An Empirical study on E-Government Intentions and Adoption: Mediating effects of Bangladeshi Citizens' Attitudes and Trust in Government

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ABSTRACT

Use of Information and Communication Technology to more efficiently deliver government services to citizens is known as e-government. This research investigated the factors that influence e-government adoption intention by Bangladeshi citizens. The study extended the basic UTAUT model to propose an e-government adoption conceptual framework. The proposed framework included attitude and trust in Government as possible mediator. The proposed framework was validated through empirical data. Using a quantitative approach, data were collected from citizens across various regions of Bangladesh through a structured survey questionnaire. Partial Least Squares – Structural Equation Modeling (PLS-SEM) method was used for data analysis. The study results revealed that performance expectancy, effort expectancy and social influence affects the Bangladeshi citizens' e-government service adoption intention. Furthermore, these relationships are mediated through attitude. The favorable attitude created through performance expectancy, effort expectancy and social influence trickles down to favorable adoption intention. Facilitating conditions supporting the e-government engagement influences the behavioral intention as well. The supporting conditions' effects are significantly and positively mediated by Bangladeshi citizens' trust in their government. By proposing and validating a new conceptual framework for studying e-government adoption, the study adds knowledge to the e-government specific literature. The validation in Bangladesh also contributed to literature by providing e-government adoption insight from developing nations' perspective. The study outcome provides an opportunity to bridge the gap between government service provider and citizen. Government policy makers can consider carrying out an investigation on the impact of the external influences to strategize more effective e-government initiatives. Accordingly, the service providers while designing e-government services should prioritize taking into consideration citizens' specific requirements. The study further contributed to the creation of awareness to the citizens on the benefits of e-governance in the provision of effective government services.

Keywords: E-government, Adoption Intention, Attitude, Trust in Government, Citizens' Perspective

INTRODUCTION

In the age of technology, we are heavily dependent on the electronic platforms for completing our tasks. People want to perform their interactions and transactions electronically. The comfort and ease of technology driven system has become essential in every aspects of our lives. This has manifested itself in the way citizens demand the government service delivery. In this tangent, electronic government (e-government) gained prominence. The United Nations defines e-government as the governments' use of Information and Communication Technology (ICT) towards achieving greater efficiency in delivering government services to citizens and business (United Nations, 2024a) . The underlying principle behind e-government is to improve the internal

government working, reducing cost, swift service delivery and integrated resource utilization (ibid). There are three main types of e-government services, namely Government-to-Government (G2G), Government-to-Business (G2B) and Government-to-Citizen (G2C). Government-to-Government (G2G) is the interaction among government agencies. The Government-to-Business (G2B) is where government agencies and business organizations interacts with one another. Finally, the Government-to-Citizen (G2C) covers the interactions between government agencies and citizens (Nemat, 2011).

The phases of e-government progresses through broadcasting, transaction stage, interaction and integration stages (Basu, 2004). The basic broadcasting stage provides static information. The interaction stage enables exchange of information through queries and downloads. The transaction stage allows the public to carry out financial transactions with the government. Finally, e-government services reach its highest efficiency in the integration stage. A collaborative effort of government agencies in providing one-stop service points to the citizens and the business is the main characteristic of the integration stage (ibid).

The United Nations in their E-government Survey captures the status of e-government of different countries (United Nations, 2024b). The E-government survey indicates the development stages of e-government for particular country using an index call E-Government Development Index (EGDI). On the other hand, using E-Participation Index (EPI) the survey report indicates the citizens' participation levels. The EGDI consists of three subcomponents, namely Online Services Index (OSI), Telecommunications Infrastructure Index (TII) and Human Capital Index (HCI). The OSI measures online service coverage and quality. The TII is the indicator of telecommunications infrastructure development. The HCI encapsulate the users' ability and readiness. The EPI has three subcomponents, namely E-information, E-Consultation and E-decision-making. E-information measures the degree to which citizens have access to public information. The e-consultation evaluates the scope of opportunities given to the citizens to contribute and deliberate on public policies and services. Finally, the e-decision-making assesses the level of citizen empowerment through the co-design of policy and co-production of services.

The overall e-government development in the world showed progress as evidenced by the fact that average EGDI score increased to 0.6382 in 2024 from 0.6102 in 2022 (scale is 0 to 1). In the regional comparison, Europe leads with the highest average EGDI value of 0.8493, followed by Asia 0.6990, the Americas 0.6701, Oceania 0.5289, and Africa 0.4247. These standings of different regions points to potential digital divide in specific countries. Digital Divide here is referring to the gap between individuals, households, businesses and geographic areas in terms of access to ICT and internet usage (OECD, 2001). The comparative picture of the EGDI is shown in Figure 1.
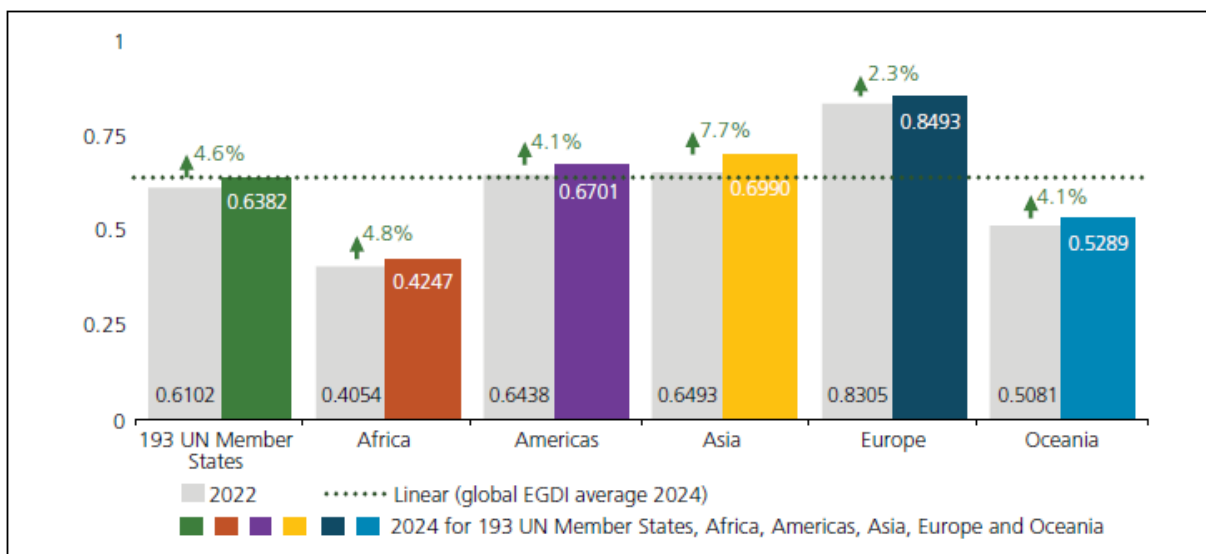

Figure 1: Global and regional EGDI averages, 2022 and 2024

Source: UN E-Government Survey (2022)

The global E-Participation Index (EPI) also has improved as depicted in Figure 2. EPI increased by 9% since the last survey in 2022. Regions around the world engaged their citizens more through e-participation. Nevertheless, similar to EGDI, broad regional and local disparities does exist in EPI as well.

Governments world over have integrated the concept of e-government in their policies. However, not all countries and regions are equally performing in the same pace when it comes to effective and efficient utilization of e-government platforms. The development of e-government services in different countries are still in the preliminary stages. One of the obstacles in ensuring equal level of technological advancement across the borders is the 'digital divide'. According to the Organization for Economic Co-operation and Development (OECD) digital divide refers to the gap between individuals, households, businesses and geographic areas in terms of access to ICT and internet usage (OECD,2001).

At this point of the study, we focus on Bangladesh, a country in the south Asian region. The total population according to the 2022 census is 165.2 million (BBS, 2022). The United Nations Population Fund (UNPF) report the figure to be 174.7 million in 2024 (UNFPA, 2024). Bangladesh is ranked 100 in the EGDI 2024 survey showing an improvement from the 111 rank in 2022. The country has a score above the World and South Asian sub-regional averages. However, it lags behind the regional average. The EGDI subcomponent scores for Bangladesh are 0.73744 for OSI, 0.65010 for TII and 0.58337 HCI. Bangladesh significantly outperforms all averages for OSI. However, for the TII, the country falls short from the rest of the world, regional and sub-regional averages. When it comes to HCI, it has a better standing than the sub-regional average. If we analyze the historical EGDI and its subcomponents for Bangladesh, we can conclude that Bangladesh has maintained gradual progression. The following tables show year wise data (since 2014) of EGDI, OSI, TII and HCI scores for Bangladesh.

Table 1: Year wise EGDI for Bangladesh

Year	2024	2022	2020	2018	2016	2014
E-Government Development Index rank	100	111	119	115	124	148
E-Government Development Index value	0.65696	0.563	0.5189	0.4862	0.37995	0.27572

Source: UN E-Government Survey (2022)

Table 2: Year wise EGDI component breakdowns for Bangladesh

Year	2024	2022	2020	2018	2016	2014
OSI	0.73744	0.6521	0.6118	0.7847	0.62319	0.34645
TII	0.6501	0.4469	0.3717	0.1976	0.11934	0.09414
HCI	0.58337	0.59	0.5731	0.4763	0.39731	0.3866

Source: UN E-Government Survey (2022)

Bangladesh has also improved its E-Participation Index ranking. The country has moved up from rank 75th in 2022 to secure the 70th rank in 2024. Table 3 shows the EPI scores for various years.

Table 3: Year wise E-Participation Index for Bangladesh

Year	2024	2022	2020	2018	2016	2014
E-Participation Index value	0.6164	0.5227	0.5714	0.8034	0.52542	0.39215
Online Service Index value	0.73744	0.6521	0.6118	0.7847	0.62319	0.34645

Source: UN E-Government Survey (2022)

PROBLEM STATEMENT

Despite the improvement in the e-government indexes for Bangladesh, many technology experts in the country are skeptical whether these indexes accurately reflect the e-government improvement in Bangladesh. They are of the opinion that the human development and telecommunication infrastructure indexes of Bangladesh are not as good as they should be ("Bangladesh's progress," 2024). E-government success depends does not only on the government's initiatives to develop the infrastructure. It requires active participation by the citizens to truly make the services effective (Shareef et al., 2011). Individual user's intention and eventual use of the e-government services, which Mensah called the demand side is equally essential (Mensah, 2019). Zhu & Kou (2019) suggested that user acceptance is the main driving force of e-government success.

The government of Bangladesh made significant progress in developing e-government services under the 'Digital Bangladesh' plan. The reflection of which is evident in the UN e-government indexes. However, the EPI index of Bangladesh remained volatile over the years, even though it improved in the last two years. The steady score can only be ascertained once a constant score improvement can be seen. The problematic EPI could stem from various factors. Familiarity with e-government among the citizen is not very promising (Ahmed & Al-Amin, 2023). In Bangladesh, there is a general lack of knowledge and familiarity among members of the public (Ahmad, 2021). Bangladeshis also have an unfavorable attitude towards using the electronic service (Rana and Rahman,2022). Furthermore, people with low digital competencies comprises most of the e-services receives in the country. Alarmingly, 27% of the citizens lack the 'know how' on how to use the basic mobile phones (Hernandez, 2019). Along with these technological hurdles, Islam & Mahmud found out that there is an overall mistrust in the society towards government officials (Islam & Mahmud, 2015). This leads to a negative social influence on using the e-government services.

Moreover, research is required to pinpoint and understand the factors affecting the citizens' behavior towards e-government services. There exist multiple well-known models to study technological adoption behavior and these include The Technology Acceptance Model (TAM) (Davis, 1989), Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), Theory of Planned Behavior (TPB) (Ajzen, 2011), Decomposed Theory of Planned Behavior (DTPB) (Taylor & Todd, 1995) and Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Previous studies have applied these technological adoption models. However, there is an argument that the universal nature of these technological adoption models does not effectively encompass the e-government specific aspects (Nguyen Trong et al., 2022). Taking the basic UTAUT model and adding attitude and trust in government as mediators, the current study propose a new conceptual framework for understanding the e-government adoption intention by Bangladeshi citizens.

The inclusion of Trust in Government (TIG) in the research framework for the current study extends the basic UTUAT model. TIG in the context of e-government refers to people's belief that the government agencies are honest, capable and competent in providing public services through electronic platforms. TIG has been identified as a critical factor in previous studies (Bélanger & Carter, 2008; Gefen et al., 2005). Karavasilis et al., (Karavasilis et al., 2016) and Mensah et al. (Mensah et al., 2017) also found direct significant influencing effect of TIG in e-government adoption. However, very few studies ventured to investigate the potential mediating effect of TIG in inducing behavioral intention toward e-government adoption. The scarcity is more acute in the Bangladeshi context.

LITERATURE REVIEW

Behavioral Intention (BI)

Researchers have done several studies in the past to investigate the e-government adoption intention by the users. Technology acceptance models have been the foundation of these researches. Ziba and Kang (2020) studied the e-government adoption intention in Malawi. In their study, they added the Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB) to the Technology-Organization-Environment (TOE) framework (Baker, 2012). In their study, Almaiah & Nasereddin (2020) utilized the extended UTAUT model

to look into the significant influencing factors for e-government use decision by the Jordanian citizen. Furthermore, Zahid et. al. (2022) extended the Decomposed Theory of Planned Behavior (DTPB) to find out the e-government adoption intention by Pakistani citizens. In all of these studies, Behavioral Intention (BI) was the dependent variable.

Behavioral Intention (BI) refers to people's inclination to use technological system. In the context of e-government, it indicates if individual is willing to try out the services. Behavioral Intention will determine whether an individual accepts or rejects the technology-based services. Encouraging BI will influence actual use of e-government services (Davis, 1989; Venkatesh et al., 2003). Governments worldwide are utilizing ICT to provide their citizens public services in an efficient manner. Despite this effort, many governments face low level of engagement by their citizens. Given this challenge, citizens' engagement becomes one of the most critical factors of e-government (Mensah et al., 2021).

Performance Expectancy (PE)

In the UTAUT model of technology adoption, Performance Expectancy (PE) is defined as users' perception of potential benefits gained from using any technology system (Venkatesh et al., 2003). Performance expectancy as a technology adoption determinant is also present in other literature. For example, Davis's (1989) Perceived Usefulness in the TAM model is equivalent to performance expectancy. Schwoerer et al. (2005) however, adds the technological proficiency alongside effectiveness to describe performance expectancy.

Performance expectancy in e-government settings refers to citizens' belief that using e-government services will bring better public services for them. The influencing effect of performance expectancy on the behavioral intention is established in previous studies. Jambulingam (2013) in a study adopted UTAUT model to understand the behavioral intention to use mobile technology. The study supported the hypothesis that performance expectancy has positive influence on behavioral intention. Mohammadi (Mohammadi, 2022) using Unified Model of E-Government Adoption (UMEGA) (Dwivedi et al., 2017) did a study in Afghanistan. The results revealed that the performance expectancy significantly influences the attitude towards e-government services. The attitude eventually influences the behavioral intention. The study in Taiwan on the university students' intention to use mobile learning, performance expectancy was identified as a significant influencing factor for behavioral intention (Chao, 2019). Nikolopoulou et al. (Nikolopoulou et al., 2021) surveyed the primary and secondary school teachers' intention to use mobile internet in Greece. Their study revealed that performance expectancy influences the technology acceptance.

Based on the findings from previous studies, current study proposes that there exists a positive and significant relationship between performance expectancy and individual's attitude [H1: Performance Expectancy (PE) positively and significantly affects individual's Attitude ATT)].

Effort Expectancy (EE)

The convenience associated with using technology is terms as Effort Expectancy (EE) (Venkatesh et al., 2012). People are more inclined to using the technology if they find it easy to operate. This resonates with Davis's (1989) Perceived Ease of Use (PEoU). Following sections present some of the earlier researches where effort expectancy was examined in the context of e-government adoption behavior.

In a study in Indonesia to understand the citizens' acceptance of e-government services, Mutaqin & Sutoyo (2020) utilized the UTAUT framework. They were able to establish their hypothesis that effort expectancy significantly influences use of e-government service. In fact, effort expectancy and performance expectancy were the two factors with the greatest influencing effect. Yet another study in Indonesia by Meiyanti et al. (20187) was conducted to understand the e-government adoption intention. This study also concluded that there is a positive significant relationship between effort expectancy and e-government use.

Mensah (Mensah, 2019) looked into the Chinese university students' preferences for using e-government services. Based on the UTAUT as their underpinning theory they analyzed 369 responses. Interestingly the

result of this study revealed no significant influence of effort expectancy on intention. Kurfali et al. (2017) in their study investigated the influencing factors driving Turkish people e-government use. Extending the basic UTAUT model, they came to similar conclusion as Mensah regarding the influence of effort expectancy on behavioral intention.

Mixed results from different studies may be attributed to contextual factors such as socio economic conditions, cultural dimensions and literacy level. However, all studies emphasized the inclusion of effort expectancy as a possible factor. Therefore, contextual analysis of e-government adoption by citizens cannot ignore the importance of effort expectancy as an influencing factor. Nevertheless, the cultural and socio-economic aspects of the study should decide the significance of the inclusion of effort expectancy.

Consistent with the earlier researches that looked into the role of effort expectancy in shaping attitude, the current study includes a hypothesis that effort expectancy has a positive and significant impact on shaping individual's attitude towards e-government services [*H2: Effort expectancy (EE) positively and significantly affects individual's Attitude (ATT)*].

Social Influence (SI)

When individual intents to use technology they are influenced by people in the society, especially the people who are close to him or her (Mensah et al., 2017). People are influenced by whether people approve their behavior. The same is true in the case of technology adoption. Social Influence (SI) is individual's perception of others' approval of using new system (Venkatesh et al., 2003). When it comes to e-government, people look for validation of utilizing the services. The favorable use and influence of others will significantly enhance the adoption in this scenario.

A study was carried out among Indonesian citizens to understand the factors influencing e-government service use (Fakhruzzaman & Dimitrova, 2020). The study was based on the Technology Acceptance Model (TAM). The results of the survey established a significance positive effect of social influence on Indonesians' e-government use. Jin & Amin (2020) conducted a similar study in Malaysia to understand the influencing factors to adopt e-government. The results of this study also supported that social influence positively influences behavioral intention to use e-government services. In UAE, the mobile government (m-government) adoption was investigated by Ahmad and Khalid (2017). They used and expanded TAM framework to include other factors such as social influence, trust and variety of services. The result showed that social influence affects the intention to use m-government services in UAE. The studies discussed suggest that social influence is one of the crucial determining factors for e-government services.

The capture the impact of social influence on e-government adoption intention, the current study hypothesizes that social influence positively and significantly affects citizens' attitude towards e-government services [*H3: Social Influence (SI) positively and significantly affects individual's Attitude (ATT)*].

Attitude as a Possible Mediator

Individual's favorable or unfavorable assessment towards technology adoption including e-government is explained as attitude towards technology adoption (Mensah et al., 2020). After analyzing various technology adoption models, Venkatesh et.al. (2003) concluded that the generalized feeling related to using technology is individuals' attitude towards technology adoption. Individual with favorable attitude are more inclined to engage in e-government services than those with unfavorable attitude.

Previous researchers have looked in the roles of attitude in shaping the behavioral intention to use e-government services. Gultom et.al (2020) did a study in Indonesian individuals Intentions to Use E-Government (ITUEG). Their survey of 477 Indonesian citizen and subsequent analysis revealed that attitude affected the ITUEG. Other scholars (Eid et al., 2021; Sarasati & Madyatmadja, 2020) drawn similar correlation between attitude and e-government adoption intention.

In addition to playing a direct role in the behavioral intention, Attitude (ATT) has been studied as a mediator in other researches. Dwivedi et al. (2017) in their Unified Model of E-Government Adoption (UMEGA)

suggested that attitude is the internal cognitive mechanism that leads to behavioral inclination by assimilates the external factors of performance expectancy, effort expectancy and social influence. Previous studies (Lallmahomed et al., 2017; Weerakkody et al., 2013) have established performance expectancy as a significant influencing factor for e-government behavioral intention. Opposing results were also obtained in some studies (Krishnaraju et al., 2016). Similarly, effort expectancy (Venkatesh et al., 2012; Weerakkody et al., 2013) and social influence (Oliveira et al., 2016; Šumak & Šorgo, 2016) have been established as influencing factors in e-government adoption intention. Nevertheless, there are studies that could not significantly establish these relationships (Lallmahomed et al., 2017; Weerakkody et al., 2013).

Scholars attempted to explain the contradictions of results in the studies discussed in previous section. The conclusion was that the performance expectancy, effort expectancy and social influence impact the behavioral intention through the moderating effect of attitude (Lin et al., 2011; Šumak & Šorgo, 2016). Taking this conclusion into account the current study tested the mediating effect of attitude as well.

Considering the earlier research findings, it is evident that attitude plays an important role in developing behavioral intention to use e-government services. Moreover, the mediating role of attitude for shaping behavioral intention is also noticeable from those studies. Aligning with these finding, the current study acknowledges that there exists a direct positive and significant relationship between individuals' attitude and their intention to use e-government services [*H4: Individuals' Attitude (ATT) positively and significantly affects behavioral intention to use e-government services (BI)*].

Furthermore, the mediating effect of attitude is captured in this study as well. The study proposes that attitude mediates the relationship between performance expectancy and behavioral intention [*H7: The relationship between Performance Expectancy (PE) and Behavioral Intention (BI) is mediated by Attitude (ATT)*]. Attitude also mediates the effect of effort expectancy on behavioral intention [*H8: The relationship between Effort Expectancy (EE) and Behavioral Intention (BI) is mediated by Attitude (ATT)*]. Finally, it is proposed that there also exist a mediating effect of attitude in the relationship between social influence and behavioral intention to use e-government services [*H9: The relationship between Social Influence (SI) and Behavioral Intention (BI) is mediated by ATT*].

Facilitating Conditions (FC)

Technology system requires appropriate infrastructure and support to be successful. Facilitating the systems use therefore is critical. In the realm of technology adoption, Facilitating Conditions (FC) is the measure of peoples' confidence in the associated organizational and technical support (Venkatesh et al., 2003). The e-government facilitating conditions relates to citizens beliefs that necessary resources are available for them to use and access the services (Verkijika & De Wet, 2018).

The role of facilitating conditions in the e-government adoption has been examined in various studies. In 2019, a study was done in Togo to understand the influencing effects of various factors on e-government adoption. One of the conclusions of that study was that facilitating conditions significantly and positively influence the e-government adoption intentions of citizens of Togo (Chen & Aklikokou, 2020). Alraja (2016) used the social influence and facilitating conditions constructs from UTAUT model to investigate employees' intention to use e-government in Oman. The study results support the significant positive relationship between facilitating conditions and behavioral intention. Similar study by Susanto and Aljoza (Susanto & Aljoza, 2015) in Indonesia, however, could not find any significant relationship between facilitating conditions and intention. This variation of result could be explained by the contextual nature of the studies. Nevertheless, studies on e-government adoption intention generally include facilitating conditions as an influencing factor.

Trust in Government (TIG) as a Possible Mediator

Trust in Government (TIG) in the context of e-government services refers to citizens' faith in the ability of their governments to provide high quality services. Trust in government plays a crucial role in e-government adoption (Bélanger & Carter, 2008; Gefen et al., 2005).

Previous scholars have examined the role of trust in government as the intermediary. Study by Hooda et. al. (2022) looked into the effects of trust in the intention to use e-government services. They found out that performance expectancy, effort expectancy and social influence and facilitating conditions affects the trust in government, which in turns affects the e-government adoption intention. In a study in Malaysia, Kamarudin et. al. (2021) studied the responses of 388 participants of telecenters in rural Malaysia. The results demonstrated that trust partially mediated the use of the telecenter services. Abu-Shnab and Al-Azzam (2012) investigated e-government use intention among Jordanian citizens. They were able to establish that trust in government significantly mediates behavioral intention to use e-government services.

In the UTAUT model, the facilitating condition is hypothesized as not having any effect on the behavioral intention. However, previous sections provided literature evidence that facilitating conditions affects behavioral intentions through the mediating role of trust in government. Considering these scholarly findings, the current study also investigated the mediating role of trust in government in the relationship between facilitating conditions and behavioral intention. A hypothesis is included in the current study that speculates that facilitating will influence how much people trust their government [*H5: Facilitating Conditions (FC) positively and significantly affects Trust in Government (TIG)*]. It is also stipulated that trust in government will increase the behavioral intention to use e-government services [*H6: Trust in Government (TIG) positively and significantly affects Behavioral Intention (BI)*]. Furthermore, when people develop trust in their government by experiencing enabling conditions, they are more likely to use the e-government services [*H10: The relationship between Facilitating Conditions (FC) and Behavioral Intention (BI) is mediated by Trust in Government (TIG)*].

Underpinning Theory

The study used the basic premise of the UTAUT model. The well-established UTAUT model (Venkatesh et al., 2003) suggests that there performance expectancy, effort expectancy and social influence impact the behavioral intention that eventually leads to actual use of the technology. It further suggests that facilitating conditions influences the use behavior directly and does not affect behavioral intention. Additionally, the model incorporates that gender, age, experience and voluntariness of use moderates other relationships. The following figure presents a diagram of UTAUT model.
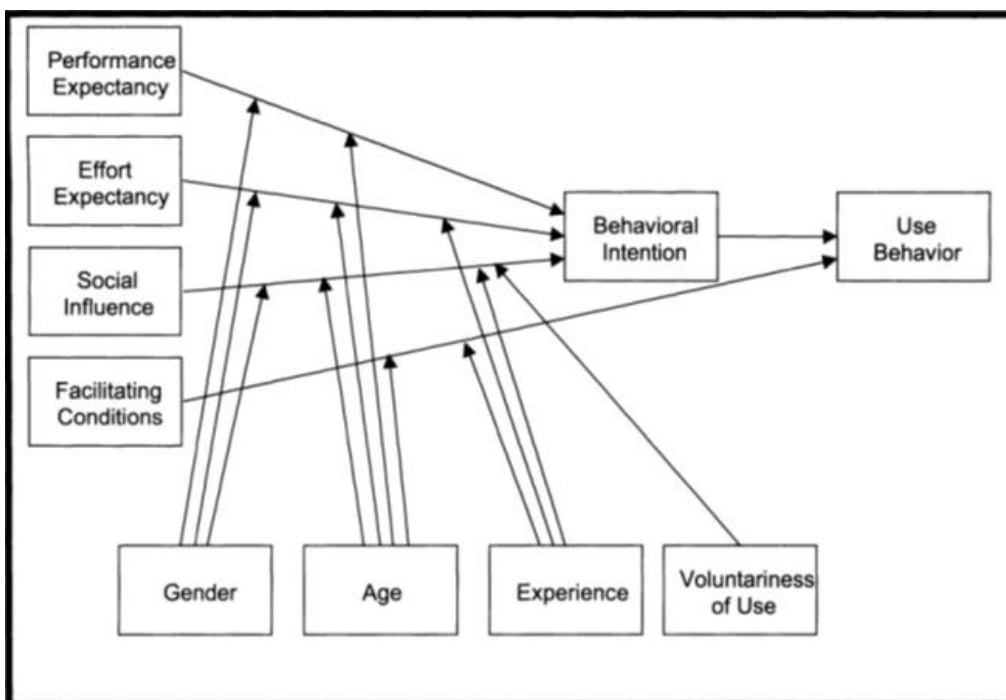

Figure 2: Unified Theory of Acceptance and Use of Technology (UTAUT)

Source Venkatesh et.al. (2003)

RESEARCH FRAMEWORK

Based on the underpinning UTAUT model and literature review presented in the earlier sections, the current research used the following research framework for investigating the e-government adoption of Bangladeshi citizens.
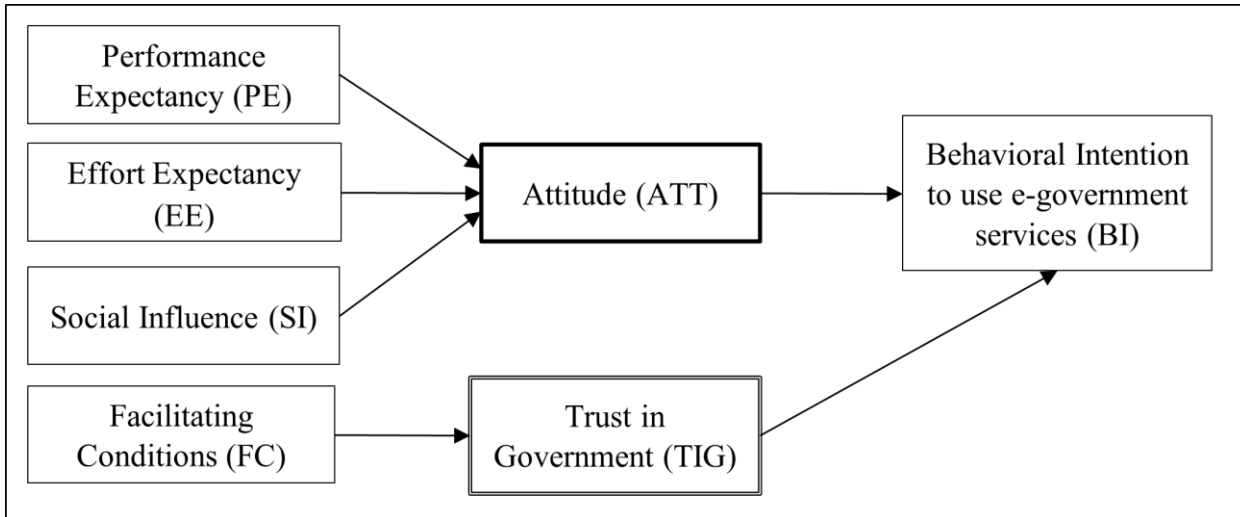

Figure 3 Proposed E-government Adoption Intention Research Framework (based on UTAUT framework)

The research framework suggests that performance expectancy, effort expectancy and social influence affect people attitude towards the e-government services. Favorable attitude will eventually result in an intention to use the services. The framework also indicates that e-government related facilitating conditions will build trust in government among the public, which will propel a behavioral intention to use e-government services.

METHODOLOGY

The study was conducted in Bangladesh. The exploratory research design with purposive sampling was used for conducting the research. Data were collected from Bangladeshi citizens aged between 18-64 years and who have used or at least are familiar with e-government services available in the country. According to Statista (2023), the population of Bangladesh is about 116 million. 67.9% of this population makes up the age group between 18-64. Sekaran and Bougie (2016) provided a sample -size determination table. According to their table, for any population of more than 1,000,000 the sample size should be 384. Current study follows this guideline. Subsequently, the sample size was set at minimum of 384. This study used quantitative research method. For data collection a questionnaire was developed. The items in the questionnaire were adapted from earlier studies (Bélanger & Carter, 2008; Davis, 1989; Dwivedi et al., 2017; Venkatesh et al., 2003). A pilot survey was conducted to test the reliability and validity of the questionnaire. Satisfactory Cronbach's alpha coefficient for the test was obtained to proceed with data collection. 450 respondents were provided with the Google form questionnaire. 390 responses were achieved. After filtering the outliers, 384 usable data were used for the analysis. The study used SPSS 27 software for data cleaning and screening. SMART-PLS 4.0.1.8 for Partial Least Squares Structural Modeling (PLS-SEM) was used considering complexity of the model and the non-parametric nature of the data. The validity and reliability were ensured through PLS algorithm. Bootstrapping of 5000 resamples was used to evaluate the structural model. Path coefficients, t-values, R^2 values, effect sizes (f^2), and predictive relevance (Q^2) were examined as suggested by Hair et al. (Hair et al., 2019).

RESULTS AND DISCUSSION

A survey questionnaire was electronically distributed using Google forms to collect data. The collected data were cleaned and screened using SPSS27. PLS-SEM was used to analyze the data using SMART PLS 4.0.1.8

as per the guidelines of Ringle et. al. (Ringle et al., 2015). The following sections present different findings from the analyses.

Data Screening

450 questionnaires were distributed and 390 successful responses were amassed providing an 86.7% response rate. The high response rate helped in ensuring representative and reliable data for analysis.

Outliers

Using the visual methods of box plots in SPSS software outliers were detected. The cutoff range of ±3 standard deviation was chosen. 6 outliers were detected in the process and they were excluded from the data set. Finally, 384 responses were analyzed further.

Demographic Profile

The demographic profile of the respondents collected from SPSS is presented in the following table.

Table 4: Demographic Profile of the respondents

Demographic Characteristics	Frequency	Percentage
Gender		
Male	215	56.00
Female	169	44.00
Age		
18-24	73	19.00
25-34	199	51.80
35-44	56	14.60
45-54	49	12.80
55-64	7	1.80
Highest Education		
Bachelors	220	57.30
Master's	138	35..90
Advanced Degrees	26	6.80
Occupation		
Employed	217	56.50
Self-Employed	65	16.90
Unemployed	103	26.60

(Source: SPSS 27 generated)

The representation of male and female are not significantly with 56% and 44% respectively. The maximum number of respondents belong to the age group 25-34 (51.8%) indicating that relatively young adults were the dominating participants in the survey. About 57% of the respondents hold a Bachelor's degree followed by 35% with Master's level educational qualification. This indicates that the sample is highly educated sample. Finally, employment status suggests that the highest number of the sample population are either employed or self-employed (about 73.4%).

Common Method Bias

Using the Herman's Single Factor Test, the Common Method Bias was tested for the study. Table 5 shows the result for the test.

Table 5: Harman's Single Factor test for Common Method Bias

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	15.713	44.893	44.893	15.713	44.893	44.893

(Source: SPSS 27 generated)

The result shows that the single component was associated with 44.893% of the variance. This is less than the 50% threshold recommended (Kock, 2020) confirming that the study is free from any common method bias issue.

Measurement Model Assessment

For assessing the measurement model of the study, PLS algorithm was used to evaluate factor loadings, convergent validity, discriminant validity, reliability, multicollinearity and model fit. The following sections provide the results of these evaluations.

Construct Validity

To assess the construct validity, the indicator and cross loading were examined. Table 6 shows the results of the outer loading scores. According to Hair et. al. (Hair et al., 2019), values 0.7 and above is the cut-off range for indicator loadings.

Table 6: Outer loading scores

	ATT	BI	EE	FC	PE	SI	TIG
ATT1	0.857						
ATT2	0.875						
ATT3	0.877						
ATT4	0.779						
ATT5	0.831						
BI1		0.893					
BI2		0.870					
BI3		0.896					
BI4		0.878					
BI5		0.901					
EE1			0.806				
EE2			0.836				
EE3			0.824				
EE4			0.834				
EE5			0.742				
FC1				0.784			
FC2				0.784			
FC3				0.787			
FC4				0.855			
FC5				0.787			
PE1					0.758		

PE2					0.803		
PE3					0.895		
PE4					0.893		
PE5					0.850		
SI1						0.812	
SI2						0.866	
SI3						0.871	
SI4						0.874	
SI5						0.726	
TIG1							0.860
TIG2							0.873
TIG3							0.857
TIG4							0.857
TIG5							0.862

(Source: PLS-SEM Algorithm using SMART PLS 4.1.0.8)

The VIF loading scores for all items are higher than the recommended cut of 0.7. This indicates that the items in the constructs are satisfactory and construct validity is established.

Convergent Validity

The convergent validity measure how well the items converge to the same construct they were meant to measure (Hair et al., 2019). Using the Average Variance Extracted (AVE) method the convergent validity is measured. AVE greater than 0.5 is required to confirm the convergent validity of each element (Fornell & Larcker, 1981). As seen from Table 7, the AVEs of all constructs are more than the recommended value of 0.5 establishing good convergent validity for the current study.

Table 7: AVE scores

	Average variance extracted (AVE)
ATT	0.714
BI	0.788
EE	0.654
FC	0.640
PE	0.708
SI	0.691
TIG	0.743

(Source: PLS-SEM Algorithm using SMART PLS 4.1.0.8)

Discriminant Validity

For assessing the discriminant validity for the study Fornell-Larcker criterion and Heterotrain-Montrait (HTMT) ratio were used. Fornell and Larcker recommended that to establish discriminant validity, the square root of each construct's AVE be greater than correlation coefficients (Fornell & Larcker, 1981). As shown in Table 8, all square roots of AVE of the constructs for this study fulfill Fornell and Larcker criterion.

Table 8: Fornell-Larcker Criterion Scores

	ATT	BI	EE	FC	PE	SI	TIG
ATT	0.845						
BI	0.785	0.888					
EE	0.593	0.670	0.809				
FC	0.641	0.675	0.646	0.800			
PE	0.668	0.649	0.663	0.566	0.841		
SI	0.500	0.571	0.637	0.555	0.495	0.832	
TIG	0.438	0.480	0.518	0.382	0.342	0.508	0.862

(Source: PLS-SEM Algorithm using SMART PLS 4.1.0.8)

The study also applied HTMT to confirm the discriminant validity. The stricter guideline of 0.85 threshold (Henseler et al., 2015) was used for the study. Table 9 shows the result of the HTMT test. It shows that values are lower than that threshold ensuring discriminant validity.

Table 9: HTMT scores

	ATT	BI	EE	FC	PE	SI	TIG
ATT							
BI	0.857						
EE	0.666	0.742					
FC	0.748	0.763	0.731				
PE	0.740	0.707	0.741	0.651			
SI	0.556	0.626	0.722	0.618	0.550		
TIG	0.479	0.515	0.584	0.398	0.371	0.560	

(Source: PLS-SEM Algorithm using SMART PLS 4.1.0.8)

Reliability

For the testing the reliability, this study used Cronbach's alpha and Composite reliability. Hair et. al. (Hair et al., 2019) recommended 0.7 or higher as the threshold level for confirming the reliability. The test results for the Cronbach's alpha and Composite reliability are tabulated in Table 10. All values meet the 0.7 threshold establishing the reliability for the study's constructs.

Table 10: Cronbach's alpha and Composite reliability scores

	Cronbach's alpha	Composite reliability
ATT	0.899	0.926
BI	0.933	0.949
EE	0.868	0.904
FC	0.864	0.899
PE	0.896	0.924
SI	0.887	0.918
TIG	0.914	0.935

(Source: PLS-SEM Algorithm using SMART PLS 4.1.0.8)

Model Fit

The Standardized Root Mean Square Residual (SRMR) was used to ensure adequate model fit for the study. Hair et. al (Hair et al., 2019) recommended a value lower than 0.08 for satisfactory fit. The study's SRMR score was 0.056, which is lower than the 0.08 threshold ensuring adequate model fit. The SRMR data was generated using Source: PLS-SEM Algorithm in SMART PLS 4.1.0.8.

Structural Model Assessment

In the structural model assessment phase, Muliti-collinearity assessment, Coefficient of Determination (R^2) assessment, Effect Size (f^2) assessment and Predictive Relevance (Q^2) assessment were carried out. Finally, Path Coefficient assessment was carried out to test the hypotheses. The following sections detail the results of these assessments.

Muliti-collinearity Assessment

The Variance Inflation Factor (VIF) was used for assessing the collinearity among the indicators. Hair et. al. (Hair et al., 2017) recommended a VIF score of lower than 5 to avoid high collinearity effects. The VIF scores for this study are provided in Table 11.

Table 11: VIF scores of the indicators

Items	VIF
ATT1	2.543
ATT2	2.995
ATT3	2.958
ATT4	1.767
ATT5	2.244
BI1	3.440
BI2	2.830
BI3	3.465
BI4	3.193
BI5	3.488
EE1	2.223
EE2	2.481
EE3	2.108
EE4	2.203
EE5	1.659
FC1	1.890
FC2	2.076
FC3	1.509
FC4	2.467
FC5	2.341
PE1	1.824
PE2	2.078
PE3	3.416
PE4	3.518
PE5	2.428
SI1	2.120

SI2	2.552
SI3	2.706
SI4	2.614
SI5	1.563
TIG1	2.870
TIG2	3.123
TIG3	2.524
TIG4	2.574
TIG5	2.412

(Source: PLS-SEM Algorithm using SMART PLS 4.1.0.8)

From the table it is seen that all values meet are lower than the threshold value of 5 indicating no issues with collinearity in the model.

Coefficient of Determination (R2) Assessment

Coefficient of Determination (R^2) represents the portion of endogenous construct variation that is explained by its exogenous constructs (Hair et al., 2017). R^2 values for the study are tabled in Table 12.

Table 12: Coefficient of Determination (R^2) values

Constructs	R-square	R-square adjusted
ATT	0.499	0.495
BI	0.638	0.637
TIG	0.146	0.144

(Source: PLS-SEM Algorithm using SMART PLS 4.1.0.8)

According to R^2 table, it can be concluded that 49.5% of the variance in Attitude (ATT) is explained Performance Expectancy (PE), Effort Expectancy (EE) and Social Influence (S). The R^2 adjusted valued of 0.637 points that the 63.7% Behavioral Intention (BI) variation is attributed to PE, EE, SI, FC (Facilitating Conditions), ATT and TIG (Trust in Government). Finally, the 14.4% (R^2 adjusted value of 0.144) variation in TIG is explained by FC.

Based on these result, it is seen that model has good explanatory power for BI and ATT. The explanatory power for TIG is low. However, given that the TIG is influenced by numerous external factors, the variation explanation of one factor of FC is not expected to be high. Besides, the indirect effect of TIG shows statistically significant result (p value of 0.001) which suggest that TIG plays and important role as the mediator. The full results of indirect effects are discussed in later sections.

Effect Size (f2) Assessment

Effect Size (f^2) represents the impact of endogenous variable on the exogenous variables. Cohen categorized the f^2 into three levels. Small effect size ranges between 0.02 to 0.15, medium size ranges between 0.15 to 0.35 and large size are above 0.35 (Cohen, 2013). Table 13 shows the effect size results.

Table 13: Effect Size (f^2) values and interpretation

Predictors	f^2 Values	Result Interpretation
Attitude (ATT)	1.129	Large Effect
Effort Expectancy (EE)	0.030	Small Effect
Facilitating Conditions (FC)	0.171	Medium Effect

Performance Expectancy (PE)	0.245	Medium Effect
Social Influence (SI)	0.026	Small Effect
Trust in Government (TIG)	0.063	Small Effect

(Source: PLS-SEM Algorithm using SMART PLS 4.1.0.8)

Comparing the effect size results with Cohen's categories, it is found that ATT has large effect on BI. TIG, on the other hand has small effect on BI. PE has medium effect on ATT. However, EE and SI have small effect on ATT. Finally, FC shows medium effect on TIG. The large effect of ATT is consistent with previous research findings (Ajzen, 1991; Venkatesh et al., 2012). Despite the small effect of TIG, the inclusion of TIG is justified as it is statistically significant (p=0.001).

Predictive Relevance (Q2) Assessment

Predictive relevance tells us the level of accuracy of indicators. Hair et. al. (Hair et al., 2017) suggested that cross validated redundancy method is most effective in assessing the predictive relevance. In SMART-PLS 4.1.08, using the blindfolding technique with an omission distance of 7, Stone-Geisser's Q^2 was calculated. Stone-Geisser's Q^2 low, medium and high predictive relevance benchmark at 0.02, 0.15 and 0.35 respectively were employed to assess the Q^2 for the study. The following table details the result.

Table 14: Predictive Relevance (Q^2) results and interpretation

	SSO	SSE	Q² (=1-SSE/SSO)	Interpretation
Attitude (ATT)	1920.000	1256.450	0.346	High predictive relevance
Behavioral Intention (BI)	1920.000	963.655	0.498	High predictive relevance
Trust in Government (TIG)	1920.000	1716.666	0.106	Low predictive relevance

(Source: PLS-SEM Blindfolding method using SMART PLS 4.1.0.8)

The high values of Q^2 for ATT and BI indicate that the structural model has very good predictive relevance to predict the citizens' attitude and intention to adopt e-government services. On the other hand, the low predictive relevance of TIG indicates that the model can partially predict the.

Path Coefficient Assessment and Hypotheses Testing

To assess the direct and indirect relationships, this study applied the bootstrapping method with 5000 resampling as recommended by Hair et. al. (Hair et al., 2017). The resulting p values were used to decide on the hypotheses. The following sections discusses in detail that path coefficient assessment and subsequent hypotheses decisions.

Path Coefficient of Direct Relationships

Following table presents the hypothesized direct relationships, path coefficient results and hypotheses decisions.

Table 15: Hypothesis and Path Coefficient results of direct relationships

No.	Hypothesis	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H1	**PE -> ATT**	0.472	0.472	0.066	7.109	0.000	Supported
H2	**EE -> ATT**	0.186	0.185	0.072	2.589	0.010	Supported
H3	**SI -> ATT**	0.148	0.149	0.049	2.989	0.003	Supported

H4	**ATT -> BI**	0.711	0.710	0.031	23.096	0.000	Supported
H5	**FC -> TIG**	0.382	0.389	0.048	7.923	0.000	Supported
H6	**TIG -> BI**	0.168	0.169	0.041	4.093	0.000	Supported

(Source: PLS-SEM Bootstrapping method using SMART PLS 4.1.0.8)

The results in Table 15 show that with, hypotheses are 1, 2 and 3 are all supported. Respective β values of 0.472, 0.186 and 0.148, T values of 7.109, 2.589 and 2.989 and p values of 0.000, 0.010 and 0.003 suggest that Performance Expectancy, Effort Expectancy and Social Influence positively and significantly influence individual's attitude toward e-government adoption intention. This is consistent with findings in earlier researches of Dwivedi et. al (Dwivedi et al., 2017), Fakhruzzaman & Dimitrova (Fakhruzzaman & Dimitrova, 2020), Lin et. al (Lin et al., 2011), Meiyanti et al. (Meiyanti et al., 2018), Mohammadi (Mohammadi, 2022) and Šumak & Šorgo (Šumak & Šorgo, 2016).

With supporitng values of β = 0.711, T=23.096 and p=0.000 hypothesis 4 is supported indicating a positive and significant relationship between individual's attitude towards e-government services and their adoption intention of the same services. This finding aligns with findings by previous scholars (Dwivedi et al., 2017; Eid et al., 2021; Gultom et al., 2020; Sarasati & Madyatmadja, 2020).

The relationship between Facilitating Conditions and Trust in Government (hypothesis 5) as well as the relationship between Trust in Government and Behavioral Intention (hypothesis 6) were established. Facilitating conditions positively and significantly influences Trust in Government (β = 0.382, T=7.923 and p=0.000). While β = 0.168, T=4.093 and p=0.000 for hypothesis 6 suggests that if people trust their government it will positively and significantly influence their intention to use e-government services. The relationship of FC with TIG found in this study is evident in previous study by Hooda et. al (Hooda et al., 2022). The TIG-->BI relationship is evident in stud of Hooda et. al (2002) (Hooda et al., 2022) and Kamarudin et. al. (2021).

Path Coefficient of Indirect Relationships

Path coefficients results of indirect relationships are presented in Table 16.

Table 16: Hypothesis and Path Coefficient results of indirect relationships

No.	Hypothesis	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H7	PE -> ATT -> BI	0.132	0.132	0.052	2.538	0.011	Supported
H8	EE -> ATT -> BI	0.335	0.335	0.049	6.877	0.000	Supported
H9	SI -> ATT -> BI	0.105	0.106	0.036	2.948	0.003	Supported
H10	FC -> TIG -> BI	0.064	0.066	0.019	3.358	0.001	Supported

(Source: PLS-SEM Bootstrapping method using SMART PLS 4.1.0.8)

Mediating Effect of Attitude (ATT)

From Table 16 shows that the effects of Performance Expectancy and Effort Expectancy on Behavioral Intention though Attitude hypothesized in hypothesis 7 and 8 are supported. The Respective Path coefficient β values of 0.132 and 0.335, the Test Statistic T values of 2.538 and 6.877 and Probability p values of 0.011 and 0.000 indicates that when people perceive better performance from the e-government services and believes that it is easy to use the services, they form positive and significant favorable attitude towards the services. This eventually makes them inclined to towards the available e-government services. This finding is consistent with earlier research by Dwivedi et al., (Dwivedi et al., 2017), and Venkatesh et. al. (Venkatesh et al., 2012).

The Social Influence has positive and significant impact on peoples' Attitude towards e-government services. This was the essence of hypothesis 9 of this study. The favorable results (β =0.105, T=2.948 and p=0.003) as presented in Table 16 supports the hypothesis. It implies that if people are positively influenced by others in the society, they will favorably evaluate e-government services and lean towards using them. The study results align with similar results found earlier studies (Dwivedi et al., 2017; Oliveira et al., 2016; Šumak & Šorgo, 2016).

Mediating Effect of Trust in Government (TIG)

The mediating effect of Trust in Government in the relationship between Facilitating Conditions and Behavioral Intention was captured in hypothesis 10 of this study. The results from Table 16 supports this hypothesis (β =0.064, T=3.358 and p=0.001). It implies that ensuring adequate support for using e-government services by the government will develop and trust in people that the government is sincere in supporting them in using the services. The high trust in government will in turn incline people to use the e-government service.

DISCUSSION AND CONCLUSION

This study used a research framework based on UTAUT model to investigate the factors influencing e-government adoption intentions among Bangladeshi citizens. Ten hypotheses were developed and tested in the study. Statistically significant results were found for all hypotheses.

It is concluded from the tested hypotheses that Performance Expectancy, Effort Expectancy and Social Influence have positive and significant influence on Attitude formation. This implies that when citizens perceive that the use of e-government service platform will bring them more benefit than the traditional platform, they are likely to develop a positive attitude towards it. Similarly, if people start to believe that using e-government is not present difficulties for them their attitude towards e-government will be favorable. Finally, when individuals get the encouragement and approval from their social circle, they are likely to be curious about the e-government services. As their social setting encourages them to try out e-government services, they will approach it with a favorable mindset.

The role of attitude is critical in shaping positive behavioral intention to adopt e-government services. When people build a favorable attitude towards the services, they are more likely to engage and adopt. The antecedent environment supporting the perception of better outcome, easy operation and social support creates the favorable attitudinal component among people towards e-government services. The positive attitude elicits a favorable behavioral inclination that results in more engagement in e-government services.

The study was able to establish the crucial role of Bangladeshi citizens' trust in their government in the context of e-government adoption behavior. It is concluded that if people trust their government, they are more likely engage in e-government services provided by their government. The trust in government builds through different sources. The adequate and efficient support by the government is one of them. When people want to use the e-government services, they expect that the necessary institutional and technical support is available. The supporting conditions enable a trusting relationship between the citizen and the government. If people face inadequate support they starts to question the sincerity of the government in making the e-services successful. The lack of supporting environment creates doubt in peoples' mind and it deters them from engaging in e-government services.

The study results points out that simply rolling out e-government services is fruitless unless people's engagement is ensured. The sophistications of the system do not guarantee success of e-government endeavors. Rather when citizen with favorable attitude approach and engage in the deployed services, it enhances the chance of attaining the true benefits. The citizens need to have a positive mindset and trust their government for them to truly participate in the e-government services. Developing favorable attitude and trust on government requires ensuring higher performance from the services, easy operation of the systems, engaging broader society and adequate support.

By extending the UTUAT in the e-government setting, this study contributes towards the scarcity of literature directed towards e-government adoption instead of technology adoption. introducing and investigating the mediating role of attitude and trust in government provides dimensions that are not included in UTAUT. The study presented a new research framework for analyzing influencing factors of e-government adoption. It contributes to the field of e-government study by providing some unexplored dimensions of analysis. The study also validated the presented framework with empirical data. It contributes toward future research along this line using the same framework. Moreover, analyzing in the Bangladeshi context provides a platform for understanding e-government adoption status in developing nations. The study outcomes offer the policymaker guideline to develop and deploy citizen centric e-government services. The Bangladesh government can incorporate these findings in their e-government strategy to ensure better participation of the citizen. They can use these findings to develop and implement platforms fulfilling the requirements of the Bangladeshi citizens. Additionally, the government can design the monitoring plan keeping the crucial factors discussed in this study. From the system developers' point of view, they can use these findings to design the tailor made systems incorporating the unique requirement of citizens of Bangladesh. The citizens can also benefit from this study by understanding the factors that is shaping up their behavior. In doing so, they can be more informed about the using the e-government platforms. The government of Bangladesh should invest in creating positive perception about the e-government services before they actually roll the platforms. They could educate people about the benefits of the services. They could do it through social campaigns to create a ripple effect. Additionally, by developing and publicizing the supporting facilities to use e-government services, the government should ensure that people develop a trusting viewpoint about the government. The government should test the platforms before rolling out to ensure the minimum possible difficulties faced by the citizen when they actually participate.

The study did not include all regions of Bangladesh in the data collection phase. This creates potential hurdle in drawing general conclusion about the entire population of Bangladesh. The framework used was restricted to limited number of factors. The model explains about 63% of variance suggesting that excluded factors could provide a higher explanatory score. The factors like digital literacy, cyber security and mobile density could have been incorporated in the study to give more robust analysis framework. In the study, the trust in government is looked into from the perspective of facilitating conditions only. The explanatory power of about 14% suggests that there are other components associated with trust in government. Inclusion of factors like perceived competence, corruption, political stability and service quality could have improved the study findings. Finally, the quantitative method of the study does not provide nuanced insight possible with qualitative method. For future research, the scope could be extended to other regions of Bangladesh. The research framework could be extended by incorporating other factors such as digital literacy and cyber security. More comprehensive research design could be used to investigate the trust in government more comprehensively. Additionally, a mix method approach could be used in the future research to provide the qualitative explanations to the statistical outcomes.

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