training and testing was 0.121 and 0.115, respectively for model 1; and 0.141 and 0.162, respectively for model 2. Given the relatively small RMSE values, we can conclude that the network models were quite reliable in capturing the numerical relations between the predictors and the outputs.

4.4.2 Sensitivity analysis. The normalized importance ratio is calculated as "the ratio of the importance of each predictor to the highest importance value" (Chong *et al.*, 2015). Table VI summarizes the average relative importance and normalized relative importance (in percentage) reported by neural network models 1 and 2. In neural network model 1, MCS is the most important predictor of satisfaction followed by perceived mobility. This indicates that there is no change in the order of the importance of the predictors of performance expectancy in SEM and neural network results. Next, using neural network

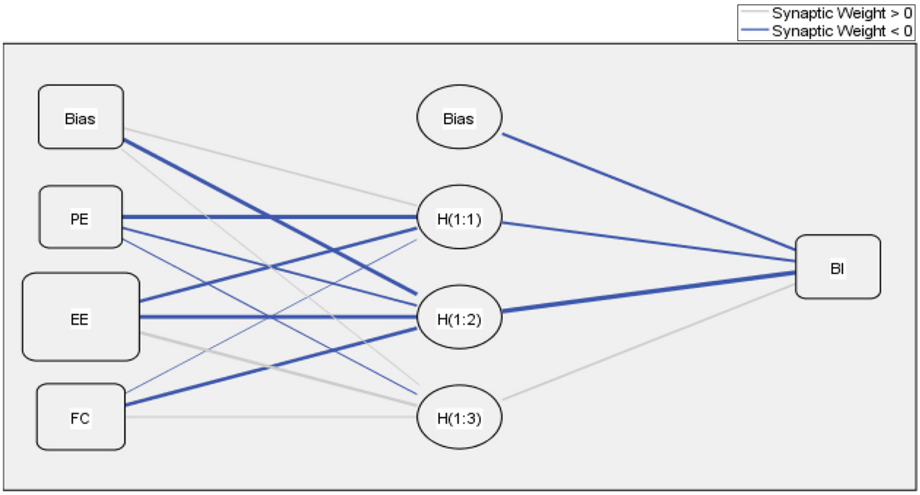

Figure 3. Neural network Model 2

Notes: Hidden layer activation function: Hyperbolic tangent, Output layer activation function: Identity

Network	Model 1 Training	Model 1 Testing	Model 2 Training	Model 2 Testing
ANN1	0.116	0.115	0.142	0.167
ANN2	0.124	0.122	0.138	0.153
ANN3	0.109	0.093	0.128	0.156
ANN4	0.128	0.127	0.145	0.169
ANN5	0.122	0.108	0.151	0.163
ANN6	0.115	0.118	0.147	0.159
ANN7	0.131	0.112	0.136	0.161
ANN8	0.107	0.109	0.153	0.178
ANN9	0.142	0.126	0.124	0.136
ANN10	0.113	0.117	0.144	0.175
Mean	*0.121*	*0.115*	*0.141*	*0.162*
SD	*0.011*	*0.010*	*0.009*	*0.012*

Note: SD: Standard deviation

Table V. Neural network validations

Networks	Model 1: Output PE MCS	Model 1: Output PE PM	Model 2: Output BI FC	Model 2: Output BI PE	Model 2: Output BI EE	Model 2: Output BI SI
ANN1	0.492	0.326	0.592	0.472	0.258	0.218
ANN2	0.505	0.378	0.571	0.464	0.279	0.247
ANN3	0.459	0.367	0.563	0.494	0.283	0.256
ANN4	0.444	0.337	0.587	0.502	0.271	0.225
ANN5	0.447	0.346	0.579	0.483	0.273	0.238
ANN6	0.463	0.349	0.598	0.476	0.268	0.218
ANN7	0.479	0.366	0.574	0.478	0.284	0.262
ANN8	0.498	0.341	0.567	0.481	0.298	0.255
ANN9	0.482	0.335	0.583	0.498	0.275	0.207
ANN10	0.501	0.375	0.556	0.462	0.281	0.234
Avg.	0.477	0.352	0.577	0.481	0.277	0.236
Normalized importance	100%	74%	100%	83%	48%	41%

Table VI. Importance of independent variables

model 2, facilitating conditions is the key predictor of intention to use m-government services followed by performance expectancy and effort expectancy. However, performance expectancy is the most important predictor of the intention to use m-government services followed by facilitating conditions, effort expectancy, and social influence in the SEM results. This difference in the results of SEM and neural network modeling may be supported by the higher order of predictive power and non-compensatory nature of the latter model. Despite this difference, this outcome may be considered as the validation of the results.

5. Discussion and implications

According to the results summarized in the previous section, the proposed research model examined in this study was able to achieve a satisfactory level of predictive power extracted by dependent constructs: performance expectancy (39.2 per cent) and intention to use (59.4 per cent). In addition to these satisfactory results, reliability and validity of constructs were within the acceptable limits. Based on the results obtained using neural networks, the most significant predictor of behavioral intention is facilitating conditions, which positively influences citizens' intentions towards the adoption of m-government services. The result indicates that arranging training programs, providing organizational and technological infrastructures, and making relevant resources available to facilitate the use of m-government services are some of the mechanisms a government can use to significantly improve its citizens' intention to use m-government services.

This study also confirms the significant influences that performance expectancy and effort expectancy have on behavioral intention to adopt m-government services. Results indicate that an individual's intention can be determined by the ease of use of the m-government system (i.e. is less complex) and the degree to which it may prove useful and beneficial (i.e. has greater performance) to the users.

Most interestingly, the study found that MCS have a strong influence on performance expectancy, effort expectancy and perceived mobility. This study considered technological factors like signal quality, network coverage, transmission speed, services content and service assurance to have a substantial impact on m-government service adoption in developing countries. This study is the first approach that considers the effects of MCS from three different perspectives. First, this study found MCS had a significant effect on perceived mobility. This result indicates that while users access and use m-government services according to their convenience (anytime and anywhere) (Anckar and D'incau, 2002), they need suitable and reliable MCS (Huang *et al.*, 2007). Second, this study found MCS (t = 3.162) to have a positive influence on performance expectancy. MCS help users to use m-government services whenever and wherever they are required, thus making such services more convenient and useful. Third, this study found MCS have a significant impact on effort expectancy. Ahn *et al.* (2007) stated that high-quality systems provide users faster access to information with less effort. A reasonable number of previous empirical studies have found that the quality of MCS significantly influence user satisfaction and attitude towards behavioral intention to use mobile-based technologies (Chen *et al.*, 2016; Hung *et al.*, 2013; Shieh *et al.*, 2014; Wu *et al.*, 2009).

Further, this study identifies that mobility has a significant effect on performance expectancy towards behavioral intention to use m-government services. Park and Joon Kim (2013) stated that perceived mobility is an antecedent of performance expectancy and a key feature for mobile-based service development. This finding is consistent with a number of studies that have found mobility to be a significant determinant of mobile-based technology adoption in general (Huang *et al.*, 2007), and m-government adoption in particular (Alotaibi and Roussinov, 2016; Wang, 2014).

Finally, in contrast with most of the existing studies (Talukder *et al.*, 2019; Thongsri *et al.*, 2019), we found social influence to be a non-significant antecedent of behavioral intention. According to modernization theory (Cowgill and Holmes, 1972), today's modernized and scientific society can trigger a loss of social status for the elderly because knowledge from the book is now valued more than knowledge acquired through personal experience (Brown, 1996). People tend to disregard the influence of societal pressure, image, and social status and tend to pursue more emotionally meaningful goals (Carstensen *et al.*, 2003). Therefore, and as confirmed by the results, people of Bangladesh no longer place high importance on their previous habits, and are ready to change their modes of receiving m-Government services if necessary. Additionally, this finding is consistent with some of the previous results reported in different IS domains (Cimperman *et al.*, 2016; Sharma *et al.*, 2018).

5.1 Implications for research

This study provides a number of useful insights to academicians and researchers. First, it has extended the existing literature by adding two additional contextual constructs, namely quality of MCS and mobility into the UTAUT model to explain the behavioral intention towards m-government in the context of a developing country. The inclusion of MCS makes this study novel and MCS might be the most significant construct in mobile application literature. MCS and mobility make mobile-based services more effective and efficient. This study will add more knowledge regarding m-government service adoption, specifically in the study of mobile applications.

Second, the application of an innovative two-stage SEM-neural network modeling approach provides a holistic understanding from an analytical point of view. The application of neural network modeling is an attempt to address one of the limitations of many previous studies on technology adoption by developing a non-compensatory model to predict behavioral intention of citizens towards m-government services in developing countries. Neural network modeling is non-compensatory in nature and overcomes the weaknesses of compensatory nature of linear SEM. This study demonstrated the validity of the research model using SEM for understanding the effect of independent constructs on a dependent construct, and neural network modeling was used to validate the SEM results and to rank significant independent constructs.

5.2 Implications for practice

This study has several practical implications for the stakeholders involved in the development and implementation of m-government systems in Bangladesh, such as relevant policymakers, government officials and system developers. Citizens' adoption and utilization rate of m-government services can be improved in several ways as discussed below.

Results found performance expectancy and effort expectancy to be the most important antecedents of behavioral intention to use m-government services. This implies that individuals attribute substantial importance to the technological efficacy of an m-government system and its ease of use. Therefore, designers, system analysts and developers responsible for the design and development of m-government systems should focus more on minimizing the complexities associated with exploration and use of the system, if there are any, and improving the usefulness of the system.

We also found that facilitating conditions had a direct impact on behavioral intention to use m-government services. This suggests that individuals may place importance on facilitating conditions such as help desks, technological and infrastructural resources, and training programs, as well as the experiences of other individuals in using the m-government system in question. Therefore, concerned government organizations or departments should consider equipping their training program centers with adequate infrastructural and technological facilities for providing the prerequisite training to users. Such actions can positively impact the use and adoption of relatively new and useful m-government systems.

Furthermore, the most critical MCS such as signal quality, network coverage, transmission speed, service content and service assurance strongly influence perceived mobility, performance expectancy, and effort expectancy towards the adoption of m-government services. The government can collaborate with already established private mobile network service providers through Private Public Partnership (PPP) to provide government services over all geographical locations. It could be a win-win situation for both the government (cost reduction) and the private mobile operators (profit sharing). The development of 4G high-speed data transmission throughout the country would further help improve the quality of MCS and enable the government to realize the objective of providing m-government services to its citizens at their doorsteps. Finally, the government should ensure high availability and reliability of m-government systems so users can access and use them anytime and from anywhere. The results of the research model will also be useful to the developers and designers of m-government services in guiding them towards implementing new m-government services and updating existing services to ensure better acceptance by the citizens

5.3 Limitations and future directions

Despite the contributions, this study has a few limitations that need to be considered when interpreting the findings. First, m-government is still relatively new and an emerging trend in developing countries such as Bangladesh. Future studies can consider measuring the diffusion of m-government activities across time, and examine whether the variables in this study change at various m-government diffusion stages. Second, future study should use the longitudinal method to explain the causal relationship between variables over time since the model in this study is cross-sectional, which measures the intention only at a single point in time. Finally, this study only examines behavioral intention to use m-government services. Future studies to examine citizens' continuous usage intention and to evaluate the results with the intention to use m-government application is highly recommended, as the initial-adoption and continuance usage behaviors are two theoretically distinct concepts and the latter is more important than former (Bhattacherjee, 2001).

6. Conclusion

This study presented an integrated model to predict the adoption of m-government services among the citizens of Bangladesh. The main research model was divided into two sub models: Model 1 (independent variables: perceived mobility, MCS and dependent variable: performance expectancy) and Model 2 (independent variables: performance expectancy, effort expectancy and facilitating conditions and dependent variable: behavioral intention to use). In this study, it was found that quality of MCS and perceived mobility are the key determinants influencing performance expectancy and behavioral intention to use m-government services. The obtained results also suggest that higher level of facilitating conditions and higher performance expectancy will help in attracting new and potential users. A combination of SEM and neural network modeling was employed, which provides an additional originality to this study. SEM has been used to test and verify the research hypotheses in many prior studies, but has rarely been combined with machine learning models. SEM is primarily used to test linear models and sometimes oversimplifies the complexities involved in the adoption models in business domains. In this study, SEM was used to test research hypotheses and identify statistically significant predictors and the neural network model used these predictors as input and ranked them for better decision-making insights. Thus, this study provides very useful theoretical as well as practical implications for researchers, academics and m-government service providers.

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Appendix 1

Construct	Corresponding items	Items sources
Performance expectancy	PE1. I find m-government service useful in my daily life PE2. Using m-government service helps me accomplish things more quickly PE3. Using m-government service increases my productivity PE4: Using m-government service improves my quality of work	Talukder *et al.* (2019), Venkatesh *et al.* (2003)
Effort expectancy	EE1. Learning how to use m-government service is easy for me EE2. My interaction with m-government service is understandable EE3. I find m-government service easy to use EE4. It is easy for me to become skillful at using m-government service	Talukder *et al.* (2019), Venkatesh *et al.* (2003)
Social influence	SI1: People who are important to me think that I should use m-government system SI2: People who influence my behavior think that I should use m-government system SI3: I would use m-government system if my friends and colleagues used them	Talukder *et al.* (2019), Venkatesh *et al.* (2003)
Facilitating conditions	FC1. I have the resources necessary to use m-government service FC2. I have the support necessary to use m-government service FC3. M-government is compatible with other technologies I use	Talukder *et al.* (2019), Venkatesh *et al.* (2003)
Mobile communication services	QMS1: Our mobile telecommunications services incorporated with many services contents (such as; content richness, real-timeliness, and personalization) QMS2: Our mobile telecommunications services incorporated with service assurance (such as; comprehensive customer service and service accessibility) QMS3: Our mobile telecommunications services incorporated with network reliability (such as; transmission speed, signal quality and network coverage)	Chen *et al.* (2016), Shieh *et al.* (2014), Wu *et al.* (2009)
Perceived Mobility	PM1: It is convenient to access m-government systems anywhere at any time PM2: I expect that mobile government services would be available for use whenever I need it PM3: I would find mobile government services to be easily accessible and portable	Alotaibi and Roussinov (2016), Huang *et al.* (2007)
Behavioral Intention	BI1. I intend to use m-government service in the future BI2. I will always try to use m-government service in my daily life BI3. I plan to use m-government service frequently	Talukder *et al.* (2019), Venkatesh *et al.* (2003)

Table AI. Measurement items

Appendix 2

Table AII. Demographic information

Descriptions	Frequency	(%)
Gender		
Male	133	62
Female	83	38
Age		
Less than 20	10	5
20-40	192	89
40-60	14	6
Occupation		
Government employee	44	20
Private sector employee	56	26
Business sector	14	6
Student	92	43
Others	10	5
Mobile using experience		
Less than 1 years	2	1
1-3 years	34	16
4-6 years	124	57
7-9 years	32	15
More than 10 years	24	11

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