SOUTH ASIAN JOURNAL OF SOCIAL SCIENCES & HUMANITIES

ISSN: 2582-7065 (Online) SAJSSH, VOL 6, ISSUE 5, PP. 117-138

Modeling the Impact of Mobile Financial Services on Financial Literacy in Rural Bangladesh: A UTAUT2-Based Approach

Md Asad Noor

Assistant Professor, Green Business School, Green University of Bangladesh, Bangladesh.

Email: asadronnie@gmail.com

Received: 28th June 2025 **Accepted:** 22nd August 2025 **Published:** 5th October 2025

ABSTRACT

This paper examines how mobile financial services (MFS) shape financial literacy in rural Bangladesh through the UTAUT2 lens. We surveyed 432 rural MFS users across five districts and analyzed the data with SmartPLS 4.0 using structural equation modeling. The measurement model met standard criteria for reliability and convergent/discriminant validity. In the structural model, performance expectancy, effort expectancy, social influence, hedonic motivation, and price value emerged as the strongest drivers of behavioral intention to use MFS. Facilitating conditions and habit were positively related to actual use, and behavioral intention strongly translated into usage. Crucially, MFS use showed a positive and statistically significant association with financial literacy, suggesting that routine engagement with mobile money enhances users' financial knowledge, awareness, and decision-making. The findings point to practical steps for policymakers and providers: improve usability and infrastructure in rural areas and run community-based awareness campaigns to broaden adoption. Pairing in-app literacy features or programs with MFS platforms could further accelerate financial empowerment outside urban centers. Conceptually, the study extends UTAUT2 by linking adoption determinants and subsequent usage to downstream financial-literacy outcomes, offering new insight into the socioeconomic effects of digital financial inclusion in rural settings.

Keywords: Digital Financial Inclusion, Financial Literacy, Mobile Financial Services, Rural Bangladesh, Structural Equation Modeling, UTAUT2.

DOI: 10.48165/sajssh.2024.6508

INTRODUCTION

In Bangladesh, mobile financial services (MFS) have become a backbone of financial inclusion, especially outside major towns where bank branches and ATMs are scarce. Platforms such as bKash, Nagad, and Rocket give rural households practical ways to send and receive money, set aside small savings, pay utility bills, and purchase airtime (Hasan et al., 2023). As access to these digital tools widens, questions remain about users' financial capability and whether routine engagement with MFS actually strengthens financial knowledge and sound decision-making (Rahman & Jahan, 2022).

By financial literacy, we mean the knowledge and skills needed to manage money effectively—budgeting, personal financial management, and basic investing (Lusardi & Mitchell, 2014). Despite rapid growth in MFS usage, studies continue to report low levels of financial literacy in rural Bangladesh, which can blunt the empowerment potential of these services (Sultana et al., 2022). Limited know-how also leaves users exposed to fraud, misuse, and suboptimal financial behavior (Akter et al., 2023).

To explain technology adoption, this study draws on UTAUT2, which models behavioral intention and use through constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit (Venkatesh et al., 2012). Prior work has applied UTAUT2 to mobile banking in emerging markets (Islam et al., 2023; Karim & Noor, 2022), but has rarely connected these adoption drivers to downstream gains in financial literacy, particularly in rural settings.

Against this backdrop, we examine whether and how MFS usage influences financial literacy among rural residents in Bangladesh, using the UTAUT2 framework. The study aligns behavioral determinants with financial-education outcomes to gauge the extent to which engagement with MFS portals enhances financial literacy. It also explores key socio-demographic and behavioral factors that may moderate or mediate these relationships. The insights aim to guide national policymakers, financial institutions, and development practitioners seeking effective levers for digital financial empowerment across rural Bangladesh.

LITERATURE REVIEW

Mobile Financial Services in Rural Economies

DOI: 10.48165/sajssh.2024.6508

Policies that aim to provide access to formal financial services in underdeveloped regions were first based on mobile financial services (MFS). In remote areas, where conventional banking sector coverage is limited, MFS gateways like Nagad and bKash in Bangladesh have enabled people to utilize mobile phones and maintain minimal infrastructure (Hasan et al., 2023). MFS is more beneficial for the underprivileged sectors, who are allowed to transfer and receive funds, manage utility bills, and maintain virtual savings (Rahman & Jahan, 2022). While the arguments are worth hearing, the coverage for the MFS remains inadequate for inclusive financial empowerment, particularly for populations with limited financial and digital capabilities (Sultana et al., 2022).

Financial Literacy in Developing Countries

At the core of making prudent money decisions and achieving long-term financial independence is financial literacy. In line with Lusardi and Mitchell (2014), we define it as a combination of financial literacy that enables individuals to make wise financial choices and strengthens their financial security. Evidence from Bangladesh indicates that many rural residents lack basic concepts, which constrains their safe and effective use of financial services (Akter et al., 2023). Strengthening financial literacy in rural communities is therefore critical for unlocking the full developmental benefits of mobile financial services (MFS).

Interlinkages Between MFS and Financial Literacy

While the MFS opened the door, financial literacy is about informed use. There is a recognized positive association between the extent of financial literacy and digital financial access, particularly among users who significantly utilize MFS applications and derive complementary financial education (Demirgüç-Kunt et al., 2022; Alam & Hossain, 2023). In most cases, however, users utilize the MFS because they are required to do so, rather than because they understand the features comprehensively or their implications. This behavioral disconnect highlights the need for research on how the use of the MFS, shaped by various socio-technical forces, can promote the maximization of financial literacy outcomes.

The UTAUT2 Framework in Financial Technology Research

Enhancing the first UTAUT, UTAUT2 (Venkatesh et al., 2012) incorporates consumer-focused elements such as hedonic incentive, price value, and habit in addition to the fundamental drivers of performance expectation, effort expectancy, social impact, and enabling circumstances. Research on the usage of mobile banking, fintech, and electronic wallets in low-

DOI: 10.48165/sajssh.2024.6508

income areas has made extensive use of this approach (Karim & Noor, 2022; Islam et al., 2023). Yet most applications emphasize intention and actual use, with far fewer examining downstream outcomes—such as whether adoption improves financial literacy.

Gaps in the Existing Literature

In light of the increasing volume of research addressing MFS adoption and financial inclusion, empirical research examining the effect of MFS on financial literacy—specifically from a behavioral technology perspective—is scarce. Additionally, the majority of currently available studies have targeted urban users, while the specific challenges experienced by rural users in Bangladesh have been largely ignored. The application of UTAUT2 in this area represents an opportunity to model behavioral and environmental drivers for MFS use and estimate their impact on financial literacy outcomes. This research bridges the important gap by applying the UTAUT2 model in a rural context within Bangladesh and empirically testing the interrelations between the determinants of MFS use and financial literacy.

Theoretical Framework and Hypotheses Development

People in rural Bangladesh were surveyed using the UTAUT2 framework to learn more about their financial literacy and the factors that influence their decision to utilize mobile financial services. Along with the fundamental drivers of performance and effort expectation, social influence, and enabling circumstances, UTAUT2 (Venkatesh et al., 2012) expands the original model by adding consumer-oriented dimensions—hedonic motivation, price value, and habit—to the mix. This study's context and questions are well-suited to the framework because of its emphasis on individual intention and actual usage while also integrating communal effects.

Performance Expectancy (PE)

According to Venkatesh et al. (2012), performance expectation refers to the conviction that MFS would really facilitate the simplification, acceleration, and simplification of monetary operations. Within the MFS framework, it embodies the user expectation that a mobile app can safely and effectively manage transactions such as transfers and bill payments. This apparent benefit is likely to be the deciding factor in the adoption of MFS in locations where bank branches are sluggish or far away, such as several rural villages. According to previous research, there is a strong correlation between the expectation of good performance and the likelihood that customers would use mobile banking services (Karim & Noor, 2022; Islam et al., 2023).

DOI: 10.48165/sajssh.2024.6508

H1: Performance expectancy will be positively associated with rural users' intention to use MFS.

Effort Expectancy (EE)

The perceived ease of use is captured by effort expectancy (Venkatesh et al., 2012). A decreased effort barrier and increased desire to embrace MFS are achieved for users with less digital expertise via clear menus and easy, repeating processes. Users are more likely to make use of a platform if it is easy to use and comprehend (Hasan et al., 2023).

H2: Effort expectancy will positively relate to intention to use MFS among rural users.

Social Influence (SI)

Attempts to continue using MFS may be prompted or discouraged by influential persons in your life, such as family, friends, or community leaders. This is known as social influence. Such signals have a significant impact on intentions in collectivist contexts (Venkatesh et al., 2012). According to Alam and Hossain (2023), social norms have a considerable impact on how people in collectivist countries, such as Bangladesh, adopt new technologies. This is because individuals's interactions with others greatly impact their conduct.

H3: Social influence will be positively related to intention to use MFS among rural users.

Facilitating Conditions (FC)

Reliable network coverage, agent access points, device availability, and timely assistance channels are examples of facilitating characteristics that make utilization practicable (Venkatesh et al., 2012). This includes having access to mobile networks, agents or stores, and customer service. Having the right conditions can make it easier for people in remote rural areas to use technology.

H4: Facilitating conditions will positively relate to actual MFS usage.

Hedonic Motivation (HM)

Although utility is the main motivator for most users in rural areas, hedonic motivation refers to the satisfaction or feeling of empowerment that users have when using their phones for money management (Venkatesh et al., 2012). MFS are mostly useful, but younger or more tech-savvy users may continue to use them because they feel empowered or satisfied when they can manage their finances through mobile apps (Sultana et al., 2022).

DOI: 10.48165/sajssh.2024.6508

H5: Hedonic motivation will positively relate to intention to use MFS.

Price Value (PV)

Price value weighs perceived benefits against fees and charges. When users feel the time savings and convenience outweigh costs, intention to adopt strengthens (Venkatesh et al., 2012). People in rural areas who do not have much extra money may not use MFS due to the transaction fees and service charges associated with it. A good price-benefit perception is likely to lead to more people using it.

H6: Price value will positively relate to intention to use MFS among rural users.

Habit (HT)

Habit captures the extent to which MFS use becomes automatic through repetition, making continued usage more likely over time (Venkatesh et al., 2012). As people get used to using MFS for everyday transactions, it may become a habit that keeps them using it. The power of habit is magnified in communities where literacy rates are low, since the act of utilizing something over and over again brings about a sense of familiarity and comfort.

H7: Habit will positively relate to actual MFS usage among rural users.

Behavioral Intention and MFS Usage

Behavioral intention is a proximal driver of actual behavior: favorable beliefs about MFS typically translate into observable usage. People who plan to use MFS because they have positive views on UTAUT2 constructs are more likely to become regular users (Islam et al., 2023).

H8: Behavioral intention will positively predict MFS usage.

MFS Usage and Financial Literacy

The study posits that more frequent MFS use builds practical financial know-how—budgeting, fee awareness, and transaction planning—thereby supporting financial literacy. Researchers believe that people will become more financially literate as they increasingly use mobile financial platforms. This is because they will learn more about money, become better at planning transactions, and feel more confident about managing their money (Rahman & Jahan, 2022).

H9: Greater MFS usage will be positively associated with financial literacy among rural users.

DOI: 10.48165/sajssh.2024.6508

METHODOLOGY

Research Design

The researcher fielded structured survey with **432** rural participants drawn from **five districts** of Bangladesh. The instrument covered the UTAUT2 constructs, patterns of MFS use, a brief financial-literacy battery, and demographics (gender, age, education, income, and prior usage experience).

I used descriptive statistics to describe the sample and chi-square tests to examine the use of MFS across different demographics and the level of financial literacy. Afterwards, I conducted a PLS Multi-Group Analysis (MGA) to explore the possibility of gender and education-based differences in important structural routes.

I can identify the demographic elements influencing correlations between the behavioral drivers of MFS adoption and these drivers by combining basic group comparisons with multi-group modeling.
This research makes use of a quantitative, cross-sectional approach. Using PLS-SEM in SmartPLS 4.0, I approximated the measurement and structural models. To assist the exploratory parts of the study, PLS-SEM works well with small to medium samples, is tolerant of non-normal data, and supports models with several latent constructs and indicators (Hair et al., 2021).

Population and Sample

The study's intended participants were people living in rural areas of Bangladesh who made regular use of mobile money services like bKash, Nagad, or Rocket. To make sure that we included only relevant MFS users in our sample, we used a non-probability purposive sampling approach. Kurigram, Bogura, Barisal, Cumilla, and Sunamganj are five districts with sizable rural populations, and a total of 432 legitimate respondents were surveyed from each of these areas. We chose these areas based on how far along the spectrum of digital and financial inclusion they are.
We used Hair et al.'s (2021) suggestion of using at least ten times the number of indicators for PLS-SEM to estimate the sample size, which should be sufficient for statistical analysis. The sample satisfies the criteria with 35 measurement items across nine components.

Instrument Development

DOI: 10.48165/sajssh.2024.6508

Using scores that have been verified and modified from previous research, a structured questionnaire was created. A total of five questions measuring each UTAUT2 framework concept were administered using Likert scales with values ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The five self-report elements that make up the financial literacy assessment measure indicate knowledge, awareness, and responsible conduct when it comes to money.

Measurement sources included:

- UTAUT2 constructs: Venkatesh et al. (2012)
- MFS usage: Karim & Noor (2022), Islam et al. (2023)
- Financial literacy: Lusardi & Mitchell (2014), Sultana et al. (2022)

The questionnaire was pretested with 30 respondents in a pilot study to ensure clarity, reliability, and internal consistency. Minor revisions were made based on the pilot results.

Data Collection Procedure

From January to May of 2025, trained field enumerators interviewed people in person to gather data. The interviews were necessary due to the limited digital access and literacy levels of some respondents. Verbal consent was obtained prior to each interview, and participants' anonymity was assured. Participation was voluntary, and ethical standards were upheld throughout the research process.

Data Analysis Techniques

The data were analyzed using a two-step SEM approach in **SmartPLS 4.0**:

- **Measurement Model**: The items' intended constructions were verified for strong loadings (outer loadings ≥ 0.70) before anything else. Next, I checked for internal consistency using Cronbach's α and composite reliability, which were both more than or equal to 0.70. To determine convergent validity, we used an AVE of 0.50 or higher, and to validate discriminant validity, we used the Fornell-Larcker criteria in conjunction with HTMT ratios.
- **Structural Model**: After that, I looked at each endogenous construct's path coefficients and variance explained (R^2). I used bootstrapping with 5,000 resamples to test for significance. I also provided effect sizes (f^2) and predictive relevance (Q^2).

DOI: 10.48165/sajssh.2024.6508

To further rule out multicollinearity, the research checked for common method bias using VIF values and Harman's single-factor test.

RESULTS: DEMOGRAPHIC PROFILE, SMARTPLS OUTPUT, AND MODEL DEVELOPMENT

Demographic Profile

From rural MFS users in five districts of Bangladesh, 432 valid replies were obtained. Table 1 provides a concise overview of the important demographic details.

Table 1: *Demographic Analysis (n = 432)*

Variable	Category	Frequency	Percentage (%)
Gender	Male	260	60.2%
	Female	172	39.8%
Age (years)	18–25	98	22.7%
	26–35	143	33.1%
	36–45	112	25.9%
	46 and above	79	18.3%
Education	Primary or below	120	27.8%
	Secondary	174	40.3%
	Higher Secondary	88	20.4%
	Bachelor and above	50	11.6%
Monthly Income	< BDT 10,000	145	33.6%
	BDT 10,001 – 20,000	172	39.8%
	BDT 20,001 – 30,000	78	18.1%
	> BDT 30,000	37	8.6%
MFS Usage Experience	< 1 year	126	29.2%

DOI: 10.48165/sajssh.2024.6508

	1–3 years	202	46.8%
	> 3 years	104	24.0%

Demographic Analysis

- ✓ **Gender:** Men make up 60.2% of the sample, with women at 39.8%. The split hints at ongoing hurdles to equal access in rural areas.
- ✓ **Age:** Most participants (55.8%) are 26–45 years old, the economically active group that typically adopts MFS earlier (Islam et al., 2023).
- ✓ **Education:** A large share (68.1%) has secondary schooling or less, underscoring the need for clear, easy-to-use MFS interfaces.
- ✓ **Income:** Nearly three-quarters (73.4%) earn under BDT 20,000 per month, showing that low-income households are using MFS as a cost-effective option.
- ✓ **Usage experience:** About half (46.8%) have used MFS for 1–3 years, suggesting the technology has moved beyond early adopters yet continues to gain ground in rural communities.

Implications for Analysis

- ✓ Sociodemographic factors such as age, education, and income could act as moderators in the relationship between MFS adoption and financial literacy. For example, more educated users may acquire literacy faster through MFS.
- ✓ Gender differences could be explored to assess digital financial inclusion for women.
- ✓ Experience with MFS usage may impact habit formation, influencing long-term financial literacy outcomes.

Demographic Differences: Statistical Tests

Chi-Square Test

We conducted **Chi-square (χ^2) tests** to examine whether demographic variables significantly influence the frequency of MFS usage and financial literacy levels.

- ✓ **Gender vs. MFS Usage Frequency:** $\chi^2(2) = \mathbf{6.84}$, $p = 0.033$ → **Significant**

DOI: 10.48165/sajssh.2024.6508

- ✓ Male respondents reported slightly higher usage frequency compared to females, suggesting gendered access barriers in rural communities.
- ✓ **Age vs. MFS Usage Frequency:** $\chi^2(6)$ = **14.92**, $p = 0.020$ → **Significant**
- ✓ Younger respondents (18–35 years) used MFS more frequently than older groups.
- ✓ **Education vs. Financial Literacy Levels:** $\chi^2(6)$ = **28.51**, $p < 0.001$ → **Highly significant**
- ✓ Higher education levels strongly correlated with higher financial literacy.
- ✓ **Income vs. Financial Literacy Levels:** $\chi^2(6)$ = **19.34**, $p = 0.004$ → **Significant**

Households with higher incomes showed better literacy, possibly due to a greater variety of transactions.

Implication: Education and income play critical roles in maximizing the literacy benefits of MFS adoption.

Multi-Group Analysis (MGA) in SmartPLS

We performed **PLS-MGA** to test whether the structural relationships differ by **gender** and **education level**.

Gender-Based MGA

- ✓ **Behavioral Intention → MFS Usage**: No significant difference ($\Delta\beta = 0.041$, $p > 0.05$)
- ✓ **MFS Usage → Financial Literacy**: Significant difference ($\Delta\beta = 0.098$, $p = 0.029$)
  → **Females showed a stronger relationship between MFS usage and financial literacy**, suggesting that women may gain relatively more knowledge per usage instance compared to men.

Education-Based MGA

- ✓ **Performance Expectancy → Behavioral Intention**: Significant difference ($\Delta\beta = 0.112$, $p = 0.018$) → More educated users rely less on perceived usefulness and more on convenience/effort expectancy.

DOI: 10.48165/sajssh.2024.6508

- ✓ **MFS Usage → Financial Literacy**: Stronger for low-education group ($\Delta\beta = 0.085$, $p = 0.037$) → Less educated users experience a **greater literacy gain** from using MFS, showing its potential to bridge knowledge gaps.

Narrative Linking Demographics with Results

The demographic analysis enriches the interpretation of the structural model:

1. **Younger and moderately educated rural users are the primary adopters of MFS.** Their stronger digital engagement aligns with prior findings that younger populations tend to adapt more quickly to mobile technologies (Islam et al., 2023).
2. **Women's MFS usage shows higher literacy benefits,** suggesting that digital financial services can be a transformative tool for women's empowerment in rural areas where traditional financial education is scarce (Rahman & Jahan, 2022).
3. **Education amplifies literacy outcomes,** but interestingly, less educated users benefit more proportionally from repeated MFS usage, indicating that experiential learning through digital transactions helps fill financial knowledge gaps.
4. **Low-income users widely adopt MFS for essential transactions**, but their literacy levels remain constrained by limited financial diversity. Policy interventions could integrate targeted financial literacy content within MFS interfaces for this segment.

Thus, **demographic diversity significantly influences adoption behaviors and literacy outcomes, underscoring the importance of inclusive design and context-specific policies**.

Measurement Model Evaluation

Consistent with Hair et al. (2021), I examined the measurement model's reliability and validity.

Indicator Reliability

With item loadings ranging from 0.72 to 0.88, all indicators correctly reflect their respective constructs, above the acceptable criterion of 0.70. Everything remained as there was a statistically significant result for all outside loadings ($p < 0.001$).

Internal Consistency Reliability

DOI: 10.48165/sajssh.2024.6508

Composite Reliability (CR) and Cronbach's Alpha (CA) were used to evaluate internal consistency. See Table 1 for details on the excellent dependability indicated by CA and CR values, both of which are above 0.70.

Convergent Validity

The latent structures explained a significant amount of the indicator variation, as the Average variation Extracted (AVE) for all constructs was between 0.59 and 0.66, which is higher than the suggested criterion of 0.50.

Table 2: ***Reliability and Convergent Validity***

Construct	Items	Cronbach's Alpha	Composite Reliability	AVE	Outer Loadings
Performance Expectancy	5	0.876	0.913	0.654	0.74–0.87
Effort Expectancy	4	0.852	0.890	0.612	0.72–0.85
Social Influence	3	0.789	0.851	0.598	0.70–0.83
Facilitating Conditions	4	0.843	0.884	0.622	0.73–0.84
Hedonic Motivation	3	0.790	0.847	0.590	0.70–0.82
Price Value	3	0.801	0.860	0.605	0.71–0.83
Habit	4	0.842	0.885	0.615	0.74–0.85
Behavioral Intention	4	0.879	0.911	0.663	0.75–0.88
Financial Literacy	5	0.867	0.902	0.640	0.73–0.86

These results confirm the **internal consistency** and **convergent validity** of all constructions.

Discriminate Validity

Discriminant validity was evaluated using two approaches:

First, there is the Fornell-Larcker criteria, which looks at the correlations between different constructs and the square root of each construct's AVE (the values on the bold diagonal in Table 2). The condition is met, signifying discriminant validity, if the former is bigger than the latter.

Table 3: *Discriminant Validity (Fornell-Larcker Criterion)*

DOI: 10.48165/sajssh.2024.6508

Construct	PE	EE	SI	FC	HM	PV	HT	BI	FL
Performance Expectancy	**0.81**								
Effort Expectancy	0.52	**0.78**							
Social Influence	0.44	0.46	**0.77**						
Facilitating Conditions	0.40	0.42	0.55	**0.79**					
Hedonic Motivation	0.43	0.45	0.40	0.38	**0.77**				
Price Value	0.47	0.44	0.39	0.41	0.40	**0.78**			
Habit	0.48	0.50	0.44	0.43	0.42	0.45	**0.78**		
Behavioral Intention	0.65	0.60	0.55	0.52	0.50	0.53	0.54	**0.82**	
Financial Literacy	0.35	0.30	0.28	0.32	0.31	0.33	0.36	0.40	**0.80**

Second, the Heterotrait-Monotrait (HTMT) ratio was less than 0.85 for all samples. This proves the discriminant validity by showing that the constructs are different in practice.

Undoubtedly, the measurement model's reliability and validity stand as pillars of this research, ensuring its robustness and credibility.

Structural Model Evaluation

The assessment of the structural model followed the confirmation of the measurement model. No multicollinearity problems were detected since the Collinearity Assessment Variance Inflation Factor (VIF) was less than 3.3, ranging from 1.23 to 2.85.

Testing Hypotheses using Path Coefficients: To determine the relevance of the route, the bootstrapping method with 5,000 resamples was used.

Table 4: *Hypothesis Testing Results*

Hypothesis	Relationship	β	t-value	p-value	Result
H1	PE → Behavioral Intention	0.285	5.23	<.001	Supported
H2	EE → Behavioral Intention	0.212	4.12	<.001	Supported
H3	SI → Behavioral Intention	0.165	3.54	<.001	Supported

DOI: 10.48165/sajssh.2024.6508

H4	FC → MFS Usage	0.198	4.10	<.001	Supported
H5	HM → Behavioral Intention	0.125	2.78	0.006	Supported
H6	PV → Behavioral Intention	0.143	3.01	0.003	Supported
H7	Habit → MFS Usage	0.235	5.30	<.001	Supported
H8	Behavioral Intention → Usage	0.458	9.12	<.001	Supported
H9	MFS Usage → Financial Literacy	0.392	7.01	<.001	Supported

All hypothesized paths are **positive and significant**, supporting the proposed model.

Coefficient of Determination (R^2)

- **Behavioral Intention** R^2 = **0.564**, indicating that PE, EE, SI, HM, and PV explain 56.4% of its variance.
- **MFS Usage** R^2 = **0.498**, indicating moderate explanatory power from Behavioral Intention, Habit, and Facilitating Conditions.
- **Financial Literacy** R^2 = **0.341**, showing that MFS Usage explains 34.1% of variance.

Effect Size (f^2)

- Performance Expectancy had the **largest effect** on Behavioral Intention (f^2 = 0.20), followed by Effort Expectancy (0.12) and Social Influence (0.08).
- Behavioral Intention had a **substantial effect** on MFS Usage (f^2 = 0.35).
- MFS Usage showed a **medium effect** on Financial Literacy (f^2 = 0.25).

Predictive Relevance (Q^2)

Blindfolding results revealed positive Q^2 values:

- Behavioral Intention (Q^2 = 0.38)
- MFS Usage (Q^2 = 0.31)
- Financial Literacy (Q^2 = 0.27)

This confirms the model's robust predictive relevance for endogenous constructs, providing a strong foundation for future research and policy decisions.

DOI: 10.48165/sajssh.2024.6508

Model Fit

- The model's fit is superb; the SRMR (Standardized Root Mean Square Residual) is 0.052, which is far lower than the cutoff of 0.08. This bodes well for the model's validity and reliability.

Structural Model Interpretation

1. **Drivers of Behavioral Intention:**

   Performance Expectancy emerged as the **strongest predictor**, suggesting rural users prioritize tangible benefits (time savings, convenience) when adopting MFS. Effort Expectancy and Social Influence were also significant, emphasizing the importance of ease of use and community endorsement in rural adoption contexts.

2. **Determinants of Actual Usage:**

   Habit and Facilitating Conditions significantly influenced actual MFS usage. This underscores that sustained adoption requires repeated exposure and reliable infrastructure. Behavioral Intention was the **most influential predictor** of actual use.

3. **Impact on Financial Literacy:**

   Crucially, MFS Usage had a **positive and significant effect** on Financial Literacy. This indicates that frequent engagement with mobile platforms enhances financial knowledge, budgeting skills, and overall awareness, supporting the notion that technology can serve as an informal channel for financial education.

Summary

The UTAUT2 components and their important significance in promoting MFS adoption are validated by the model's great explanatory and predictive power.

RESULTS AND DISCUSSION

Measurement Model Evaluation

Complete tests for discriminant validity, convergent validity, internal consistency, and indicator reliability were conducted on the measurement model. Strong indication reliability was supported by all item loadings, which were more than 0.70 and ranged from 0.72 to 0.88. High levels of internal consistency were shown by composite reliability coefficients and

DOI: 10.48165/sajssh.2024.6508

Cronbach's Alpha, both of which were more than 0.80. Furthermore, the Average Variance Extracted was found to be between 0.59 to 0.66, which is greater than the 0.50 criterion and indicates convergent validity (Hair et al., 2021).

When the square root of each construct's AVE was greater than its correlations with other constructs, discriminant validity was established using the Fornell-Larcker criteria. The fact that all of the Heterotrait-Monotrait (HTMT) ratios were less than 0.85 further supports the idea that the constructs in question are empirically separate.

Now that we know the measurement model is reliable and valid, we can go on to measuring the structural model, according to the results.

Structural Model Evaluation

The structural model was evaluated using path analysis, explanatory power, effect sizes, predictive relevance, and model fit after the measurement model was shown to be adequate.

Collinearity and Model Fit

No problems with multicollinearity were detected since the Variance Inflation Factor (VIF) values were between 1.23 and 2.85, which is much lower than the crucial threshold of 3.3. With an SRMR of 0.052—well below the suggested threshold of 0.08—the model seems to have been well-fitted.

Hypothesis Testing

The significance of the route coefficients was estimated using bootstrapping with 5,000 resamples. The suggested model was supported by all predicted connections, which were positive and statistically significant ($p < 0.01$) (refer to Table 1).

Table 5: *Results of Testing Hypotheses*

Hypothesis	Relationship	β	t-value	p-value	Result
H1	PE → Behavioral Intention	0.285	5.23	<.001	Supported
H2	EE → Behavioral Intention	0.212	4.12	<.001	Supported
H3	SI → Behavioral Intention	0.165	3.54	<.001	Supported
H4	FC → MFS Usage	0.198	4.10	<.001	Supported

DOI: 10.48165/sajssh.2024.6508

H5	HM → Behavioral Intention	0.125	2.78	0.006	Supported
H6	PV → Behavioral Intention	0.143	3.01	0.003	Supported
H7	Habit → MFS Usage	0.235	5.30	<.001	Supported
H8	Behavioral Intention → Usage	0.458	9.12	<.001	Supported

Explanatory Power (R^2)

The model demonstrated **moderate-to-high explanatory power** for key endogenous constructions:

The factors of performance expectation, effort expectation, social influence, hedonic motivation, and price value account for 56.4% of the variation in behavioral intention, as shown by the coefficient of determination (R^2) of 0.564.

Behavioral intention, habit, and facilitating conditions account for almost half of the variation in actual use behavior, according to MFS use: $R^2 = 0.498$.

$R^2 = 0.341$ for Financial Literacy shows that MFS Usage accounts for 34.1% of the variation in Financial Literacy.

These values meet the benchmark for substantial predictive relevance in behavioral studies (Hair et al., 2021).

Effect Sizes (f^2)

The **effect size analysis** revealed that:

- ✓ **Performance Expectancy** had the largest effect on Behavioral Intention ($f^2 = 0.20$).
- ✓ **Effort Expectancy** ($f^2 = 0.12$) and **Social Influence** ($f^2 = 0.08$) had moderate-to-small effects.
- ✓ **Behavioral Intention** exhibited a **large effect** on MFS Usage ($f^2 = 0.35$), indicating its central role in translating user perceptions into actual adoption.
- ✓ **MFS Usage** showed a **medium effect** on Financial Literacy ($f^2 = 0.25$), confirming its meaningful contribution to improving financial knowledge and behavior.

Predictive Relevance (Q^2)

DOI: 10.48165/sajssh.2024.6508

The model's good predictive potential for future outcomes was shown by Q^2 values for Behavioral Intention (0.38), MFS Usage (0.31), and Financial Literacy (0.27), all of which were larger than zero when the blindfolding process was used.

DISCUSSION

The findings provide robust empirical evidence for the UTAUT2 model in explaining the adoption of MFS in rural Bangladesh and highlight the socioeconomic benefits of digital financial inclusion.

Drivers of Behavioral Intention:

Previous research has shown that perceived utility is a key motivator for technology adoption (Islam et al., 2023), and our findings show that performance expectation was the biggest predictor. Significant results were also obtained from effort expectation and social influence, demonstrating the importance of community support and user-friendly interfaces as key drivers in rural settings. Users in remote areas saw Mobile Financial Services (MFS) more as a need than an experience that should be pleasurable, even while Hedonic Motivation and Price Value were also identified as important elements, their influence was very limited.

Determinants of Actual Usage:

Behavioral intention showed the greatest significant impact on Mobile Financial Services (MFS) utilization, supporting UTAUT2's conceptual framework, where intention plays a leading role in determining behavior. Habit and facilitating conditions also showed significant contributions, further supporting that infrastructure reliability, e.g., from agent networks, as well as sustained exposures, play critical roles in sustained usage.

Impact on Financial Literacy:

Notably, adoption of Mobile Financial Services (MFS) showed a significant and statistically significant impact on Financial Literacy, thus supporting the research's basic hypothesis. Frequent interaction on MFS platforms makes users accustomed to transactional protocols, budgeting tools, and sources of financial decision-making, all of which cumulatively enhance their knowledge and skills in finance. The finding supports ever-growing claims that digital finance can be an informal channel of financial education to marginalized populations (Rahman & Jahan, 2022).Overall, the model's **moderate-to-high explanatory power (R^2)** and **predictive relevance (Q^2)** demonstrate that integrating UTAUT2 constructs with financial

DOI: 10.48165/sajssh.2024.6508

literacy outcomes offers a valuable framework for understanding the impacts of digital inclusion in rural contexts.

Summary

The empirical analysis confirms that MFS adoption is driven by perceived usefulness, ease of use, and social endorsement, while actual usage fosters financial empowerment through improved literacy. These insights have important implications for policymakers, financial service providers, and development practitioners aiming to bridge the digital financial divide in rural Bangladesh.

CONCLUSION, RECOMMENDATIONS, AND FUTURE RESEARCH

Conclusion

This research used the UTAUT2 model to look at how MFS affected people's knowledge of personal finance in rural Bangladesh. Results showed that price value, social influence, hedonic motivation, performance expectation, and effort expectancy are the most important factors influencing the inclination to use MFS. Additionally, behavioral intention demonstrated a clear correlation with use behavior, and enabling environments and habits are important predictors of use as well. The results showed that more people are using MFS, which means that people in rural areas have better access to electronic financial services, which means they have better financial literacy.

By building on previous research that found a correlation between financial literacy outcomes and technology adoption, this study expands UTAUT2's conceptual framework beyond its original scope of use and intention to encompass digital financial inclusion's more far-reaching socioeconomic effects.

Recommendations

Based on the findings, several actionable recommendations are proposed:

1. **Enhance User-Friendly Platforms:** Financial service providers should prioritize simplifying MFS interfaces to improve usability for low-literacy users.
2. **Strengthen Rural Infrastructure:** Policymakers should invest in network coverage and agent accessibility to improve facilitating conditions.
3. **Leverage Social Networks:** Community-driven awareness campaigns can amplify social influence and encourage trust in MFS platforms.

DOI: 10.48165/sajssh.2024.6508

4. **Integrate Financial Literacy Programs:** Combining digital financial services with structured financial education modules can accelerate the empowerment of rural communities.

5. **Promote Habit Formation:** Incentivizing regular MFS use (e.g., through reward programs) can help form habits that lead to sustainable adoption and deeper financial engagement.

Future Research Directions

While this study provides valuable insights, it also opens several avenues for future research:

- **Longitudinal Studies:** Future research should adopt longitudinal designs to assess how sustained MFS usage affects financial literacy over time.
- **Qualitative Exploration:** In-depth interviews or focus groups could provide a richer contextual understanding of behavioral barriers and motivations.
- **Comparative Studies:** Cross-country comparisons could reveal cultural and policy-driven differences in how MFS adoption impacts financial literacy.
- **Integration with Fintech Innovations:** Future work could explore how emerging technologies like micro-insurance or digital credit further influence financial literacy outcomes.
- **Gender-Based Analysis:** Investigating gender-specific adoption patterns could reveal unique challenges faced by women in rural communities.

Acknowledgement

The article was conceived, executed, and written by a single author. Language-editing software was used only to improve grammar and clarity; all ideas, data collection, analyses, and interpretations are solely the author’s own.

DOI: 10.48165/sajssh.2024.6508

REFERENCES

Akter, S., Hossain, M. A., & Uddin, M. S. (2023). Risks and barriers in mobile financial service usage in rural Bangladesh: A qualitative analysis. *Journal of Financial Services Marketing, 28*(1), 12–24. https://doi.org/10.1057/s41264-023-00165-4

Alam, M. S., & Hossain, M. T. (2023). Digital finance and financial literacy: Evidence from low-income users in South Asia. *South Asia Economic Journal, 24*(1), 45–65.

Demirgüç-Kunt, A., Klapper, L., Singer, D., & Ansar, S. (2022). *The Global Findex Database 2021: Financial inclusion, digital payments, and resilience in the age of COVID-19*. World Bank Publications.

Hair, J. F., Jr., Ringle, C. M., & Sarstedt, M. (2021). Partial least squares structural equation modeling: Rigorous applications, better results, and higher acceptance. *Journal of Marketing Theory and Practice, 29*(2), 139–155. https://doi.org/10.1080/10696679.2021.1893717

Hasan, M. R., Rahman, M. M., & Alam, S. M. (2023). Mobile financial services and financial inclusion in Bangladesh: An empirical study. *Information Development, 39*(2), 153–166. https://doi.org/10.1177/02666669221119963

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hu, L.-T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Islam, M. T., Kabir, M. R., & Ali, M. Y. (2023). Adoption of mobile banking in rural areas of Bangladesh: Applying UTAUT2 model. *Asian Journal of Technology & Management Research, 13*(1), 45–58.

Karim, R., & Noor, M. A. (2022). Understanding mobile banking adoption in Bangladesh: An extension of UTAUT2 model. *International Journal of Bank Marketing, 40*(5), 985–1002. https://doi.org/10.1108/IJBM-09-2021-0365

Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature, 52*(1), 5–44. https://doi.org/10.1257/jel.52.1.5

Rahman, M., & Jahan, N. (2022). Digital financial literacy in rural Bangladesh: Gaps and opportunities. *Bangladesh Development Studies, 45*(3), 101–122.

Sultana, N., Begum, M., & Haque, T. (2022). Financial literacy and mobile money usage: Evidence from rural households in Bangladesh. *Journal of Development Research, 15*(2), 89–104.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157–178. https://doi.org/10.2307/41410412

DOI: 10.48165/sajssh.2024.6508