Post COVID-19 and Mobile Financial Service Adoption: A Study on Micro Enterprises in Dhaka City

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Abstract

The COVID-19 lockdown highlighted the value of remote transactions, with many micro-enterprises facing significant setbacks. Recognising this shift, the adoption of mobile financial services (MFS) is now seen as crucial for economic resilience, especially for economies where banking participation boosts national savings. This study uses the Unified Theory of Acceptance and Use of Technology (UTAUT) model to assess factors shaping the perception of Bangladesh's entrepreneurs towards mobile financial services (MFS) changed during the COVID-19 pandemic. It seeks to rank the importance of these factors and explore what micro-entrepreneurs value in MFS adoption to identify desired reforms that may increase financial inclusion. The analysis of the study is primarily quantitative involving Structural Equation Modelling with Partial Least Squares (PLS-SEM). Findings indicate a generally positive shift toward MFS adoption among micro-entrepreneurs due to the pandemic, though the results lack strong statistical significance due to sample limitations. Notably, educated, middle-to-upper-income female entrepreneurs reported higher ease and intention to use MFS, challenging initial UTAUT hypotheses. As profitability and operational efficiency remain a primary concern for micro-entrepreneurs, MFS providers should market these benefits. Additionally, digital literacy and female-focused MFS initiatives could foster greater adoption.

Keywords: mobile financial services, adoption, digital financial inclusion, UTAUT, micro enterprises, COVID-19, pandemic

Introduction

The COVID-19 pandemic created a new technological compatibility challenge across Bangladesh's economic sectors. Lockdowns emphasised the demand for remote transactions, which Mobile Financial Services (MFS) helped to fulfil by enabling mobile-based financial transactions (Kim et al., 2018; Yang et al., 2012). Between 2017 and 2021, bank account ownership expanded in both

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conventional and mobile banking, with significant increases among lower-income populations: account holders in the poorest 40% grew from 40.08% to 48.65%, while the wealthiest 60% remained near 56%. Female account ownership rose notably from 35.84% to 43.46%, even as male account ownership declined from 64.59% to 62.86%. These changes suggest that the pandemic contributed to increased financial inclusion in Bangladesh.

MFS gained popularity as the pandemic unfolded, with registered accounts jumping from 82.576 million in March 2020 to 102.715 million by July 2021, a 24.39% rise. Active accounts saw an even larger increase, growing by 53.32% from 26.845 million to 41.158 million. This surge highlights the growing importance of MFS during periods of restricted mobility. By the end of August 2024, the number of registered accounts and active accounts rose to 230.122 million and 90.645 million respectively. Thus, it can be hypothesised that the increase in bank account holders mentioned before among the lower-income group and the female group may have been influenced by the ever-growing popularity of MFSs.

Micro-enterprises form the largest segment of businesses in Bangladesh, with nearly 7.8 million enterprises identified in the 2013 Economic Census by BBS. Of these, 88.85% are cottage and micro-enterprises, which collectively employ around 56% of the country's workforce. However, a major barrier for these businesses is limited access to financing (ADB, 2018). To address this, integrating micro-entrepreneurs into the financial system is essential for expanding their financing options. The Bangladesh Bank is actively encouraging micro-entrepreneurs to register through Mobile Financial Services (MFS), though internet access and digital literacy are critical for effective MFS use.

According to the "learning by doing" theory, using MFS could gradually improve digital literacy; as individuals repeatedly use the technology, they become more comfortable with it. It is, therefore, crucial to assess micro-entrepreneurs' perceived readiness to operate MFS, as this confidence could influence their adoption of the technology. Additionally, understanding the factors that drive MFS adoption among micro-entrepreneurs will help MFS providers tailor their services to better support financial inclusion within this essential sector.

Recent studies in Bangladesh have explored factors driving Mobile Financial Service (MFS) adoption, with some linking it to COVID-19's impact using the UTAUT and UTAUT 2.0 models (Hassan et al., 2022; Himel et al., 2021; Khan et al., 2021; M. A. Rahman & Islam, 2022; S. A. Rahman et al., 2020; Saima et al., 2022; Yan et al., 2021). These studies largely target specific groups like university students or diverse samples from rural Bangladesh (Alam

& Rahman, 2022; Khan et al., 2021; Saima et al., 2022; Yan et al., 2021), leaving a gap in research focusing on micro-enterprises and the specific impact of COVID-19 on their MFS adoption (M. A. Rahman & Islam, 2022; S. A. Rahman et al., 2020). Though a few studies have examined this impact without employing the UTAUT model, this paper addresses the gap by assessing MFS adoption among micro-entrepreneurs during the pandemic. Previous research often overlooked a specific user community and lacked direct reference to COVID-19 in their survey questions (Khan et al., 2021); this study narrows its focus to Dhaka's micro-entrepreneurs, directly querying changes in their MFS usage during the pandemic.

This study aims to identify the factors that influence MFS adoption among micro-enterprises in Dhaka city. Specifically, it seeks to quantify the influence of various factors shaping micro-entrepreneurs' perceptions of MFS and rank the influence of these factors to highlight potential reforms that micro-entrepreneurs might seek from MFS providers. It empirically investigates whether the COVID-19 pandemic impacted MFS usage behaviour and explores whether findings match the earlier UTAUT model studies based on the technology being assessed.

This paper addresses several key research inquiries regarding Mobile Financial Service (MFS) adoption among micro-enterprises in Dhaka city. It explores the factors that influence MFS adoption, examines whether the COVID-19 pandemic has moderated the relationship between micro-entrepreneurs' intentions to use MFS and their actual usage behaviour, and identifies steps to increase MFS penetration and financial inclusion. Additionally, it investigates what aspects of MFS micro-entrepreneurs prioritise and considers whether hypotheses based on prior research might change when the population of MFS users is disaggregated by profession or technology type.

Background

Digital Financial Inclusion (DFI) aims to tackle the issue of the unbanked poor being excluded from financial services (Lyman & Lauer, 2015). DFI consists of three key components: digital inclusion, financial inclusion, and social inclusion (Aziz & Naima, 2021). Essentially, DFI is a system that ensures access to various digital services for financial purposes. The potential economic benefits of enhanced DFI are significant, as it is expected to boost social inclusion, foster digital literacy, and support micro-entrepreneurs. Research by Khera et al. (2021) indicates that a 0.1205 index point increase in DFI could lead to a 1.61% rise in annual real GDP, and increasing DFI from 25% to 75% may result in a 2.2% GDP increase. Additionally, improving DFI could facilitate digital inclusion in remote areas. Given the rising popularity of MFS, Bangladesh can use the potential of this technology to increase its DFI.

According to the World Bank, financial inclusion offers multiple benefits. Households receiving money directly into bank accounts tend to have increased consumption and savings, often retaining more money in accounts instead of converting it to cash (Blumenstock et al., 2018). In Kenya, financial support from relatives abroad helped reduce families' vulnerability to economic shocks (Jack & Suri, 2014). Furthermore, Lee et al. (2021) found that rural migrants in Bangladesh sent higher remittances to their families through mobile transactions, allowing these households to avoid financial difficulties. Mobile financial services can also lower government payment costs (Aker et al., 2016; Muralidharan et al., 2016).

In Bangladesh, the rapid growth of mobile phone subscribers is notable, with 175 million subscriptions—outnumbering the population (Khan et al., 2021). The World Bank reports that mobile phone subscriptions per 100 people rose rapidly up to 109 until 2021 following a decline to 105 in 2022. Mobile Financial Services (MFS) are expanding in Bangladesh, transitioning from mobile banking interoperability to utility and merchant payment services. More financial services are being integrated into mobile banking apps. To facilitate greater financial inclusion, Bangladesh Bank and the ICT Division have signed an agreement to provide an API platform for fintech institutions, as outlined in the National ICT Policy 2018 (ICT Division, 2018).

MFS is increasingly utilised for wage payments to Ready-Made Garment (RMG) workers (Holy, 2020). In August 2024, the number of transactions was 577.23 million compared to 512.29 million in August 2023 (a 12.68% rise). The transaction volumes increased from nearly 1095.55 billion BDT to 1379.2 billion BDT (a 25.93% rise) and the average transaction value grew from approximately 35.34 billion BDT to 44.5 billion BDT within the same time frame. This underscores the continuous rise in MFS's crucial role in financial transactions in Bangladesh.

Literature Review

Khalily et al. (2020) explain that enterprises are typically classified based on employment size, turnover, or asset value. However, due to the lack of accessible income statements and balance sheets for most micro-enterprises, classifying them by turnover or assets is challenging. Consequently, many developing countries rely on employment size as a classification criterion for small and medium-sized enterprises (SMEs). For instance, Egypt defines SMEs as having between 5 to 50 employees, while Vietnam sets the range at 10 to 300 employees (Chowdhury et al., 2013). International organizations like the World Bank, EU, and OECD also use employee count to define SMEs, with the World Bank identifying SMEs as those with fewer than 300 employees, $15 million in annual revenue, or $15 million in assets (Chowdhury et al., 2013). Additionally, the EU and OECD categorize SMEs into micro-enterprises, which have fewer than 10 employees (European Commission, 2017; OECD, 2022).

Given that employee numbers are readily observable, this paper defines micro, small, and medium enterprises (MSMEs) in Bangladesh based on this criterion. However, variations in definitions by Bangladesh Bank and the Ministry of Industries create confusion surrounding the terms MSME and SME (Chowdhury et al., 2013). This study adopts the EU's definition to categorize enterprises in Dhaka as MSMEs, recognizing the influence of institutional frameworks on such classifications. Institutional Theory is particularly relevant here, as it highlights how regulatory environments and organizational norms shape enterprise classifications and their access to resources and technologies (Li & Abiad, 2009).

Technology adoption among enterprises, including MSMEs, is often explained using models like the Technology Acceptance Model (TAM; Davis, 1989), Theory of Reasoned Action (TRA; Fishbein & Ajzen, 1975), and Theory of Planned Behaviour (TPB; Ajzen, 1991). These models share common variables, such as perceived ease of use, attitudes, and behavioural intentions. The Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) was developed to integrate these models into a comprehensive framework for understanding technology acceptance. UTAUT introduces key moderators, including voluntary usage (VOL), experience (EXP), age (AGE), and gender (GEN), and predicts "Behavioural Intention" (BI) using three exogenous constructs: "Performance Expectancy" (PE), "Effort Expectancy" (EE), and "Social Influence" (SI). The "Use Behaviour" (UB) construct, in turn, is determined by facilitating conditions (FC) and behavioural intention.

Applying Resource-Based View (RBV) to the MSME context, enterprises' size and resources influence their ability to adopt MFS (Barney, 2000). As micro-enterprises are often constrained by limited financial and human resources, they may prioritize facilitating conditions (FC). On the other hand, small and medium enterprises might focus more on performance expectancy (PE) due to their complex operations. Within the context of MSMEs in Bangladesh, previous studies have indicated that digital literacy and access to financial resources are critical barriers to MFS adoption. The Diffusion of Innovations Theory provides insights into how these barriers influence the adoption of mobile financial services (Rogers et al., 2008). As the findings of the study suggest, educated middle to upper-income female entrepreneurs may represent early adopters in this diffusion process, driven by perceived ease of use and compatibility with their business operations.

This study utilises the UTAUT model to assess MFS adoption among Bangladeshi entrepreneurs, connecting these theoretical frameworks to understand the nuanced factors shaping their perceptions. Performance Expectancy refers to the belief that using technology will enhance job performance, correlating positively with the intention to adopt mobile financial services (MFS). Effort expectancy reflects the perceived ease of using technology, which is also positively correlated with behavioural intention. Social Influence encompasses the opinions of others regarding technology use and is expected to affect the intention to adopt MFS positively. Facilitating Conditions relate to the belief in the availability of support for using technology, which positively influences use behaviour. These hypotheses are provided in Table 1.

Table 1: list of primary hypotheses

Hypotheses		Reference
1	Performance expectancy positively influences the behavioural intention of MFS users	Venkatesh et al., 2003; Alalwan et al., 2017; Hongxia et al., 2011
2	Effort expectancy positively influences the behavioural intention of MFS users	Venkatesh et al., 2003; Alalwan et al., 2017; Chong, 2013; Jadil et al., 2021
3	Social influence positively influences the behavioural intention of MFS users	Venkatesh et al., 2003; Hongxia et al., 2011; Leong et al., 2013; Zuiderwijk et al., 2015
4	Facilitating conditions positively influence use behaviour	Venkatesh et al., 2003; Alalwan et al., 2017; Mohamad & Kassim, 2019
5	Behavioural intention influences use behaviour positively	Venkatesh et al., 2003; Sheppard et al., 1988

Table 2 enlists the secondary hypotheses within each primary hypothesis. They include the influence of gender, age, experience and voluntariness on the relationship between independent and dependent constructs.

Table 2: list of secondary hypotheses

1a	The effect of performance expectancy on behavioural intention is stronger for male entrepreneurs	Minton & Schneider, 1980; Morris & Venkatesh, 2000
1b	The relationship between performance expectancy and behavioural intention is negatively moderated by age	Levy, 1988
2a	The effect of effort expectancy on behavioural intention is greater for male entrepreneurs	Morris & Venkatesh, 2000
2b	The relationship between effort expectancy and behavioural intention is negatively moderated by age	Plude & Hoyer, 1986
2c	The relationship between effort expectancy and behavioural intention is positively moderated by experience	Venkatesh et al., 2003
3a	The effect of social influence on behavioural intention is stronger for female entrepreneurs	Miller, 1987; Venkatesh et al., 2003
3b	The relationship between social influence and behavioural intention is positively moderated by age	Morris & Venkatesh, 2000
3c	The relationship between social influence and behavioural intention is positively moderated by experience	Agarwal & Prasad, 1997; Hartwick & Barki, 1994; Karahanna et al., 1999; Taylor & Todd, 1995; Thompson et al., 1991; Venkatesh & Davis, 2000
3d	The relationship between social influence and behavioural intention is positively moderated by voluntariness	Hartwick & Barki, 1994
4a	The relationship between facilitating conditions and use behaviour is positively moderated by age	Venkatesh et al., 2003
4b	The relationship between facilitating conditions and use behaviour is positively moderated by experience	Venkatesh et al., 2003

Figure 1 illustrates the relationship between independent and dependent constructs. The arrows begin with the influencing construct (independent construct) and end with the influenced construct (dependent construct). The "Pandemic Impact" construct moderates the relation between "Behavioural Intention" and "Use Behaviour".

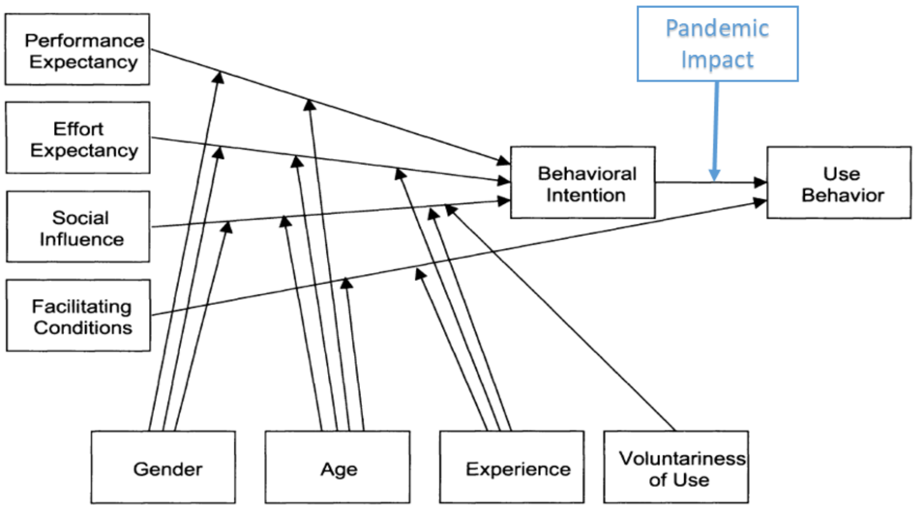

Figure 1: reliability plot of M1 (left panel) and M2 (right panel).

Methodology

Data for this study was gathered through face-to-face or online surveys as deemed necessary, focusing on micro-entrepreneurs, including stationery shop owners, apparel shop owners, electronic shop owners, spectacle shop owners, and student entrepreneurs. The questionnaire utilized Likert scale responses. Quantitative analysis was conducted using "R Studio," along with the "SeminR" package, while the predictive power of the model was assessed using SmartPLS 4. Stratified sampling was employed to select samples from various areas of Dhaka city, specifically Shegun Bagicha, Mohammadpur, Mirpur-12, and Badda, chosen based on the availability of micro-enterprises. The questionnaire was divided into two sections: the first part included socio-demographic questions, and the second part covered constructions such as performance expectancy, effort expectancy, social influence, facilitating conditions, behavioural intention, and use behaviour. Aiming to increase the response rate, the questionnaires were restricted to 27 questions. A total of 120 responses were collected. Most responses from female entrepreneurs were obtained online via Google Forms, as their numbers were scarce in field surveys (i.e. only four women identified as part-time workers in tea stalls owned by their husbands). Some responses were omitted due to uncertainty regarding their classification as entrepreneurs or workers.

According to SME Foundation statistics, the total number of recorded wholesale and retail traders in Dhaka district is 755,478 in urban areas and 1,130,509 in rural areas, resulting in an estimated population of approximately 1,885,987 for this study. This indicates that the percentage of registered MSMEs in urban Dhaka is 40.06%. Using the standard Cochran formula for sample size determination, if a 95% confidence interval (Z = 1.96) and a margin of error of 0.05 is considered, the adjusted sample size is 369. On the other hand, GPower is a tool used to determine sample sizes based on the statistical power of various tests, including t-tests, f-tests, and χ^2 tests (Faul et al., 2009). For this study, the f-test for linear multiple regression was conducted using GPower 3.1 software, which showed five predictor variables in the UTAUT model, corresponding to five arrows indicating relationships without considering moderators. However, when moderators are included, there are 17 arrows representing the prediction of various endogenous variables. With a targeted minimum f-square of 0.15, a significance level of 0.05, and a statistical power of 0.9, the sample size required is 116 without moderators and 179 with moderators. Thus, the number of samples collected is adequate for testing the UTAUT model without moderators, but a larger sample size is necessary for more accurate predictions of the moderators' effects.

Effect of Moderator

A moderator variable influences the relationship between a predictor construct and an endogenous construct, known as the moderating effect. This study primarily focuses on the moderator effect of the pandemic variable (pand), which assesses respondents' perceptions of how the COVID-19 pandemic impacted the adoption of mobile financial services (MFS) through Likert scale responses. The conceptual framework discusses the moderating effects of gender, age, experience, and voluntariness, which are inherent in the UTAUT model. The equation representing the effect of the pandemic moderator is as follows:

$$Y_2 = (\beta_1 + \beta_3 \cdot M) \cdot Y_1 + \beta_2 \cdot M$$

Here, Y_2 represents use behaviour (UB), Y_1 indicates behavioural intention (BI), and M is the pandemic effect (Pand). This equation can also be expressed as:

$$Y_2 = \beta_1 \cdot Y_1 + \beta_3 \cdot M \cdot Y_1 + \beta_2 \cdot M$$

This highlights that the total effect of the moderator on the relationship between the constructs comprises two components: the interaction term β_3 and the direct effect β_2. To evaluate the moderating effect, a two-stage approach is employed due to its greater statistical power and better parameter recovery compared to other methods like the product indicator approach and orthogonalizing approach (Becker et al., 2018; Henseler et al., 2015). The two stages are: estimating the direct or main effect model β_1 and measuring the interaction term.

For gender, a dichotomous dummy variable ("gen") is used, with 1 for male respondents and 2 for female respondents. A positive effect of the gender moderator suggests a stronger relationship for female entrepreneurs. Age is categorized using an ordinal dummy variable ("age") with five groups based on age ranges, while experience is assessed with an ordinal dummy ("exp") classifying respondents by years of operating their enterprise. A positive effect indicates a stronger relationship for more experienced individuals. Voluntariness is represented by a dichotomous dummy ("vol") where 1 indicates voluntary MFS adoption and 2 indicates compelled to use; a positive effect here suggests stronger relationships in mandatory settings. Finally, the pandemic effect is measured through a Likert scale with five response options, assessing whether respondents felt their MFS usage increased during the COVID-19 pandemic. A positive effect indicates a stronger relationship between the constructions during the pandemic.

Measurement Model:

The measurement model analysed the relationships between items and constructs in the path model. Prior to structural model analysis, the measurement model evaluated the redundancy of constructs and indicators. Indicator reliability was tested through loadings, assessing how well a construction explained the variance of its items. Construction explained over 50% of its indicator's variance when loading exceeded 0.708. Indicators with loadings below 0.4 were discarded, while those between 0.4 and 0.708 were only removed if they increased internal consistency reliability (Hair et al., 2016).

Internal Consistency Reliability:

The study measured internal consistency reliability using rhoA, composite reliability (rhoc), and Cronbach's alpha to describe the associations among indicators of the same construct. A composite reliability value over 0.95 indicated redundancy, distorting the construct's validity. As the study was not exploring, rhoA, Cronbach's alpha, and rhoc were required to exceed 0.7. Table 3 indicates that rhoA was below 0.7 for social influence (0.552), primarily due to low loadings for si_4. The researchers reassessed reliability after removing si_4, and despite some loading being below 0.708, all other reliability measures remained within acceptable limits.

Table 3: internal consistency reliability & convergent validity

Constructs	Indicators	Loadings	Cronbach's Alpha	RhoC	AVE	RhoA
PE	pe_1	0.827	0.753	0.843	0.575	0.772
	pe_2	0.817				
	pe_3	0.663				
	pe_4	0.713				
EE	ee_1	0.698	0.774	0.852	0.593	0.835
	ee_2	0.757				
	ee_3	0.868				
	ee_4	0.746				
SI	si_1	0.828	0.782	0.808	0.526	0.552
	si_2	0.737				
	si_3	0.837				
	si_4	0.421				
FC	fc_1	0.803	0.816	0.877	0.642	0.872
	fc_2	0.666				
	fc_3	0.850				
	fc_4	0.871				
UB	ub_1	0.858	0.858	0.912	0.776	0.885
	ub_2	0.852				
	ub_3	0.852				
BI	bi_1	0.889	0.815	0.890	0.729	0.817
	bi_2	0.904				
	bi_3	0.849				

Convergent Validity:

Convergent validity measured the overall indicator loadings for each construct. The average variance extracted (AVE) was used to evaluate convergent validity, with a target AVE of 0.5 or higher to confirm that a construct explained at least 50% of the variance of its indicators (Hair et al., 2016). In Table 3, all constructions had AVE values greater than 0.5. The researchers then checked if removing indicators with loadings below 0.708 would enhance internal consistency reliability. They noted that removing an indicator might decrease content validity, which reflects a construct's ability to capture relevant aspects of its concept. Thus, they considered omitting only si_4 due to its low rhoA measure.

Table 4: internal consistency reliability comparison

Construct	Cronbach's alpha		Rho_C		AVE		Rho_A	
	M1	M2	M1	M2	M1	M2	M1	M2
PE	0.753	0.753	0.843	0.843	0.575	0.575	0.772	0.772
EE	0.774	0.774	0.852	0.852	0.593	0.593	0.835	0.835
SI	0.782	0.746	0.808	0.852	0.526	0.658	0.552	0.772
FC	0.816	0.816	0.877	0.877	0.642	0.642	0.872	0.872
BI	0.858	0.858	0.912	0.912	0.776	0.776	0.885	0.886
UB	0.815	0.815	0.890	0.890	0.729	0.729	0.817	0.817

Table 4 illustrates changes in internal consistency reliability. Model 1 (M1) represented the original model, while Model 2 (M2) resulted from removing si_4. After this removal, rhoA significantly increased above 0.7 for social influence, along with its AVE. Consequently, si_4 could be omitted, allowing M2 to be used for further analysis. Although Cronbach's alpha decreased for social influence, it remained above 0.7. Figure 2 visually represents Table 4, with a horizontal line at 0.7 indicating the threshold for internal consistency. The rhoA for M1 was below this threshold, revealing construct redundancy, which M2 successfully addressed.

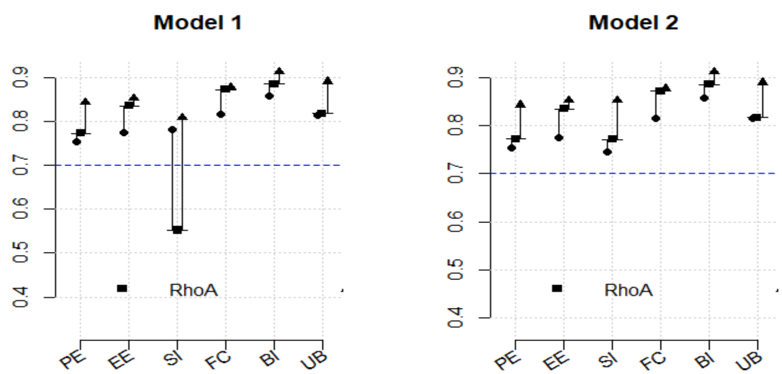

Figure 2: reliability plot of M1 (left panel) and M2 (right panel).

Discriminant Validity:

Discriminant validity assessed the similarity among constructs, with a greater similarity potentially making one redundant. The heterotrait-monotrait (HTMT) ratio served as the primary measure, where the numerator indicated the average correlation between indicators of different constructs and the denominator represented the geometric mean for the analysed construct. A lower HTMT value signifies increased relevance. According to Henseler et al. (2015), an acceptable threshold for the HTMT ratio is below 0.85. Results in Table 5 show that all HTMT ratios were under this threshold, confirming no significant correlations among constructions. The Fornell-Larcker Criterion also evaluated discriminant validity by comparing the squared root of each construct's average variance extracted (AVE) to correlations with other constructs. As presented in Table 6, the squared root of AVE exceeded correlations, affirming that discriminant validity was upheld.

Table 5: Heterotrait-monotrait ratio (HTMT)

Constructs	PE	EE	SI	FC	BI	UB
PE	-	-	-	-	-	-
EE	0.690	-	-	-	-	-
SI	0.201	0.218	-	-	-	-
FC	0.282	0.199	0.172	-	-	-
BI	0.590	0.466	0.274	0.142	-	-
UB	0.744	0.829	0.188	0.245	0.668	-

Table 6: Fornell-Larcker criterion

Constructs	PE	EE	SI	FC	BI	UB
PE	0.758	-	-	-	-	-
EE	0.540	0.770	-	-	-	-
SI	0.156	0.168	0.811	-	-	-
FC	0.223	0.141	0.048	0.801	-	-
BI	0.491	0.414	0.220	0.104	0.881	-
UB	0.594	0.678	0.147	0.208	0.577	0.854

Structural Model:

The structural model analysed relationships between endogenous and exogenous constructs, requiring various validity and reliability tests. Variance inflation factor (VIF) values correlations among predictors to avoid endogeneity issues (Sarstedt & Mooi, 2019). The R-square value indicated the explanatory power of the model, representing the variance explained by predictors, while the f-square value reflected changes in the R-square when an exogenous variable was removed. Cohen (1977) indicated that an f-square less than 0.15 represents a small effect and values over 0.35 indicate a large effect.

Collinearity and Explanatory Power:

Collinearity was examined among predictors, where a VIF above 5 would indicate severe issues (Hair et al., 2012). Table 7 reveals that all VIF values were below the conservative threshold of 3.3, with a maximum value of 1.428, suggesting that collinearity was not a significant concern. The R-square values for predicting behavioural intention and use behaviour were 0.294 and 0.356, respectively, which might suggest low explanatory power, yet such values are acceptable in social science research. A model predicting human behaviour should not exhibit excessively high explanatory power (above 0.9) to avoid overfitting (Sharma et al., 2019). The inclusion of moderator effects raised the R-square values to 0.389 for behavioural intention and 0.463 for use behaviour.

Table 7: structural model assessment

Constructs	VIF	f-square		R-square	Q-square
		BI	UB		
PE	1.420	0.130			
EE	1.428	0.037			
SI	1.040	0.021			
FC	1.011		0.032		
BI	1.011		0.474	0.289	0.241
UB				0.355	0.308

Predictive Power of the Model:

The predictive power evaluated how well the model predicted new observations, comparing root-mean-square error (RMSE) and linear regression model benchmark (LM benchmark) values. Only key endogenous constructions were used for comparison, including behavioural intention and use behaviour. RMSE was calculated as the square root of the average squared differences between predicted and actual values, while mean absolute error (MAE) measured the average absolute differences. Table 8 shows that the PLS-SEM regression model generally exhibited lower RMSE and MAE values than the LM benchmark, except for ub_3. The positive Q-square values for all indicators confirmed the model's predictive capabilities, demonstrating that the PLS-SEM regression estimates were generally more accurate than the LM benchmark, reinforcing the model's effectiveness.

Table 8: predictive error evaluation

Indicators	Q-square	PLS-SEM_RMSE	LM_RMSE	PLS-SEM_MAE	LM_MAE
bi_1	0.264	0.869	1.066	0.667	0.827
bi_2	0.099	1.151	1.366	0.918	1.093
bi_3	0.075	1.091	1.31	0.864	1.026
ub_1	0.227	0.916	1.05	0.751	0.821
ub_2	0.211	0.991	1.094	0.847	0.898
ub_3	0.253	1.076	0.963	0.939	0.786

Path Coefficients:

Path coefficients reflect the strength of relationships between constructs, indicating the extent of influence one construct has on another. These coefficients, expressed in standardized units, represent the average change in the endogenous construct per standard deviation change in the predictor. The significance of these coefficients was assessed using a two-tailed test. As shown in Table 9, performance expectancy (PE) had the highest positive influence on behavioural intention (BI), while effort expectancy (EE) also had a significant positive impact. Social influence (SI) had the weakest, though still statistically significant, influence at a 90% confidence level.

Table 9: path coefficients evaluation

Relation	Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	2.5% CI	97.5% CI
PE -> BI	0.366	0.376	0.090	4.079	0.199	0.540
EE -> BI	0.195	0.194	0.097	2.015	0.001	0.377
SI -> BI	0.131	0.138	0.078	1.689	-0.017	0.283
FC -> UB	0.150	0.168	0.082	1.827	-0.008	0.302
BI -> UB	0.561	0.561	0.062	9.080	0.430	0.677

Table 9 summarizes the estimates, showing that BI significantly influences use behaviour (UB) with a coefficient of 0.561, indicating a strong and statistically significant relationship at a 98% confidence level. However, facilitating conditions (FC) had a low influence on UB, significantly only at the 90% level. The total effects on UB were further evaluated in Table 10, confirming that PE and EE exert a significant influence on UB, while the direct effect of SI was insignificant.

Table 10: total effects evaluation

Relation	Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	2.5% CI	97.5% CI
PE -> BI	0.366	0.376	0.090	4.079	0.199	0.540
PE -> UB	0.205	0.211	0.056	3.634	0.108	0.323
EE -> BI	0.195	0.194	0.097	2.015	0.001	0.377
EE -> UB	0.109	0.111	0.059	1.858	0.000	0.229
SI -> BI	0.131	0.138	0.078	1.689	-0.017	0.283
SI -> UB	0.073	0.077	0.045	1.649	-0.009	0.166
FC -> UB	0.150	0.168	0.082	1.827	-0.008	0.302
BI -> UB	0.561	0.561	0.062	9.080	0.430	0.677

Moderation:

Model 2 was refined by adding moderators (gender, age, experience, voluntariness, and pandemic effects), leading to an increase in R-squared values, indicating improved explanatory power. Despite reduced t-statistics for predictor constructs, PE and BI maintained high statistical significance. In Table 11, PE's effect on BI was positively moderated by gender and age, contradicting hypotheses H1b and H1c, but the low significance suggests these findings can be dismissed.

Table 11: moderation effects

Relation	Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	5% CI	95% CI
PE -> BI	0.381	0.385	0.123	3.098	0.187	0.584
EE -> BI	0.178	0.165	0.117	1.519	-0.023	0.356
SI -> BI	0.100	0.097	0.091	1.092	-0.054	0.243
GEN -> BI	-0.182	-0.177	0.103	-1.774	-0.355	-0.005
AGE -> BI	-0.050	-0.035	0.166	-0.300	-0.305	0.212
AGE -> UB	0.354	0.369	0.112	3.167	0.195	0.565
EXP -> BI	-0.019	-0.020	0.154	-0.124	-0.271	0.241
EXP -> UB	0.010	-0.001	0.130	0.079	-0.238	0.203
VOL -> BI	0.038	0.024	0.096	0.396	-0.151	0.184
PE*GEN -> BI	0.004	0.004	0.136	0.032	-0.206	0.190
PE*AGE -> BI	0.042	0.050	0.116	0.361	-0.147	0.239
EE*GEN -> BI	0.245	0.255	0.114	2.142	0.050	0.428
EE*AGE -> BI	-0.150	-0.152	0.144	-1.039	-0.402	0.069
EE*EXP -> BI	0.211	0.186	0.160	1.319	-0.073	0.474
SI*GEN -> BI	-0.038	-0.043	0.107	-0.356	-0.208	0.129
SI*AGE -> BI	0.084	0.066	0.210	0.397	-0.264	0.398
SI*EXP -> BI	-0.062	-0.059	0.157	-0.394	-0.332	0.171
SI*VOL -> BI	-0.076	-0.079	0.107	-0.709	-0.242	0.097
FC -> UB	0.110	0.119	0.082	1.338	-0.014	0.239
BI -> UB	0.471	0.463	0.079	5.941	0.336	0.597

PAND -> UB	0.071	0.072	0.082	0.872	-0.073	0.201
FC*AGE -> UB	0.105	0.089	0.107	0.976	-0.097	0.249
FC*EXP -> UB	-0.102	-0.092	0.128	-0.798	-0.306	0.127
BI*PAND -> UB	0.045	0.051	0.068	0.662	-0.047	0.172

EE was positively moderated by gender and experience but negatively by age, which contradicts H2b and H2c, although only the gender moderation was significant at a 95% confidence level. The low representation of female respondents and their educational background may explain these results. Moderation effects of social influence on BI were insignificant, with findings showing negative moderation by gender, experience, and voluntariness, contradicting H3b, H3d, and H3e. Similarly, the effects of age and experience on FC's influence on UB were also insignificant, not supporting H4c.

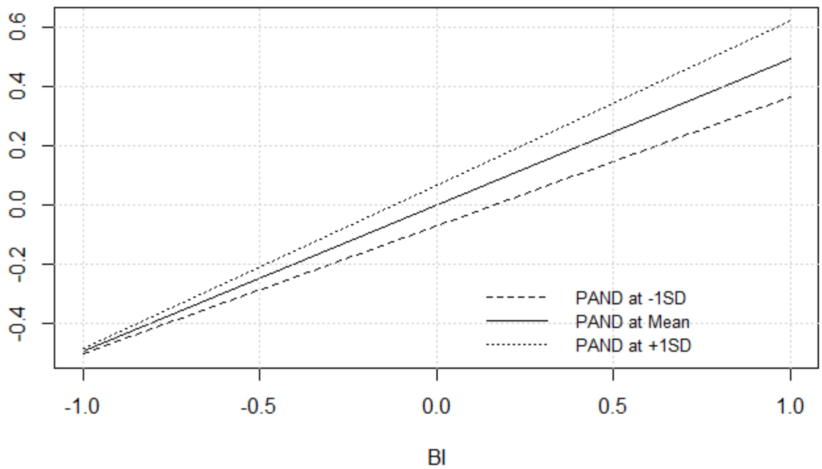

Figure 3: moderation effect of COVID-19 pandemic

The pandemic’s moderating effect on the relationship between BI and UB was a key focus. The interaction term (BI*PAND) had a positive value of 0.045, suggesting that during the pandemic, the impact of BI on UB increased to an average of 0.516. However, this effect was statistically insignificant, as indicated by low t-statistic. Figure 3 illustrates the positive relation between BI and UB during the pandemic compared to without it, suggesting a potential positive influence of the pandemic on microfinance adoption.

Discussion

This study explores the behavioural intention of micro-entrepreneurs in Bangladesh to adopt Mobile Financial Services (MFS) and how various factors influence this intention. The findings provide several contributions to the literature on financial inclusion and technology adoption. First, the study identifies performance expectancy as the most influential factor, highlighting the critical role of expectation of efficiency and profitability in driving MFS adoption. Enhanced efficiency reduces workloads and increases profitability. This is a primary incentive for these entrepreneurs. This underscores the need for MFS providers to streamline withdrawal processes and offer reduced withdrawal fees specifically for micro-entrepreneurs. Such pricing differentiation along with marketing campaigns can encourage greater adoption that emphasizes the operational benefits of MFS in simplifying financial transactions and increasing sales.

The second key finding is the role of effort expectancy, which measures the perceived ease of using MFS. The results indicate that while some entrepreneurs, especially female entrepreneurs with higher education levels, find MFS more useful than cash transactions, others are discouraged by the challenge of the learning process. This suggests that digital literacy and targeted training programs should be prioritized. Future research could examine the moderating role of educational levels in the relationship between effort expectancy and behavioural intention, particularly among diverse groups of micro-entrepreneurs.

Interestingly, social influence including pressure from peers or family to adopt MFS has a statistically insignificant impact on behavioural intention in this context. This finding reflects the urban setting of the study, where individual decision-making may outweigh social pressure. Similarly, facilitating conditions, such as access to internet connectivity and smartphones, moderately affect use behaviour, which may be attributed to the availability of urban facilities in Dhaka. Future research should extend to rural and semi-urban areas to explore geographic variations in the influence of these factors.

The study also highlights limitations that shape its contributions. First, the findings may lack generalization due to the size of the sample in Dhaka. Expanding the research to include rural and semi-urban respondents could yield more representative insights. Second, the study's quantitative approach limits the depth of understanding that qualitative methods might provide. While qualitative interviews offered insights into participants' preference for cash transactions and low trust in MFS security, a more extensive qualitative investigation is needed to explore these barriers comprehensively.

In terms of prospects for future research, this study identifies several key areas. Education level is highlighted as a potential moderator in the Unified Theory of Acceptance and Use of Technology (UTAUT) model, especially in gendered contexts. Further investigation into how education influences effort expectancy and behavioural intention could provide useful insights. Additionally, the adoption behaviours of other groups, such as migrant workers, freelancers, and rural entrepreneurs require exploration to capture a broader spectrum of MFS users. The COVID-19 pandemic's impact emerges as a significant factor, acting as a catalyst for MFS adoption among micro-entrepreneurs. However, given the unique pandemic-driven context, future research should validate these findings in a post-pandemic environment to understand long-term behavioural shifts. The study concludes by emphasizing the importance of improving trust in MFS as a secure and reliable platform. Innovations in security features and awareness campaigns to address trust issues could further enhance adoption rates.

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