



# American Journal of Economics and Business Innovation (AJEBI)

ISSN: 2831-5588 (ONLINE), 2832-4862 (PRINT)

**VOLUME 5 ISSUE 3 (2026)**

**PUBLISHED BY  
E-PALLI PUBLISHERS, DELAWARE, USA**

## Determinants of Consumers' Adoption of App-Based Mobile Financial Services in Bangladesh: The Role of Financial Trust

Masum Bellah<sup>1</sup>\*

### Article Information

**Received:** June 03, 2026

**Accepted:** August 13, 2026

**Published:** October 06, 2026

### Keywords

*App-Based Mobile Financial Services, Bangladesh, Behavioral Intention, Financial Trust, Fintech Adoption, PLS-SEM*

### ABSTRACT

This paper looks at the drivers of behavioral intention of consumers to adopt app-based mobile financial services in Bangladesh, especially focusing on financial trust. A survey survey was conducted which yielded 430 valid responses. In the proposed PLS-SEM Model, the following predictors of behavioral intention were included performance expectancy, effort expectancy, social influence, facilitating conditions, perceived financial value and financial trust. The measurement model obtained a satisfactory level of indicator reliability, internal reliability, convergent and discriminant validity. Such issues as common method bias and structural collinearity were not major issues. The structural model accounted 61.68% of the variance in behavioral intention and was significantly predictively relevant. The most positive influence was on performance expectancy and next, financial trust. Effort expectancy, perceived financial value, and social influence also had a significant positive impact. There was no statistically significant direct effect of conditions that facilitated. According to the out of sample test, the PLS model produced smaller root mean squared prediction errors in comparison to the linear benchmark in all indicators of behavioral intentions. The results suggest that consumers embrace mobile financial application when they perceive that it has a distinct functional advantage, the providers are trustworthy to safeguard financial interests, the applications are user friendly and are getting reasonable value. The research provides practical recommendations to the providers, regulators, and platform designers aiming to adopt sustainably, reasonably, and inclusively.

### INTRODUCTION

Fintechs transform how consumers access, transfer, store, and manipulate money. The change is particularly apparent in Bangladesh in terms of smartphone applications that facilitate mobile financial services. These applications enable consumers to send and receive money, pay merchants, recharge mobile accounts, pay utility bills, buy goods, cash in or cash out, and utilize the choice of savings or other financial features (M. Anwarul Islam *et al.*, 2024). They are relevant in more than convenience in transactions. Mobile financial services created through apps can help break the reliance on physical branches, reduce the time spent on making transactions, enhance the availability of services, and bridge consumers to formal or semi-formal financial intermediaries. Such benefits are significant in a nation where geographic location, service overload, and ad hoc working schedules and skewed access to traditional banking can limit financial inclusion. Quick access, however, is not a sure sign of adoption (Emini *et al.*, 2026). The mobile finance application is considered by consumers based on a number of practical and psychological factors. Their questions are: Will performance of transactions be improved? Is the application easy to learn? Do people around them approve of using the application? Do they have resources and knowledge to use it? Do they see the value of transaction charges and other costs to be worthwhile? As money, personal details, and relying on a digital

mediator are used, the consumers also evaluate whether the provider is trustworthy, honest, safe, and able to solve the issues (Sandhu *et al.*, 2022). An application that is technically functional might thus not be used fully when the consumers lack trust in the provider or are expecting to lose money.

Access to education is not just a matter of simple access. A consumer can have an internet connection and own a smartphone but not use it on a regular basis. A different consumer can learn the interface, but choose cash due to the high cost of a digital fee. The current users can restrict themselves to mobile recharge or transfer as opposed to its wider financial capability (Hosmani & Raghukant, 2025). Consumers can also differentiate between awareness, trial, subsequent intention and increased usage. These disparities show that infrastructure is insufficient to determine adoption. To address functional expectations, user effort, social pressures, enabling conditions, value judgments and trust, a multidimensional model is necessary.

This paper is specifically devoted to mobile financial services implemented using apps and not the sector of FinTech. FinTech encompasses online loan brokering, financial application, insurance tech, cryptocurrencies, crowdsourcing, robo-advice, and many more (Nedeljković, 2022). The mixture of these types may hinder the identification of factors affecting adoption since risk, complexity, regulation and user purpose vary significantly

<sup>1</sup> Lecturer- Economics, Begum Rahima Islam College, Charfashion, Bhola, Bangladesh

\* Corresponding author's e-mail: [masumbellah121@gmail.com](mailto:masumbellah121@gmail.com)

across services. Restricting the study operationally to app-based mobile financial services gives the study a better unit of analysis and results that are applicable to highly utilized consumer applications in Bangladesh.

The research constructs a model based on the key consumer technology-adoption mechanisms modeled by UTAUT2 but retains the research title centered on the applied phenomenon (Gani *et al.*, 2022). Technology-related determinants include performance expectancy, effort expectancy, social influence, facilitating conditions and perceived financial value. Financial trust is added to reflect the distinct vulnerability created by digital financial transactions. Behavioral intention to increase or switch to using app-based mobile financial services is a dependent construct (Adesola Oluwatosin Adelaja *et al.*, 2024). This model acknowledges the fact that technological utility and trust in the financial service relationship affect adoption choices.

The partial least squares structural equation modeling is the empirical analysis. This technique can be used to estimate a prediction-oriented model with a few latent constructs to be measured by multiple indicators. It empowers a simultaneous determination of quality of measurements as well as structural relationships. It also analyses the explanatory power, predictive relevance and out of sample prediction beyond significance testing (Mamun *et al.*, 2023). This assessment is essential since a model that is supposed to guide providers and policymakers must not be able to explain the observed sample, but it must also show useful predictive ability.

The research has three key contributions. First, it categorizes FinTech usage into a clear consumer service offering, enhancing conceptual accuracy. Second, it combines financial trust with the pre-existing technology-adoption determinants and evaluates the comparative impact of both in Bangladesh (Afrin & Sarker, 2025). Third, it measures both explanatory and predictive performance and employs a moderate PLS-SEM process. The results demonstrate that performance expectancy and financial trust are the most important determinants, whereas facilitating conditions do not lead to a significant direct influence. This trend implies that the present adoption decisions are less responsive to the availability of basic resources but rather have to deal with the perceived usefulness, credibility of the provider, ease, value, and social endorsement (Sadik & Rahman, 2024).

The rest of the paper will be structured in the following manner. The following section discusses the theoretical framework and comes up with six hypotheses. The research design, measurement, sample, data screening and the PLS-SEM procedures are described in the methodology section (Bashir & Muhammad, 2023). The results section includes the characteristics of the respondents, the measurement-model evaluation, the structural-model, and the predictive analysis. The findings are interpreted in the discussion concerning the consumer behavior and the Bangladeshi mobile financial environment. The last parts are theoretical and practical

implications, the limitations, future research directions and the conclusion.

## LITERATURE REVIEW

### Hypothesis Development

#### Consumer adoption of app-based mobile financial services

The use of mobile financial services by consumers is a choice to start, maintain, or increase financial transactions by using an application on a smartphone (Salah Uddin & Begum, 2023). The choice is not similar to the common application adoption since users share money, transaction logs, identity, and personal contacts information with a computer system. Their reliance is also on the provider, telecommunications infrastructure, agents, banks, merchants, and support channels (Datta, 2024). Adoption thus is a combination of technology acceptance with assessments concerning financial safety and institutional reliability.

In Bangladesh, app-based services will be able to shorten the distance in the transaction and avail access outside usual business banking hours. They also can streamline low-value payments and regular transfers (Khan *et al.*, 2022). However, consumers vary in terms of digital capability, income, experience, perceived risk and trust on service providers. Adoption can thus be more appropriately seen as a type of behavior as a result of a number of complementary beliefs. Neither a model of mere usefulness nor one of mere trust would provide a complete picture of this decision (Saha *et al.*, 2026).

#### Technology-adoption perspective

UTAUT2 is an effective starting point in consumer acceptance research since it elucidates intention via foreseen performance, anticipated effort, societal impact, enabling circumstances, price value, routine, and hedonic inspiration (Budiman *et al.*, 2025). This logic is reconfigured to a financial application in the current study. Hedonic motivation has been ruled out as mobile financial services are rather instrumental and not entertainment oriented. Habit cannot be considered either since there are respondents with various prior usage of the product, such as nonusers and recent users (Dawood *et al.*, 2022). The balance between the monetary or nonmonetary costs and service benefits is expressed as perceived financial value.

Finance brings in the technology perspective. It deals with trust that the providers will perform transactions in the proper way, securing money and information and telling the truth and how to deal with the failures of the services (Tsoloane, 2025). The framework created integrates functional, usability, social, enabling, value, and relational accounts of behavioral intention.

#### Performance expectancy

The level of expected performance by the consumers on how much they believe that using an application will enhance their financial activities is known as

performance expectancy (Sumaya *et al.*, 2025). The expected performance in the mobile financial services involves quicker transactions, easier access, less traveling, ease of paying bills, instant transfer, and better control of regular payments. These advantages are tangible and directly related to the objectives of consumers (Alam *et al.*, 2025). When users think an application is a saving and transaction efficiency, adoption becomes a natural and appealing option.

Performance expectancy might also play a crucial role in Bangladesh since consumers usually compare the application with cash, agents, bank counters, and informal means of transferring money (Jagatia, 2023). An electronic alternative should have a distinct benefit compared to known substitutes. Applications that operate well, provide the relevant services, and minimize the effort in procedures would be more likely to be seen as useful. Greater usefulness beliefs ought to consequently boost intention (Ahmed *et al.*, 2025).

**H1:** *Performance expectancy has a positive effect on consumers' behavioral intention to adopt app-based mobile financial services in Bangladesh. H1: Performance expectancy has a positive effect on consumers' behavioral intention to adopt app-based mobile financial services in Bangladesh.*

### Effort expectancy

Effort expectancy: It is the perceived ease of using and learning a technology. Mobil financial applications entail registration, authentication, menu navigation, selecting a recipient, entering amount, verification, and confirmation (Osakwe *et al.*, 2022). Complex interfaces or vague instructions can cause anxiety, more errors in transactions and can demoralize low-digital consumers. On the other hand, a clear interface saves on the amount of cognitive effort and facilitates confidence.

The ease of use applies not only during first adoption but also afterwards. Potential users might shun an application when they anticipate a hard learning process (Gbongli, 2022). Current users are likely to limit the use when new less familiar functions seem complex. These barriers can be reduced using language clarity, logical navigation, visible confirmation, and easy recovery procedures. Consumers are more likely to have intentions to use regularly when they think that they can become competent within a short period of time (Amnas *et al.*, 2023).

**H2:** *Effort expectancy has a positive effect on consumers' behavioral intention to adopt app-based mobile financial services in Bangladesh.*

### Social influence

The perceived expectations and recommendations of individuals that are relevant to the consumer show up in social influence (Akteer *et al.*, 2021). Financial applications are usually distributed within a family, friends, colleagues, merchants and at the community level. Such teams can offer information, show transactions, aid with registration, or normalize digital payment (Chowdhury & Hussain, 2022). When consumers lacked penetrating experience, their acceptance may decrease uncertainty.

This effect can be because of both normative pressure and observational learning. Consumers can access an app since other people anticipate that they will get transfers or pay using the internet (M. Anwarul Islam *et al.*, 2024). They can also deduce quality by the commonality with people whom they trust. Observable acceptance results in social legitimacy and lessening the notion that the service is exotic or potentially hazardous. Adoption intention should thus be enhanced by positive social influence.

**H3:** *Social influence has a positive effect on consumers' behavioral intention to adopt app-based mobile financial services in Bangladesh.*

### Facilitating conditions

Facilitating conditions are the resources, knowledge, compatibility, and aid required to utilize a service (Emini *et al.*, 2026). Mobile finance using apps presupposes an appropriate smartphone, network connection, power, registration data, digital literacy and access to customer care. There might also be a need of compatible bank accounts, agents, merchants, or payment channels by the consumers (Sandhu *et al.*, 2022). In cases where such conditions are not present, intention can be low despite a perceived usefulness.

This is especially necessary when a transaction fails or if users lose credentials. Operation barriers can be minimized with accessible customer service, comprehensible instructions and good complaints resolution (Hosmani & Raghukant, 2025). Nevertheless, with increasing access and low levels of familiarity with smartphones, the enabling conditions can be like a minimum requirement and not a robust driving force. Nevertheless, the consumers with a higher perception of enabling support should increase their intention (Nedeljković, 2022).

**H4:** *Facilitating conditions have a positive effect on consumers' behavioral intention to adopt app-based mobile financial services in Bangladesh.*

### Perceived financial value

Perceived financial value is the judgment of the consumer based on whether the advantages of a service surpass its monetary and nonmonetary expenses. Examples of such costs are transaction fees, cash-out fees, internet expenses, time learning, and potential inconvenience (Gani *et al.*, 2022). The benefits are speed, less travelling, promotional rewards, broad availability and access to payments. When this overall exchange is fruitful, then adoption will rise (Adesola Oluwatosin Adelaja *et al.*, 2024).

It is possible that consumers will ignore a useful service when the charges seem to be too high or unpredictable. They can also compare online expenses with cash, bank transfers or agent-facilitated options (Mamun *et al.*, 2023). Value is enhanced by transparent fees and visible savings. Due to high frequency and relatively low amounts of mobile financial transactions, small fees can influence behavior. Perceived value ought to be strong then raise willingness to adopt and expand usage (Afrin & Sarker, 2025).

**H5:** *Perceived financial value has a positive effect on consumers'*

*behavioral intention to adopt app-based mobile financial services in Bangladesh.*

### Financial trust

Financial trust is the belief that the provider is trustworthy, honest, competent, secure, and concerned about the financial interests of consumers (Sadik & Rahman, 2024). The trust is needed since the users cannot monitor the way transactions are conducted, or the way personal data is stored. They have to submit to system malfunction, fraud, unauthorized access, time lag transfer and poor responses to complaints (Bashir & Muhammad, 2023). The convenience may be less than the lack of trust.

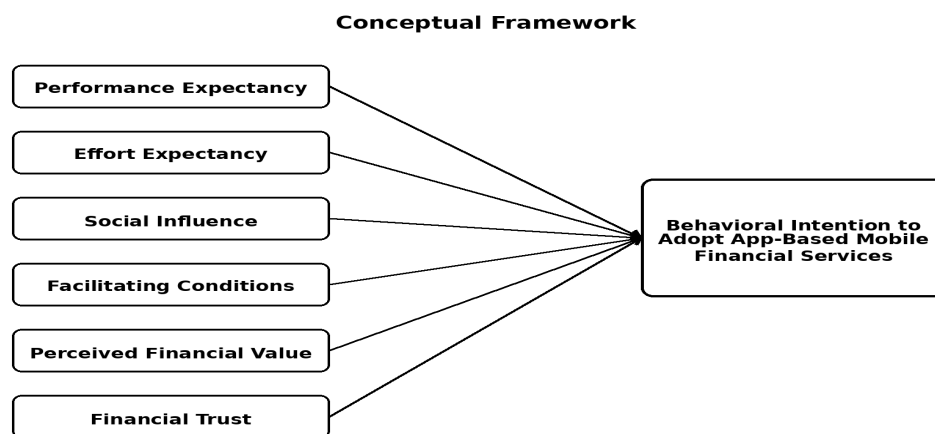
Perceived uncertainty can be mitigated by trust, which is then beneficial in enabling dependence on the application. Consumers tend to send or keep balances when they think that the provider will deliver the transactions as expected and keep confidential information secure (Salah Uddin & Begum, 2023). Adequately solving the problem is also essential since sometimes failures in complicated service systems are inevitable. The adoption should be therefore facilitated by confidence in provider integrity and competence (Datta, 2024).

**H6:** *Financial trust has a positive effect on consumers' behavioral intention to adopt app-based mobile financial services in Bangladesh.*

### Conceptual framework

The conceptual framework places performance expectancy, effort expectancy, social influence, facilitating conditions, perceived financial value, and financial trust as direct predictors of the behavioral intention (Khan *et al.*, 2022). The six relationships enable the comparison of the independent contributions of their contributions as well as controlling the overlap of the constructs. The structure is parsimoniously inclined. It captures key technology and financial relationship aspects without introducing undue mediators or moderators (Saha *et al.*, 2026). This framework facilitates easy testing of hypotheses and a basis that can be interpreted to offer managerial action.

Behavioral intention is also considered as the motivational outcome since the questionnaire has nonusers, occasional users and experienced users. According to this method, respondents are allowed to indicate willingness despite a variation in their transaction frequency. It also includes the desire to expand or augment usage among current customers (Budiman *et al.*, 2025). Through simultaneous examination of the six predictors, the model determines which beliefs are relevant in consideration of the effects of other determinants when included in the structural equation.



**Figure 1:** Proposed conceptual framework.

## MATERIALS AND METHODS

### Research design and context

The research design was quantitative, cross-sectional survey. This design suited best as the research goal was to provide estimates of relationships between multiple latent consumer perceptions at a specified time. The empirical setting was mobile financial services, particularly in Bangladesh in the form of apps. To simplify its operations, the term was used to mean smartphone applications that are utilized in operations like sending or receiving money, paying a merchant, paying utility bills, mobile recharge, cash-in or cash-out, online shopping, saving, and other financial functions (Dawood *et al.*, 2022). Out of the scope of the study were broader FinTech categories, such as cryptocurrency, crowdfunding, automated investment and specialized digital lending.

### Population, eligibility, and sampling

The sample population was made up of adult consumers in Bangladesh who had knowledge of mobile financial services in form of apps. The respondents needed to be at least eighteen years old, reside in Bangladesh, and be knowledgeable about the study details and have adequate awareness of the type of service to assess the questions on the questionnaire (Tsoloane, 2025). The current usage was not obligatory as the dependent construct was behavioral intention and the sample was to be as inclusive of nonusers as of recent and established users.

Criterer based, non-probability sampling was used to recruit the respondents. This strategy allowed reaching consumers with appropriate awareness in various demographic and geographic groups. Participation was voluntary. The last data set consisted of 430 responses.

All 430 records met the screening criteria and were stored to be analysed (Sumaya *et al.*, 2025). The sample size was sufficient to support a PLS-SEM model having six predictors that would be targeted to a single endogenous construct and sufficiently conferred enough observations to offer stable measurements and prediction evaluation.

### Questionnaire development

A self-administered questionnaire was used to gather data in the form of a structured questionnaire. The tool consisted of four sections (Alam *et al.*, 2025). The introduction section included the purpose of the study, confidentiality, information on voluntary participation, and the consent question. The second section filtered age, residence, familiarity and previous use. The third section noted demographic and services-use features. The last section was a measure of the latent constructs.

Measurement statements were all based on a five-point Likert scale (between 1, strongly disagree and 5, strongly agree). The language was adjusted to the particular environment of mobile financial services that are based on apps. Statements were written in clear, single-idea statements and were not technical. Technology-adoption beliefs were operationalized using performance expectancy, effort expectancy, social influence, facilitating conditions, and perceived financial value. Financial trust was a belief in reliability, honesty, safety, competence and equitable resolution of problems by the provider (Jagatia, 2023). Behavioral intention was a manifestation of intentions to use, select or escalate the utilization of app-based mobile financial services.

### Construct measurement

There were four indicators used to measure performance expectancy, based on speed, convenience, efficiency and usefulness. Effort expectancy employed four indicators including learning, clarity, ease of operation and skill development. Social influence had four indicators that included encouragement, opinions that are highly valued, and usage by many relevant people. The facilitating conditions encompassed four predictors that involved resources, knowledge, technological correspondence and assistance available (Ahmed *et al.*, 2025). The perceived monetary worth was quantified using four indicators related to reasonable charges, time and cost savings, benefit-cost balance and value in general.

Five indicators were in financial trust. These items evaluated the honesty in completing transactions, securing money and financial information, trustworthiness of providers, promise keeping and equitable resolution of transaction issues (Osakwe *et al.*, 2022). Behavioral intention was comprised of five indicators that dealt with regular use in the future, suitability to financial needs, expected use in 6 months, preferences to traditional methods when suitable, and plans to use more. The model featured thus seven reflective constructs with thirty measures.

### Data collection and ethical safeguards

The survey was conducted to the relevant consumers by using reachable respondent networks and online channels of distribution. Respondents were asked to go through the information about the study. None of the respondents were pressured to take part and noncompliance was not disadvantageous. The questionnaire did not seek personal identifiers (Gbongli, 2022). The responses were analyzed in a group and were utilized in accordance with the mentioned research purpose.

Procedural safeguards were used to decrease common method problems. The survey indicated that there were no right or wrong answers. The respondents were advised to give candid judgments. The description of constructs was not done in such a manner as to imply the anticipated relationships. Language used to describe items was brief and the questionnaire divided demographic questions with the latent measurement section (Amnas *et al.*, 2023). These were followed with statistical diagnostics post-collection of data.

### Data screening and descriptive analysis

The data was analyzed in terms of the absence of measurement responses, invalid Likert values, duplicate data, and a straight-line pattern of responses. Frequencies and percentages were used to describe demographic and usage characteristics. To determine the patterns of response and distributional characteristics, indicator means, standard deviations, minima, maxima, skew, and kurtosis were computed. The fact that PLS-SEM does not demand multivariate normality means that distribution statistics were not a strict requirement of estimation but that rather a strong effort to determine extreme irregularities.

Two diagnostics were used to measure common method bias. The single factor test developed by Harman and tested the hypothesis of whether the indicator variance was best explained by a single non-rotated factor (Akter *et al.*, 2021). Now, the main statistical diagnostic was studied, namely full-collinear variance inflation factors. The value less than the conservative value of 3.3 was taken as a sign that the cases of common method bias and pathological collinearity were not likely to endanger the model.

### PLS-SEM assessment procedure

Analysis was based on two phases of PLS-SEM. Reflective measurement model was tested and then structural paths were interpreted. Outer loading and bootstrap significance were used to determine the level of indicator reliability. Cronbach alpha, rho A and composite reliability were used to test the internal consistency. Average variance extracted was used in the evaluation of convergent validity. The heterotrait-monotrait ratio and bootstrap confidence intervals were used to test discriminant validity. Evaluation of the structural model was done using predictor VIF values, standardized path coefficients, bootstrap standard errors, t-statistic, p-value and

percentile confidence interval. Hypotheses were accepted when the direction of the path was as predicted and the bootstrap value was significant. R-squared and adjusted R-squared were used to measure the explanatory power on behavioral intention (Chowdhury & Hussain, 2022). Predictive evaluation consisted of Q2 predict and a comparison of the PLS prediction errors with a linear-model benchmark. Positive values of Q2 predict signified predictive relevance. Root mean squared error and mean absolute error were juxtaposed on each behavioral intention indicator. Reduced PLS errors than the benchmark were considered to be testimonies of greater out-of-sample prediction (M. Anwarul Islam *et al.*, 2024). This was a combined process that made sure that the conclusion would be made on the basis of reliability, validity, explanation, statistical significance,

and predictive usefulness and not on a single criterion. Standardization of all the reported coefficients was done to allow direct comparison to the predictors.

## RESULTS AND DISCUSSION

The findings are given according to the arrangement advocated by PLS-SEM listing. The first characteristics of the data quality and samples are presented (Sandhu *et al.*, 2022). This measurement assessment then progresses to indicator descriptives and common method diagnostics onto the reflective measurement model. Subsequently, structural collinearity, hypothesis testing, explanatory power, predictive relevance and out-of-sample prediction are reported. Interpretations are all done based on the 430 good observations that were retained following the screening.

**Table 1:** Data Screening and Final Sample

| Screening criterion                | Frequency |
|------------------------------------|-----------|
| Initial responses                  | 430       |
| Missing measurement-item responses | 0         |
| Out-of-range Likert responses      | 0         |
| Duplicate responses                | 0         |
| Straight-line responses identified | 0         |
| Straight-line responses removed    | 0         |
| Total excluded responses           | 0         |
| Final valid sample                 | 430       |

Table 1 indicates that the original data consisted of 430 responses and no cases were eliminated. None of the measurement items had a missing point or out-of-range Likert score. No multiple submissions or straight-line response pattern were detected. The fact that there is no difference between the original and final sample shows that this is a full dataset without any dropout due to the statistical

screening. The retention of all cases also prevented any alterations of the demographic composition that could have been brought about by selective deletion (Hosmani & Raghukant, 2025). The 430 respondents finally formed the sample which was undertaken to use descriptive analysis, measurement-model assessment, structural estimation, and predictive assessment.

**Table 2:** Demographic Profile of Respondents

| Variable  | Category                       | Frequency | Percentage (%) |
|-----------|--------------------------------|-----------|----------------|
| Gender    | Female                         | 198       | 46.05          |
|           | Male                           | 224       | 52.09          |
|           | Other                          | 2         | 0.47           |
|           | Prefer not to disclose         | 6         | 1.40           |
| Age group | 18–24 years                    | 104       | 24.19          |
|           | 25–34 years                    | 153       | 35.58          |
|           | 35–44 years                    | 99        | 23.02          |
|           | 45–54 years                    | 58        | 13.49          |
|           | 55 years or above              | 16        | 3.72           |
| Education | Bachelor's degree              | 152       | 35.35          |
|           | Diploma or technical education | 43        | 10.00          |
|           | Higher secondary education     | 69        | 16.05          |
|           | Master's degree or above       | 104       | 24.19          |
|           | Other                          | 15        | 3.49           |
|           | Secondary education or below   | 47        | 10.93          |

|                |                                 |     |       |
|----------------|---------------------------------|-----|-------|
| Occupation     | Business owner or self-employed | 71  | 16.51 |
|                | Government employee             | 37  | 8.60  |
|                | Homemaker                       | 38  | 8.84  |
|                | Other                           | 8   | 1.86  |
|                | Private-sector employee         | 134 | 31.16 |
|                | Professional                    | 43  | 10.00 |
|                | Retired                         | 8   | 1.86  |
|                | Student                         | 77  | 17.91 |
|                | Unemployed                      | 14  | 3.26  |
| Monthly income | Above BDT 100,000               | 14  | 3.26  |
|                | BDT 20,001–40,000               | 107 | 24.88 |
|                | BDT 40,001–60,000               | 74  | 17.21 |
|                | BDT 60,001–80,000               | 48  | 11.16 |
|                | BDT 80,001–100,000              | 20  | 4.65  |
|                | Below BDT 20,000                | 96  | 22.33 |
|                | No personal income              | 60  | 13.95 |
|                | Prefer not to disclose          | 11  | 2.56  |
| Residence      | Rural                           | 98  | 22.79 |
|                | Semi-urban                      | 106 | 24.65 |
|                | Urban                           | 226 | 52.56 |
| Division       | Barishal                        | 37  | 8.60  |
|                | Chattogram                      | 74  | 17.21 |
|                | Dhaka                           | 163 | 37.91 |
|                | Khulna                          | 59  | 13.72 |
|                | Mymensingh                      | 31  | 7.21  |
|                | Rajshahi                        | 40  | 9.30  |
|                | Rangpur                         | 15  | 3.49  |
|                | Sylhet                          | 11  | 2.56  |

The population was heterogeneous. It had a male respondent population of 52.09% and a population of female respondents of 46.05%. The majority of respondents fell within the age bracket of 25 to 34, then 18–24 and 35–44 years. The level of education was relatively high, with 35.35% having bachelor and 24.19% having post graduate qualifications. The greatest occupational group was employees

in the private-sector. The distribution of income categories was over the scale, but BDT 20,001–40,000 and less than BDT 20,000 was the most prevalent. Household urban dwellers were 52.56% but rural and semi-urban purchasers were also included significantly (Nedeljković, 2022). All administrative divisions were represented, with the highest share being Dhaka.

**Table 3:** Mobile Financial Service Usage Profile

| Variable         | Category                     | Frequency | Percentage (%) |
|------------------|------------------------------|-----------|----------------|
| Usage experience | 1–3 years                    | 117       | 27.21          |
|                  | 6 months to less than 1 year | 84        | 19.53          |
|                  | Have not used                | 39        | 9.07           |
|                  | Less than 6 months           | 78        | 18.14          |
|                  | More than 3 years            | 112       | 26.05          |
| Usage frequency  | Daily or almost daily        | 106       | 24.65          |
|                  | Less than once a month       | 53        | 12.33          |
|                  | Never                        | 68        | 15.81          |
|                  | Several times a month        | 111       | 25.81          |
|                  | Several times a week         | 92        | 21.40          |

|                 |                                     |     |       |
|-----------------|-------------------------------------|-----|-------|
| Primary purpose | Cash-in or cash-out                 | 30  | 6.98  |
|                 | Merchant payments                   | 85  | 19.77 |
|                 | Mobile recharge                     | 59  | 13.72 |
|                 | Online purchases                    | 33  | 7.67  |
|                 | Other                               | 16  | 3.72  |
|                 | Savings or other financial services | 18  | 4.19  |
|                 | Sending or receiving money          | 137 | 31.86 |
|                 | Utility bill payments               | 52  | 12.09 |

The usage profile consisted of adoption-stage and experienced consumers. There were only 9.07% who responded that they had never used app-based mobile financial services, but 53.26% fell under the category of having used MFS over the course of a year. There was also a range in the frequency of usage. Approximately a quarter of them attended the service on a daily or near-daily basis and the remaining 21.40 % attended

the services a few times per week. The most common one was sending or receiving money, which was cited by 31.86% of the respondents. Secondly, there were merchant payments then mobile recharge, and utility payments (Gani *et al.*, 2022). The distribution proves the fact that the sample was not restricted to one type of transactions and reflected various degrees of familiarity and service use.

**Table 4:** Indicator Descriptive Statistics

| Construct | Indicator | Mean  | SD    | Skewness | Kurtosis |
|-----------|-----------|-------|-------|----------|----------|
| PE        | PE1       | 3.305 | 1.262 | -0.273   | -0.962   |
| PE        | PE2       | 3.235 | 1.280 | -0.157   | -1.056   |
| PE        | PE3       | 3.249 | 1.269 | -0.138   | -1.111   |
| PE        | PE4       | 3.267 | 1.289 | -0.179   | -1.107   |
| EE        | EE1       | 3.228 | 1.246 | -0.154   | -1.045   |
| EE        | EE2       | 3.258 | 1.227 | -0.182   | -0.947   |
| EE        | EE3       | 3.314 | 1.294 | -0.229   | -1.081   |
| EE        | EE4       | 3.335 | 1.261 | -0.298   | -0.980   |
| SI        | SI1       | 3.188 | 1.212 | -0.128   | -0.867   |
| SI        | SI2       | 3.174 | 1.261 | -0.107   | -1.069   |
| SI        | SI3       | 3.270 | 1.226 | -0.243   | -0.887   |
| SI        | SI4       | 3.244 | 1.225 | -0.244   | -0.914   |
| FC        | FC1       | 3.212 | 1.264 | -0.132   | -1.052   |
| FC        | FC2       | 3.214 | 1.261 | -0.121   | -1.023   |
| FC        | FC3       | 3.244 | 1.258 | -0.199   | -1.038   |
| FC        | FC4       | 3.360 | 1.236 | -0.263   | -0.945   |
| PV        | PV1       | 3.153 | 1.231 | -0.046   | -1.003   |
| PV        | PV2       | 3.186 | 1.213 | -0.132   | -0.884   |
| PV        | PV3       | 3.191 | 1.199 | -0.102   | -0.956   |
| PV        | PV4       | 3.160 | 1.235 | -0.121   | -1.016   |
| FT        | FT1       | 3.202 | 1.238 | -0.174   | -0.964   |
| FT        | FT2       | 3.156 | 1.207 | -0.078   | -0.968   |
| FT        | FT3       | 3.181 | 1.270 | -0.144   | -1.068   |
| FT        | FT4       | 3.193 | 1.241 | -0.179   | -0.937   |
| FT        | FT5       | 3.228 | 1.213 | -0.223   | -0.851   |
| BI        | BI1       | 3.244 | 1.228 | -0.162   | -0.963   |
| BI        | BI2       | 3.344 | 1.245 | -0.236   | -0.976   |
| BI        | BI3       | 3.279 | 1.265 | -0.209   | -1.028   |
| BI        | BI4       | 3.319 | 1.232 | -0.255   | -0.853   |
| BI        | BI5       | 3.351 | 1.257 | -0.204   | -1.045   |

Ind [3.153-3.360], modestly positive assessments with no extremes of agreement. Some of the highest means were registered with behavioral intention items, especially BI5 and BI2, which indicates that the respondents were mostly ready to use appropriate applications and engage in more frequent application in the future. The standard deviations were near 1.20 to 1.29 among items, which meant that they have enough response variation

to perform multivariate analysis (Adesola Oluwatosin Adelaja *et al.*, 2024). Any values that were observed spanned the entire scale of 1 to 5. All indicators had a small skewness although it was slightly negative. The kurtosis values were moderate and negative as well. None of the indicators showed an extreme univariate distribution issue or a potential concentration of the answers.

**Table 5:** Common Method Bias and Full-Collinearity Diagnostics

| Panel A. Harman Single-Factor Diagnostic |        |                                     |
|------------------------------------------|--------|-------------------------------------|
| Assessment                               |        | Result                              |
| Measurement indicators                   |        | 30                                  |
| First unrotated factor variance (%)      |        | 29.99                               |
| Conventional reference (%)               |        | 50                                  |
| Preliminary interpretation               |        | First factor explains less than 50% |
| Panel B. Full-Collinearity VIF           |        |                                     |
| Construct                                | VIF    | Decision                            |
| PE                                       | 1.4281 | No critical concern                 |
| EE                                       | 1.2305 | No critical concern                 |
| SI                                       | 1.1017 | No critical concern                 |
| FC                                       | 1.2351 | No critical concern                 |
| PV                                       | 1.3133 | No critical concern                 |
| FT                                       | 1.4321 | No critical concern                 |
| BI                                       | 2.1285 | No critical concern                 |

The diagnostic by Harman revealed that the first unrotated factor could be used to explain 29.99 % of the total indicator variance that is still far below the 50 % mark. Its additional outcome did not thus suggest the pre-eminence of a single general response factor. More to the point, the full-collinearity VIF values were 1.1017 in the case of social influence, and 2.1285 in the case

of behavioral intention. All the values were less than 3.3. This evidence alone has led to the conclusion that common method bias could not have been the cause of the estimated relationships. It is also used to show that the latent variables still had sufficient empirical differentiation and that there was no critically full-collinearity behavior in any construct.

**Table 6:** Indicator Loadings

| Construct | Indicator | Loading | t       | p      | 95% CI           | Decision           |
|-----------|-----------|---------|---------|--------|------------------|--------------------|
| PE        | PE1       | 0.8810  | 23.1128 | < .001 | [0.8031, 0.9554] | Retain             |
| PE        | PE2       | 0.7748  | 17.9699 | < .001 | [0.6847, 0.8546] | Retain             |
| PE        | PE3       | 0.7886  | 17.9248 | < .001 | [0.6956, 0.8705] | Retain             |
| PE        | PE4       | 0.7776  | 17.5055 | < .001 | [0.6878, 0.8594] | Retain             |
| EE        | EE1       | 0.7965  | 15.3622 | < .001 | [0.6851, 0.8929] | Retain             |
| EE        | EE2       | 0.7957  | 14.0759 | < .001 | [0.6759, 0.9002] | Retain             |
| EE        | EE3       | 0.8558  | 15.0144 | < .001 | [0.7408, 0.9655] | Retain             |
| EE        | EE4       | 0.7583  | 12.2483 | < .001 | [0.6293, 0.8744] | Retain             |
| SI        | SI1       | 0.7158  | 7.8118  | < .001 | [0.5165, 0.8752] | Retain             |
| SI        | SI2       | 0.8226  | 9.9688  | < .001 | [0.6487, 0.9751] | Retain             |
| SI        | SI3       | 0.6487  | 6.4364  | < .001 | [0.4233, 0.8227] | Retain with review |
| SI        | SI4       | 0.8624  | 10.8565 | < .001 | [0.7015, 1.0146] | Retain             |
| FC        | FC1       | 0.7041  | 10.1377 | < .001 | [0.5536, 0.8220] | Retain with review |
| FC        | FC2       | 0.5679  | 6.9315  | < .001 | [0.3856, 0.7105] | Retain with review |
| FC        | FC3       | 0.9559  | 15.3146 | < .001 | [0.8361, 1.0810] | Retain             |

|    |     |        |         |        |                  |        |
|----|-----|--------|---------|--------|------------------|--------|
| FC | FC4 | 0.7918 | 13.3251 | < .001 | [0.6696, 0.9054] | Retain |
| PV | PV1 | 0.7628 | 14.4654 | < .001 | [0.6564, 0.8619] | Retain |
| PV | PV2 | 0.8428 | 17.0938 | < .001 | [0.7392, 0.9349] | Retain |
| PV | PV3 | 0.7345 | 13.5574 | < .001 | [0.6210, 0.8320] | Retain |
| PV | PV4 | 0.8154 | 16.0608 | < .001 | [0.7096, 0.9079] | Retain |
| FT | FT1 | 0.7609 | 15.3124 | < .001 | [0.6547, 0.8507] | Retain |
| FT | FT2 | 0.8362 | 20.6135 | < .001 | [0.7539, 0.9125] | Retain |
| FT | FT3 | 0.8667 | 22.2381 | < .001 | [0.7896, 0.9418] | Retain |
| FT | FT4 | 0.7827 | 17.1394 | < .001 | [0.6861, 0.8653] | Retain |
| FT | FT5 | 0.8091 | 19.2320 | < .001 | [0.7219, 0.8880] | Retain |
| BI | BI1 | 0.8584 | 36.4327 | < .001 | [0.8083, 0.9019] | Retain |
| BI | BI2 | 0.8049 | 30.5555 | < .001 | [0.7503, 0.8545] | Retain |
| BI | BI3 | 0.8516 | 35.7626 | < .001 | [0.8030, 0.8958] | Retain |
| BI | BI4 | 0.7789 | 24.9083 | < .001 | [0.7148, 0.8368] | Retain |
| BI | BI5 | 0.7860 | 26.1832 | < .001 | [0.7254, 0.8411] | Retain |

The thirty indicators loaded greatly on their respective constructs. The majority of loadings were above 0.70 and thus strong. The highest loading was FC3 0.9559 and the lowest FC2 0.5679. SI3 also fell below 0.70, at 0.6487, and FC1 was close to the reference at 0.7041. The retention of these weaker indicators was due to their significant bootstrap estimates, their confidence intervals

were not zero and the constructs had good composite reliability and average variance extracted (Mamun *et al.*, 2023). Theoretically important content pertaining to social endorsement, consumer knowledge and enabling support was also retained. In general, the loading pattern gave good reliability to indicators.

Each construct was proven to have internal consistency

**Table 7:** Reliability and Convergent Validity

| Construct | Cronbach's $\alpha$ | rho_A  | Composite reliability | AVE    | Decision   |
|-----------|---------------------|--------|-----------------------|--------|------------|
| PE        | 0.8811              | 0.8841 | 0.8814                | 0.6508 | Acceptable |
| EE        | 0.8780              | 0.8799 | 0.8783                | 0.6437 | Acceptable |
| SI        | 0.8484              | 0.8598 | 0.8496                | 0.5884 | Acceptable |
| FC        | 0.8496              | 0.8769 | 0.8475                | 0.5897 | Acceptable |
| PV        | 0.8690              | 0.8714 | 0.8688                | 0.6242 | Acceptable |
| FT        | 0.9061              | 0.9078 | 0.9062                | 0.6593 | Acceptable |
| BI        | 0.9087              | 0.9103 | 0.9090                | 0.6669 | Acceptable |

Note. AVE = average variance extracted. All reliability coefficients were acceptable and all AVE values exceeded 0.50.

and convergent validity. Cronbach's alpha values ranged from 0.8484 to 0.9087. rho\_A ranged from 0.8598 to 0.9103, while composite reliability ranged from 0.8475 to 0.9090. Such values denote high levels of consistency but do not imply too much redundancy. The average variance extracted was between 0.5884 and 0.6669 in social influence and behavioral intention respectively.

Due to the fact that all the AVEs were more than 0.50, all the constructs accounted more than 50 per cent of the variance of the indicators. The best estimates of reliability were obtained with financial trust and behavioral intention (Sadik & Rahman, 2024). The entire pattern justifies the further evaluation of discriminatory validity and the structural model.

**Table 8:** HTMT Discriminant Validity

| Panel A. HTMT Matrix |       |       |       |       |       |       |    |
|----------------------|-------|-------|-------|-------|-------|-------|----|
| Construct            | PE    | EE    | SI    | FC    | PV    | FT    | BI |
| PE                   | —     |       |       |       |       |       |    |
| EE                   | .3154 | —     |       |       |       |       |    |
| SI                   | .2412 | .1883 | —     |       |       |       |    |
| FC                   | .3155 | .2697 | .1551 | —     |       |       |    |
| PV                   | .3063 | .2642 | .2118 | .3259 | —     |       |    |
| FT                   | .3300 | .1596 | .1756 | .3629 | .3910 | —     |    |
| BI                   | .5953 | .4493 | .3242 | .4131 | .5067 | .5621 | —  |

| Panel B. Bootstrap Confidence Intervals |        |        |        |             |
|-----------------------------------------|--------|--------|--------|-------------|
| Construct pair                          | HTMT   | 2.5%   | 97.5%  | Decision    |
| PE-EE                                   | 0.3154 | 0.2161 | 0.4090 | Established |
| PE-SI                                   | 0.2412 | 0.1365 | 0.3469 | Established |
| PE-FC                                   | 0.3155 | 0.2146 | 0.4197 | Established |
| PE-PV                                   | 0.3063 | 0.2081 | 0.3996 | Established |
| PE-FT                                   | 0.3300 | 0.2316 | 0.4211 | Established |
| PE-BI                                   | 0.5953 | 0.5122 | 0.6708 | Established |
| EE-SI                                   | 0.1883 | 0.0924 | 0.2959 | Established |
| EE-FC                                   | 0.2697 | 0.1714 | 0.3706 | Established |
| EE-PV                                   | 0.2642 | 0.1645 | 0.3599 | Established |
| EE-FT                                   | 0.1596 | 0.0642 | 0.2653 | Established |
| EE-BI                                   | 0.4493 | 0.3561 | 0.5384 | Established |
| SI-FC                                   | 0.1551 | 0.0751 | 0.2605 | Established |
| SI-PV                                   | 0.2118 | 0.1180 | 0.3143 | Established |
| SI-FT                                   | 0.1756 | 0.0828 | 0.2808 | Established |
| SI-BI                                   | 0.3242 | 0.2212 | 0.4228 | Established |
| FC-PV                                   | 0.3259 | 0.2284 | 0.4202 | Established |
| FC-FT                                   | 0.3629 | 0.2612 | 0.4562 | Established |
| FC-BI                                   | 0.4131 | 0.3218 | 0.5028 | Established |
| PV-FT                                   | 0.3910 | 0.2931 | 0.4835 | Established |
| PV-BI                                   | 0.5067 | 0.4255 | 0.5834 | Established |
| FT-BI                                   | 0.5621 | 0.4789 | 0.6399 | Established |

The HTMT values were all less than conservative discriminant-validity values. The highest estimate was 0.5953 between the performance expectancy and behavioral intention that was then succeeded by 0.5621 between financial trust and behavioral intention. The other estimates were lower with some being below 0.30. Bootstrap confidence intervals (each constructed pair of constructs) rejected 1.00. These findings confirm that there were still empirical differences

in conceptually related variables. More specifically, performance expectation and financial trust could not be substituted by the behavioral intention, even though these two variables were more likely to be associated with behavioral intention (Bashir & Muhammad, 2023). Discriminant validity was thus determined in all the seven constructs and the direct paths are thus interpreted as relationships between different latent concepts.

**Table 9:** Structural Collinearity

| Predictor | Endogenous construct | VIF    | Decision                    |
|-----------|----------------------|--------|-----------------------------|
| PE        | BI                   | 1.2379 | No substantial collinearity |
| EE        | BI                   | 1.1452 | No substantial collinearity |
| SI        | BI                   | 1.0800 | No substantial collinearity |
| FC        | BI                   | 1.2191 | No substantial collinearity |
| PV        | BI                   | 1.2436 | No substantial collinearity |
| FT        | BI                   | 1.2566 | No substantial collinearity |

The values of structural VIF were low with a range of 1.0800 to 1.2566 corresponding to social influence and financial trust respectively. None of them met thresholds relating to problematic predictor collinearity. Performance expectancy, effort expectancy, social influence, facilitating conditions, perceived financial value, and financial trust might thus be embedded concurrently without poor estimation

of the coefficient. The low values are significant as some predictors represent positive assessments related to the same service (Salah Uddin & Begum, 2023). They have a low level of collinearity, which means that every construct provides different information in explaining behavioral intention, and the magnitude of coefficients can be compared.

**Table 10:** Path Coefficients and Hypothesis Testing

| Hypothesis | Path                | $\beta$ | SE     | t      | p      | 95% CI            | Decision      |
|------------|---------------------|---------|--------|--------|--------|-------------------|---------------|
| H1         | PE $\rightarrow$ BI | 0.3225  | 0.0448 | 7.1930 | < .001 | [0.2344, 0.4081]  | Supported     |
| H2         | EE $\rightarrow$ BI | 0.2118  | 0.0433 | 4.8938 | < .001 | [0.1297, 0.2976]  | Supported     |
| H3         | SI $\rightarrow$ BI | 0.1013  | 0.0380 | 2.6663 | .0056  | [0.0277, 0.1768]  | Supported     |
| H4         | FC $\rightarrow$ BI | 0.0743  | 0.0440 | 1.6874 | .0860  | [-0.0118, 0.1621] | Not supported |
| H5         | PV $\rightarrow$ BI | 0.1868  | 0.0441 | 4.2365 | < .001 | [0.0975, 0.2727]  | Supported     |
| H6         | FT $\rightarrow$ BI | 0.3038  | 0.0420 | 7.2269 | < .001 | [0.2197, 0.3860]  | Supported     |

All the six hypotheses were confirmed. H1 was supported as the standardized effect of performance expectancy on behavioral intention was greatest ( $\beta = 0.3225$ ,  $p < 0.001$ ). Financial trust followed closely ( $\beta = 0.3038$ ,  $p < 0.001$ ), supporting H6. Effort expectancy ( $\beta = 0.2118$ ,  $p < 0.001$ ), perceived financial value ( $\beta = 0.1868$ ,  $p <$

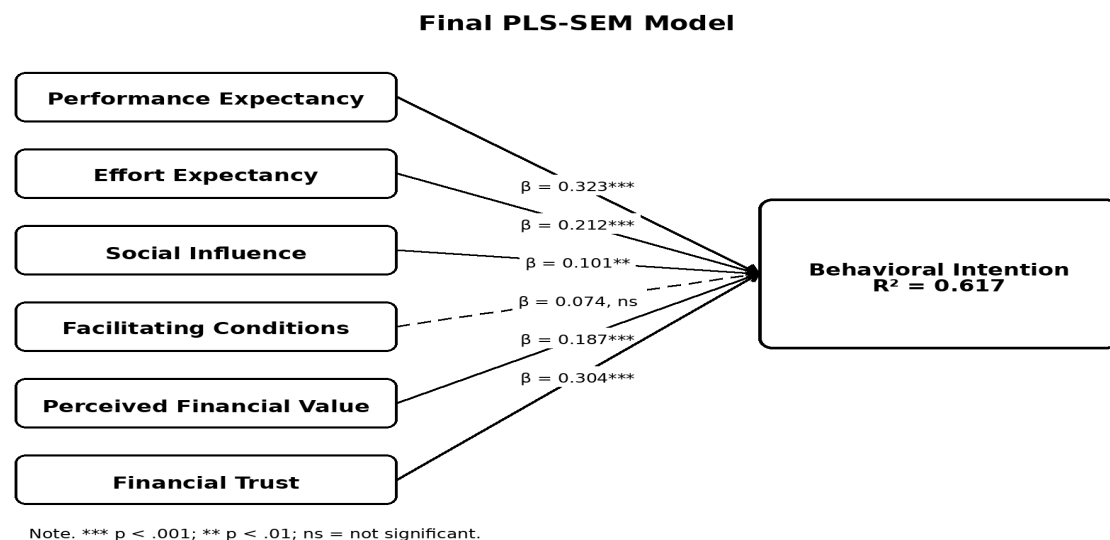
0.001), and social influence ( $\beta = 0.1013$ ,  $p = 0.0056$ ) also had significant positive effects, supporting H2, H5, and H3. The facilitating conditions resulted in a positive albeit insignificant coefficient ( $\beta = 0.0743$ ,  $p = 0.0860$ ); the interval of the coefficient crossed the value of zero, hence, H4 was not accepted.

**Table 11:** Explanatory Power

| Endogenous construct | R <sup>2</sup> | Adjusted R <sup>2</sup> | Interpretation                            |
|----------------------|----------------|-------------------------|-------------------------------------------|
| Behavioral intention | .6168          | .6114                   | Moderate-to-substantial explanatory power |

A combination of the six predictors (combined) helped to explain 61.68 % of the variance on behavioral intention. The adjusted value was also close to 61.14%, which means that the unwarranted complexity of models did not generate the explanatory performance (Datta, 2024). The outcome is a moderate-to-strong consumer behavior explanatory power. It demonstrates that functional

benefit, ease, social influence, facilitating conditions, financial worth, and trust had a significant percentage of the intentions of respondents. However, about 38 % of the variance was still not explained, so other variables, like perceived risk, financial literacy, quality of service, habit, regulatory assurance, previous experience of failure, or demographic contingencies, also could be used.



**Figure 2:** Final PLS-SEM model with standardized path coefficients.

**Table 12:** Predictive Relevance

| Endogenous construct | Mean Q <sup>2</sup> _predict | Minimum | Maximum | Indicators > 0 | Decision                         |
|----------------------|------------------------------|---------|---------|----------------|----------------------------------|
| Behavioral intention | .3724                        | .3377   | .4115   | 5 of 5         | Predictive relevance established |

The endogenous construct was predicted to be relevant. The average Q<sup>2</sup> predict value was 0.3724 with all the five indicators of behavioral intention showing values

that exceeded zero. Individual values ranged from 0.3377 to 0.4115. The positive values in all the indicators demonstrate that the model made omitted observations

better predictions as compared to the naive mean-based reference. The stability of the outcome is significant as predictive relevance was not reliant on a single abnormally strong predictor (Datta, 2024). Rather, the

model exhibited helpful prediction in terms of intentions with regard to regular use, occasion use, short-term use, preference over traditional means and intensified future use.

**Table 13:** Out-of-Sample Prediction

| Indicator | PLS RMSE | LM RMSE | $\Delta$ RMSE | PLS MAE | LM MAE | $\Delta$ MAE | Q <sup>2</sup> _predict |
|-----------|----------|---------|---------------|---------|--------|--------------|-------------------------|
| BI1       | 0.9413   | 0.9583  | -0.0170       | 0.7556  | 0.7721 | -0.0165      | 0.4115                  |
| BI2       | 0.9915   | 1.0267  | -0.0353       | 0.8103  | 0.8335 | -0.0232      | 0.3644                  |
| BI3       | 0.9747   | 0.9956  | -0.0208       | 0.7877  | 0.8032 | -0.0155      | 0.4049                  |
| BI4       | 1.0016   | 1.0132  | -0.0116       | 0.8174  | 0.8129 | 0.0045       | 0.3377                  |
| BI5       | 1.0175   | 1.0398  | -0.0223       | 0.8365  | 0.8424 | -0.0059      | 0.3434                  |

The out-of-sample analysis also confirmed the predictive ability of the model. All the five indicators of behavioral intentions showed lower RMSE values generated by PLS-SEM than the benchmark of linear-model. The changes in RMSE were between 0.0116 and 0.0353. More indicators (4) also produced lower MAE using PLS; only BI4 showed slightly higher difference in MAE at 0.0045. The model because the more variance-sensitive RMSE criterion preferred PLS to all indicators and Q<sup>2</sup> predict was positive at all times, the model exhibited a high relative predictive performance (Khan *et al.*, 2022). The results indicate that the given nonlinear composite-based model is not confined to the interpretation of the estimation sample and can be helpful towards prediction of similar consumer observations.

### Summary of empirical findings

Combined, the findings reflect an effective and educative paradigm. Measurement model reliability and validity were met, and common method and structural collinearity diagnostics were satisfactory. The sequencing of the path coefficients shows that there are two predominant adoption mechanisms. Customers demand performance benefits that they can see and at the same time, an assurance that the service provider will safeguard their monetary interests (Saha *et al.*, 2026). A second level of influence is made up of ease of use and financial value, and social endorsement creates a lesser impact. The nonsignificant facilitating-conditions path indicates that access to devices, knowledge, compatibility, and assistance might be required but not enough to generate intention when other beliefs are taken into account. Both explanatory and predictive evaluations are similar: the model can explain a portion of intention and predict unobserved cases more accurately than the benchmark. The similarity of the test of measurement, structural and prediction enhances confidence that the relationships supported are not unique statistical results, but parts of a consistent adoption effect.

### Discussion

The aim of the study was to understand the behavioral intention of consumers to use app-based mobile financial services in Bangladesh using six technology-related and

financial relationship factors. The model received good empirical support. Five hypotheses were accepted, the predictors accounted over sixty-one percent of behavioral intention and out-of-sample tests indicated usefulness of the predictions. Results indicate that there is no overall positive attitude that led to adoption (Budiman *et al.*, 2025). Rather, customers synthesize evaluations of functional functionality, provider reliability, usability, worth, and social approval.

The strongest predictor appeared to be performance expectancy. The finding implies that mobile financial applications are primarily judged by consumers based on the practical benefits that the applications provide. Quick transfers, convenient payments, less travel, convenient accessibility and speedy management of routine transactions provide an evident cause to adopt. The value of the coefficient also indicates that novelty, or exposure to promotions are not solely sufficient (Dawood *et al.*, 2022). The consumers must be convinced that the application will better address real financial tasks than cash, visiting a bank, relying on agents or other options. The essence of relevance is then functional relevance that depends on the central reliance mechanism.

The financial trust created a virtually similar impact to performance expectancy. This observation validates that digital finance is not the same as numerous consumer technologies that are low-risk. Users are not just choosing an interface; they give a provider the ability to handle money and sensitive data. Fears of unauthorized access, failed transactions, undisclosed charges, delayed reversal, fraud and inefficient complaint handling may undermine intention directly (Tsoloane, 2025). Consumers feel more confident when they are sure that the transactions will be made correctly, balances will be insured, information will be kept in a safe place and issues will be solved in a fair way, trust will be strengthened. The outcome shows that trust is not a peripheral variable of reassurance. It is an intrinsic predictor of the acceptability of perceived technological benefits as financial conduct.

The third-largest effect was on effort expectancy. Adoption increases even when a service is useful and trusted, provided that learners and operators do not face undue cognitive demands. The perceived difficulty is minimized by clear navigation, comprehensible

language, simple authentication, visible transaction confirmation and easy recovery processes (Sumaya *et al.*, 2025). The discovery is especially pertinent within a market with diverse consumers with different education, experience with digital usage, age, and frequency of use. The complexity of the interface can stop no trial, but it will turn away regular use, expansion into wider use of features or independent use. Convenience thus facilitates adoption and builds on translation of perceived benefits to intention.

Perceived financial value also positively influenced significantly. Consumers seem to evaluate the entire benefits-cost exchange. Perceived value may be decreased by transaction fees, cash-out fees, internet costs, and learning effort and increased by time savings, convenience, increased access to services and promotional benefits. The impact is not as great as performance expectancy and trust but still has a practical importance (Alam *et al.*, 2025). Such distinction means that users create a distinction between usefulness and value. Even a good service may be perceived negatively when fees are perceived to be high, ambiguous, or unreasonable when compared to the level of transaction. Clearly and fair prices are thus key to long term adoption.

The weakest supported relationship was that of social influence. Adoption may be promoted through social normalization of digital transactions by family, friends, colleagues, merchant, and other people they consider important, including their demonstration of use or recommendations (Jagetia, 2023). The smaller coefficient, however, suggests that consumers do not use social endorsement in the same strength as they use personal judgments of usefulness, trust, ease and value. This trend is understandable when it comes to a personal risk financial decision. Social networks can create awareness or decrease uncertainty, however, consumers will still need direct trust in the service to obtain a high level of intention.

There was no statistically significant direct effect of facilitating conditions. The positive coefficient indicates that resources, knowledge, compatibility and assistance direction flow in the direction of expectation but this effect faded after taking into account other predictors. The first one is that smartphones, access to the internet, and familiarity with simple applications have become threshold conditions in the target population that was sampled (Ahmed *et al.*, 2025). The more enabling resources are added to intention, the farther consumers may not be motivated by the additional enabling resources once they have enough resources to evaluate the service. The other reason is that facilitating conditions have a stronger impact on actual usage as compared to behavioral intention. Consumers might be planning to utilize a service due to the fact that it is useful and trusted but the resource limitations will define whether that intention will be converted to repeated action or not.

The outcome must not be used as a sign that the infrastructure and support are not important. Consumers

may still be left out by poor connectivity, low levels of digital literacy, unavailable avenues of complaint, or incompatible devices (Osakwe *et al.*, 2022). The insignificant coefficient simply shows that the facilitating conditions did not contribute to the unique explanatory power in this model. They could have an indirect impact via effort expectancy, trust, or perceived value. They can also differ among urban and rural users, older and younger consumers, experienced and inexperienced users. These conditional mechanisms need to be experimented in future models rather than theorise a homogeneous direct effect.

The substantive interpretation is reinforced by the predictive results. The positive prediction of all the indicators of behavioral intentions and lower PLS RMSE as compared to the benchmark suggests that more than just within-sample can be explained by the model. The fact that both explanatory and predictive evidence are converging implies that the determinants identified can inform effective interventions. The most gains should come by boosting performance benefits and trust, although other leverage can be made by adding usability and value improvements (Gbongli, 2022). These changes can be reinforced by social communication, yet it will hardly be able to offset poor functionality, uncertain charges, or concerns about financial security. Generally, the adoption process seems to be a utility judgment that relies on confidence, backed up by usability, value, and social legitimacy.

This hierarchy explains the presence of underutilized technically available services: the ability to use the service will allow participation, but the perceived benefit and institutional trust will define whether customers will actively use the application to conduct a recurring financial action every day.

## Implications

### Theoretical implications

The research helps advance the field of consumer technology-adoption studies by focusing the phenomenon under study to the narrow scope of app-based mobile financial services. Such a line minimizes the conceptual uncertainty that arises when the unrelated FinTech products are considered collectively (Amnas *et al.*, 2023). The results thus cannot be used in regular smartphone-based financial transactions as compared to investment, insurance, lending, or cryptocurrency platforms with varying risk and complexity profiles.

The model also illustrates the worth of combining financial trust and technology-adoption determinants. Financial trust was almost as strong as performance expectancy and was more potent than effort expectancy, perceived financial value and social influence as well as facilitating conditions. This finding shows that the use of conventional acceptance variables alone cannot explain services that entail monetary vulnerability (Akker *et al.*, 2021). Trust is an object of central theoretical consideration, not the addition of theoretical context.

The adapted framework is refined to the unsupported facilitating-conditions path. It also indicates that enabling resources could be a threshold state or could impact real usage as opposed to intent. Ease, trust, or value may also mediate their effect. Lastly, the research makes a prediction contribution. This is not just high coefficients in the model, it exhibited positive predictive relevance and improved performance in RMSE than the linear benchmark with all intention indicators (Chowdhury & Hussain, 2022). This enhances the theoretical soundness of the suggested determinant structure.

It also affirms that prediction evaluation is able to demonstrate validity similar to what conventional significance and explanatory statistics alone cannot validate.

### Practical implications

Those functions which yield visible performance benefits should be prioritized by the providers. Applications should always be able to get common transactions done in a short period of time, reduce unnecessary processes, have clear status, and be reliable. The product development ought to concentrate on the most common activities customers are engaged in financially; transfers, merchant payments, recharge, and utility settlement (M. Anwarul Islam *et al.*, 2024). Vowing time and convenience advantages may be better in enhancing adoption when compared to generic promotional statements.

Operational evidence is needed to build trust. Authentication, transaction notifications, transparent records, privacy, timely reversal, and easy complaint resolution should be applied by the providers. A failed transaction needs to be clarified to customers, to know who to hold culpable, and when to create solutions. Effective service recovery can be as valuable as avoiding failure since it shows incompetence and equality.

Digital experience of the interface design should be facilitated. Effort can be reduced by the use of simple language, consistent icons, confirmation screens, error prevention and guided recovery. Fee structures should also be reviewed by the dealers. Fees should be seen prior to acceptance and commensurate to transaction price (Emini *et al.*, 2026). To enhance consumer protection, interoperability, disclosure, fraud response, and responsibility of complaints, regulators and industry bodies need to be stronger. Adoption can be supported by social communication experts, using trusted figures in the community and by peer demonstration, but usefulness and safety must be stressed in campaigns. The inclusion has to be supported by infrastructure and support though their direct route was insignificant. Policy priorities should, therefore, be the rural connectivity, quality of agents, digital literacy, and support to vulnerable users.

### Limitations and Future Research

The interpretation of findings is characterized by a number of limitations. To begin with, cross-sectional design is able to capture perceptions and intentions at

a single point or instance in time. It will not be able to verify the development of intentions or whether these intentions will yield subsequent use. Longitudinal research needs to follow the consumers through awareness to trial, continued use, and increased use of the services.

Second, non-probability was employed in the study. In spite of the fact that the sample was representative of all the divisions and it consisted of urban, semi-urban and rural sample it cannot be considered a statistically representative national sample (Sandhu *et al.*, 2022). Future studies may employ stratified/multistage probability sampling and may make comparisons across regions, income levels, age levels and gender.

Third, the behavioral intention and no longer transaction behavior was confirmed. Future researchers ought to relate surveys to anonymized records of use, frequency of transactions, diversity of services or retention. Fourth, even with satisfactory common method diagnostics, there can still be recall and social desirability effects in self-reported data.

The model was purposely parsimonious. It omitted perceived risk, perceived privacy concern, financial literacy, service quality, regulatory assurance, habit, perceived experience of prior failures, or prior failure experience. These are possible to explain the rest of the variance. The mediation needs to be tested by future studies using trust and value, experience or residence as moderators, and nonlinear connections (Nedeljković, 2022). Comparative research between providers or countries would be able to reveal whether the current hierarchy of determinants will be maintained in various competitive, regulatory, and infrastructural environments.

How consumers perceive trust when transactions, scams, reversals take time or when agents are misbehaving may also be studied in qualitative interviews to show context-related issues which standardized indicators might not be able to capture fully in real-life practice.

### CONCLUSION

This research paper describes the behavioral intention of customers to use mobile financial services via apps in Bangladesh using six determinants. The model presented good reliability, discriminant validity, high explanatory power, and predictive out-of-sample. The best predictor was performance expectancy and the financial trust came close. Effort expectancy, perceived monetary worthiness and social influence also enhanced intention though facilitating conditions did not have a significant direct impact.

The results indicate that adoption is mainly a utility-and-confidence decision. The consumers require applications that enhance their financial activities and partners whom they entrust with money, information, and problem solving. Intention is further reinforced by ease, easy value, and social acceptance. Functional innovation and credible protection, fair pricing, inclusive design, and responsible support should therefore be combined by providers and regulators. This strategy can take consumers out of

awareness and occasional trial to regular, broader and sustainable use of mobile financial applications.

## REFERENCES

- Adesola Oluwatosin Adelaja, Oluwatoyin Funmilayo Ayodele, Stanley Chidozie Umeorah, & Raimat Olamide Amosu. (2024). Enhancing consumer trust in financial services: The role of technological security innovations. *Finance & Accounting Research Journal*, 6(10), 1746–1759. <https://doi.org/10.51594/farj.v6i10.1610>
- Afrin, R., & Sarker, S. A. (2025). Extending the Technology Acceptance Model: Contextualizing Trust and Usability in Shaping Online Consumer Behavior in Dhaka, Bangladesh. *Indonesian Journal of Innovation and Applied Sciences (IJLAS)*, 5(3), 242–253. <https://doi.org/10.47540/ijias.v5i3.2135>
- Ahmed, W., Farooq, O., & Shahzaib, R. (2025). The Rise of Digital Wallets: Customer Trust, Security Concerns, and Adoption in Retail Transactions. *Inverge Journal of Social Sciences*, 4(3), 337–350. <https://doi.org/10.63544/ijss.v4i3.171>
- Akter, S., Kabir, N., & Reza, T. (2021). Unfolding factors behind internet-banking adoption in Bangladesh: An extension of UTAUT2 with perceived security and trust. *The Journal of Management Theory and Practice (JMTP)*, 51–63. <https://doi.org/10.37231/jmtp.2021.2.2.111>
- Alam, Md. K., Tarun Kanti Bose, & Peulee, M. K. (2025). *Smart Banking App Adoption: Key Influences in Developing Countries with Rapid Tech Change*. Khulna University Studies. <https://doi.org/10.53808/KUS.2025.22.02.1297-mb>
- Amnas, M. B., Selvam, M., Raja, M., Santhoshkumar, S., & Parayitam, S. (2023). Understanding the Determinants of FinTech Adoption: Integrating UTAUT2 with Trust Theoretic Model. *Journal of Risk and Financial Management*, 16(12), 505. <https://doi.org/10.3390/jrfm16120505>
- Bashir, B. K., & Muhammad, T. (2023). Factors influencing the adoption of mobile financial services in enhancing financial inclusion: Using structural equation modeling for the decision-making approach. *Innovare Journal of Social Sciences*, 19–27. <https://doi.org/10.22159/ijss.2023.v11i2.47349>
- Budiman, J., Verni, & Kesumahati, E. (2025). Mediating role of trust in TAM and direct UTAUT effects on digital payment intention. *Assets: Jurnal Ekonomi, Manajemen Dan Akuntansi*, 15(2), 184–201. <https://doi.org/10.24252/assets.v15i2.62493>
- Chowdhury, N. H., & Hussain, N. (2022). Using technology acceptance model for acceptance of FinTech in Bangladesh. *International Journal of Internet Technology and Secured Transactions*, 12(3), 250. <https://doi.org/10.1504/IJITST.2022.122104>
- Datta, R. K. (2024). Fintech-Based Financial Inclusion in Bangladesh: Overview, Challenges and Policy Directives. *International Journal of Finance & Banking Studies* (2147-4486), 13(1), 01–16. <https://doi.org/10.20525/ijfbs.v13i1.3227>
- Dawood, H. M., Liew, C. Y., & Lau, T. C. (2022). Mobile perceived trust mediation on the intention and adoption of FinTech innovations using mobile technology: A systematic literature review. *F1000Research*, 10, 1252. <https://doi.org/10.12688/f1000research.74656.2>
- Emini, A., Budić, H., & Volarević, H. (2026). Consumer Trust and Adoption of Digital Payment Systems in Emerging Markets. *Business Systems Research Journal*, 17(1), 1–17. <https://doi.org/10.2478/bsrj-2026-0001>
- Gani, M. O., Alam, M. I., Alam, M. Z., Chowdhury, S. A., & Ahmed, R. (2022). Determinants of m-payment adoption behaviour in Bangladesh. *International Journal of Business Information Systems*, 40(3), 415. <https://doi.org/10.1504/IJBIS.2022.124924>
- Gbongli, K. (2022). Understanding Mobile Financial Services Adoption through a Systematic Review of the Technology Acceptance Model. *Open Journal of Business and Management*, 10(05), 2389–2404. <https://doi.org/10.4236/ojbm.2022.105119>
- Hosmani, D. A. P., & Raghukant, P. S. (2025). Decoding Fintech Adoption: The Role of Trust, Risks and Perceived Benefits. *International Journal of Research and Scientific Innovation*, 12(9), 4610–4619. <https://doi.org/10.51244/IJRSI.2025.120800419>
- Jagatia, A. (2023). The Factors that are Influencing Mobile Banking App Adoption: Focusing on Security Perceptions, Behavioral Intentions and Technological Trust in Emerging Markets. *Journal of Extension Systems*, 38(2), 16–21. <https://doi.org/10.48165/jes2022.38.2.3>
- Khan, Md. R., Rana, S., & Hosen, Md. I. (2022). Impact of Trustworthiness on the Usage of M-banking Apps: A Study on Bangladeshi Consumers. *Business Perspectives and Research*, 10(2), 234–250. <https://doi.org/10.1177/22785337211001969>
- M. Anwarul Islam, K., Hasan, Z., Taleb Tawfiq, T., Bashar Bhuiyan, A., & Faisal-E-Alam, Md. (2024). Bank becomes cashless: Determinants of acceptance of mobile banking (fintech) services among banking service users. *Banks and Bank Systems*, 19(2), 30–39. [https://doi.org/10.21511/bbs.19\(2\).2024.03](https://doi.org/10.21511/bbs.19(2).2024.03)
- Mamun, Md. A. A., Rana, M., Islam, Md. A., & Mamun, Md. A. (2023). Exploring the factors that affecting adoption of mobile banking in Bangladesh. *Journal of Global Business Insights*, 8(1), 66–79. <https://doi.org/10.5038/2640-6489.8.1.1235>
- Nedeljković, I. (2022). Determinants and consequences of user trust in mobile banking. *Bankarstvo*, 51(3–4), 170–201. <https://doi.org/10.5937/bankarstvo2204170N>
- Osakwe, C. N., Okeke, T. C., & Kwarteng, M. A. (2022). Trust building in mobile money and its outcomes. *European Business Review*, 34(2), 244–262. <https://doi.org/10.1108/EBR-09-2020-0221>
- Sadik, N., & Rahman, Md. M. (2024). Factors Affecting Digital Financial Service Adoption in Bangladesh:

- Evidence from SEM-ANN Approaches. *Journal of Risk Analysis and Crisis Response*, 14(4). <https://doi.org/10.54560/jracr.v14i4.555>
- Saha, T., Dey, T., & Hoque, Md. R. (2026). Initial Trust and Usage Intention: A Study on Mobile Payment Adoption in Bangladesh. *Global Business Review*, 27(2), 360–382. <https://doi.org/10.1177/09721509221120805>
- Salah Uddin, K. M., & Begum, T. (2023). Financial Inclusion: Factors Influencing on Customer Adoption of Mobile Banking Services in Bangladesh. *International Journal of Business and Management*, 18(3), 1. <https://doi.org/10.5539/ijbm.v18n3p1>
- Sandhu, S. K., Kai, J., Maity, R., Saad, A., Syed Abu Bakar, S. M., & Singh, H. (2022). Convenience and risk factors affecting mobile banking adoption behavior: The mediating role of trust. *Journal of Emerging Economies and Islamic Research*. <https://doi.org/10.24191/jeeir.v10i2.17624>
- Sumaya, S., Masud, A. A., Hossain, Md. A., & Hossain, Md. M. (2025). Moving toward a cashless society via e-payment: An extended technology acceptance model. *South Asian Journal of Marketing*, 6(2), 104–120. <https://doi.org/10.1108/SAJM-07-2025-0034>
- Tsoloane, M. (2025). *Mobile Transactions and Financial Services: Security, Adoption and Financial*. Zenodo. <https://doi.org/10.5281/ZENODO.17372726>