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Article

Factors Affecting Digital Financial Service Adoption in Bangladesh: Evidence from SEM-ANN Approaches

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Abstract: The rapid growth of Digital Financial Services (DFS) has revolutionized the financial landscape in developing countries, including Bangladesh. Despite its growing importance, understanding the factors influencing DFS adoption remains limited, particularly when leveraging advanced analytical frameworks. This study investigates the key drivers affecting the adoption of DFS in Bangladesh by employing Structural Equation Modeling (SEM) and Artificial Neural Network (ANN) approaches. Using survey data collected from 340 DFS users, the SEM analysis validates the proposed relationships, identifying financial literacy, trust, access to capital, digital payment usage, and digital financial inclusion as significant factors driving DFS adoption. ANN modeling further highlights the relative importance of these predictors, revealing financial literacy as the most influential factor, closely followed by digital financial inclusion, trust in digital financial services, access to capital and digital payment usage. This dual-method analysis provides nuanced insights for policymakers, financial institutions, and technology providers, aiming to enhance DFS adoption and promote financial inclusion in Bangladesh.

Keywords: Digital Financial Services; Financial Literacy; Access to Capital; Digital Payment Usage; Digital Financial Inclusion

1. Introduction

The advent of Digital Financial Services has brought transformative changes to the global financial ecosystem, offering accessible, cost-effective, and secure financial solutions to individuals and businesses alike [1-3]. These services, which include mobile banking, digital wallets, and online payment platforms, have emerged as critical tools for achieving financial inclusion, particularly in developing economies [4-6]. In countries like Bangladesh, where traditional banking infrastructure is often limited, DFS presents an unparalleled opportunity to bring financial services to underserved populations, including those in rural and low-income urban areas. However, despite the potential of DFS to revolutionize financial systems and promote equitable economic development, its adoption has been inconsistent and influenced by a myriad of factors. This inconsistency raises pressing questions about the barriers and enablers of DFS adoption in the context of a developing economy like Bangladesh.

Bangladesh has witnessed significant advancements in digital infrastructure and a growing awareness of DFS in recent years [7]. Government initiatives, private sector innovations, and widespread mobile penetration have contributed to an environment conducive to DFS growth [8].

Yet, challenges remain in understanding the complex of adoption behaviors among various demographic and socio-economic groups [9]. These challenges necessitate a deeper exploration of the factors influencing DFS adoption, including individual, technological, and institutional variables. Identifying these factors and evaluating their relative importance can provide actionable insights for stakeholders aiming to enhance the reach and effectiveness of DFS.

Despite numerous studies exploring various facets of digital financial service adoption [10-13], this research offers a holistic perspective by combining SEM and ANN approaches to uncover both linear and nonlinear relationships, ensuring a comprehensive analysis tailored to the Bangladeshi context. This study aims to evaluate and rank the factors that affect DFS adoption in Bangladesh, thereby addressing critical gaps in the literature and practice. Specifically, the study is guided by two primary research questions: (1) How do factors such as financial literacy, trust in digital finance, access to capital, digital payment use, and digital financial inclusion influence DFS adoption? and (2) How do these factors rank in importance in terms of their normalized impact on DFS adoption? These questions reflect the need for a holistic understanding of both the enabling and constraining factors that shape DFS usage in a rapidly digitizing economy.

To address these research questions, this study adopts a robust mixed-method analytical framework that combines Structural Equation Modeling and Artificial Neural Networks. The SEM approach allows for the identification and validation of statistically significant factors influencing DFS adoption, providing a theoretical foundation based on causal relationships [14]. Subsequently, the ANN method is employed to quantify the relative importance of these factors, leveraging its capacity to capture non-linear relationships and rank predictors in terms of their impact [15]. This integrated methodology ensures a comprehensive analysis that bridges theoretical insights with practical implications.

Key factors under investigation in this study include financial literacy, trust in digital financial systems, access to capital, the extent of digital payment usage, and overall digital financial inclusion [16]. Financial literacy, which reflects individuals' understanding of financial products and services, is critical for enabling informed decision-making and fostering confidence in DFS. Trust, a pivotal element in the digital ecosystem, determines users' willingness to engage with DFS platforms, particularly in contexts where security concerns are prevalent. Access to capital, encompassing both formal and informal financial sources, influences the economic feasibility of using DFS, while the usage of digital payments serves as an indicator of technological adoption and behavior. Lastly, digital financial inclusion underscores the role of institutional and infrastructural support in ensuring equitable access to DFS across different segments of the population [17].

The findings of this study hold significant implications for a range of stakeholders, including policymakers, financial institutions, technology providers, and development practitioners. By identifying the most influential factors and their rankings, this research provides a roadmap for designing targeted interventions to enhance DFS adoption. For policymakers, the results can inform the development of regulatory frameworks that address systemic barriers and promote trust and accessibility. Financial institutions can leverage these insights to tailor their product offerings and outreach strategies to better align with user needs. Technology providers, on the other hand, can prioritize features and functionalities that address user concerns, such as security and usability.

Therefore, this study makes four significant contributions to the field of digital financial service adoption research. First, it develops a conceptual model that integrates financial literacy, trust in digital finance, access to capital, digital payment usage, and digital financial inclusion as determinants of DFS adoption in Bangladesh. Second, the research uniquely employs a dual-method approach, combining Structural Equation Modeling and Artificial Neural Networks, to validate relationships and rank the normalized impact of these factors, offering a robust and nuanced understanding. Third, it provides empirical evidence by analyzing the interplay between these factors, particularly in the context of a developing country. Finally, the study delivers actionable insights for policymakers and financial institutions to enhance DFS adoption, promoting financial inclusion and advancing digital transformation in Bangladesh.

The paper is organized as follows: Section 1 introduces the study; Section 2 reviews the relevant literature and outlines the theoretical framework; Section 3 explains the methodology; Section 4 presents the results and discusses the findings; and Section 5 concludes by highlighting implications, limitations, and suggestions for future research.

2. Review of Literature and Theoretical Background

2.1. Literature Review

Digital financial services adoption (DFSA) refers to the process by which individuals, businesses, and organizations begin to use digital platforms and technologies for financial transactions. These services include mobile banking, digital wallets, online money transfers, contactless payments, and access to credit and savings through digital means [18]. DFSA is a critical driver of financial inclusion, particularly in underbanked or unbanked populations, as it enables easier, faster, and more secure financial transactions [19, 20]. Several factors influence DFSA, encompassing technological, socioeconomic, behavioral, and institutional dimensions [21, 22].

Financial literacy plays a critical role in the adoption of digital financial services [23]. It equips individuals with the knowledge and confidence to effectively use digital platforms for financial transactions [24, 25]. Financial literacy is a fundamental enabler that strengthens the connection between individuals and the digital financial ecosystem [2]. Individuals with higher financial literacy are more likely to understand the benefits of DFS, such as convenience, security, and cost efficiency, which in turn fosters greater adoption [26]. Financial literacy reduces perceived risks and barriers, such as fears of fraud or lack of trust in digital systems, enabling informed decision-making regarding financial technology [27]. In developing countries like Bangladesh, where a significant portion of the population remains unbanked, improving financial literacy can bridge the knowledge gap and empower individuals to leverage DFS for financial inclusion. Moreover, targeted financial education campaigns can address specific challenges, such as digital literacy and trust-building, which will enhance DFS adoption rates [28]. The following hypothesis thus can be proposed:

Hypothesis 1. *Financial literacy has a positive impact on digital financial services adoption.*

Trust in digital financial services is another pivotal factor influencing their adoption, particularly in emerging economies [29]. Trust mitigates perceived risks associated with data breaches, fraud, or system failures, which often deter potential users from engaging with digital financial platforms [30]. When individuals trust the reliability, security, and transparency of digital financial services, they are more likely to embrace these technologies for transactions, savings, and other financial activities. Factors such as robust consumer protection policies, positive user experiences, and reputation of service providers significantly enhance trust [31]. In Bangladesh, building trust is particularly important due to limited financial literacy and prevalent concerns about online fraud. The service providers who establish credibility through secure platforms and transparent practices can foster greater adoption of digital financial services [32]. Accordingly, the hypothesis to be tested is as follows:

Hypothesis 2. *Trust in digital financial services has a positive impact on digital financial services adoption.*

Access to capital is a significant determinant of digital financial services adoption [33]. Limited access to financial resources often restricts the affordability of devices like smartphones and internet services, which are prerequisites for engaging with DFS [34]. Moreover, access to capital enables small businesses and low-income individuals to leverage DFS for credit, savings, and investment opportunities, fostering greater adoption [35]. In developing countries like Bangladesh, where financial inclusion remains a challenge, improving access to capital can empower underbanked populations to transition from traditional cash-based systems to digital platforms. Microfinance initiatives and government-backed financial schemes that integrate DFS can further enhance accessibility and adoption, particularly for marginalized groups [36]. Thus, access to capital not only facilitates the initial adoption of digital financial services but also sustains their usage as a tool for economic empowerment and financial inclusion. Based on the preceding discussion, the following hypothesis is formulated:

Hypothesis 3. *Access to capital has a positive impact on digital financial services adoption.*

Digital payment usage is closely linked to digital financial services adoption, serving both as a driver and a key indicator of DFS integration [37]. The convenience, speed, and cost-effectiveness of digital payment systems encourage individuals to explore and adopt other financial services offered on digital platforms. Regular use of digital payments, such as mobile money transfers and online bill payments, familiarizes users with the broader DFS ecosystem and increases their trust and confidence in these technologies. In Bangladesh, where digital payment solutions are widely accessible, their usage has played a pivotal role in promoting financial inclusion by reaching unbanked and underbanked populations [38, 39]. Moreover, the COVID-19 pandemic has accelerated the reliance on digital payments, further boosting DFS adoption as individuals adapt to contactless and remote financial transactions [40, 41]. Accordingly, the hypothesis to be tested is as follows:

Hypothesis 4. *Digital payment usage has a positive impact on digital financial services adoption.*

Digital financial inclusion is a critical enabler of digital financial services adoption by focusing on providing underserved populations with affordable and convenient access to financial tools through digital platforms [2]. By bridging the gap between traditional banking services and unbanked or underbanked individuals, digital financial inclusion lays the foundation for widespread DFS adoption. Access to services like mobile money, digital wallets, and microcredit not only increases financial literacy but also builds trust and confidence in digital systems, motivating individuals to adopt DFS [42]. In Bangladesh, initiatives promoting digital financial inclusion have targeted rural populations and low-income groups, leveraging mobile banking platforms to enhance accessibility [7]. The following hypothesis is thus postulated based on the literature review:

Hypothesis 5. *Digital financial inclusion has a positive impact on digital financial services adoption.*

2.2. Theoretical Underpinning

The adoption of Digital Financial Services can be effectively explained through the Technology Acceptance Model (TAM), a well-established framework that helps in understanding the factors influencing individuals' acceptance and usage of new technologies. According to TAM, two key determinants drive the adoption of technology: Perceived Ease of Use and Perceived Usefulness [43]. In the context of DFS adoption in Bangladesh, these factors are critical in shaping user decisions and behaviors toward engaging with digital financial platforms.

Perceived ease of use refers to the degree to which a user believes that using a particular technology will be free of effort [43]. For DFS, this translates into the user's ability to understand and navigate digital platforms with minimal difficulty. Access to mobile phones and internet services, combined with user-friendly interfaces of DFS platforms through mobile banking, can significantly impact the perceived ease of use, thereby encouraging adoption [44].

On the other hand, perceived usefulness is the degree to which a person believes that using technology will enhance their financial transactions or provide additional benefits [45]. In the case of DFS, perceived usefulness can be associated with benefits such as convenience, speed, cost-effectiveness, and the ability to make financial transactions without visiting physical banking institutions. Trust in digital platforms, security measures, and positive user experiences can enhance the perceived usefulness of DFS, motivating users to adopt them [46].

Further, trust and financial literacy are external variables that affect both perceived ease of use and perceived usefulness in the context of DFS adoption. Trust in digital platforms influences users' willingness to engage with DFS, as individuals are more likely to adopt technologies, they believe are secure and reliable. Likewise, financial literacy equips individuals with the knowledge to understand and utilize digital financial services effectively, which in turn enhances both their perception of ease of use and usefulness.

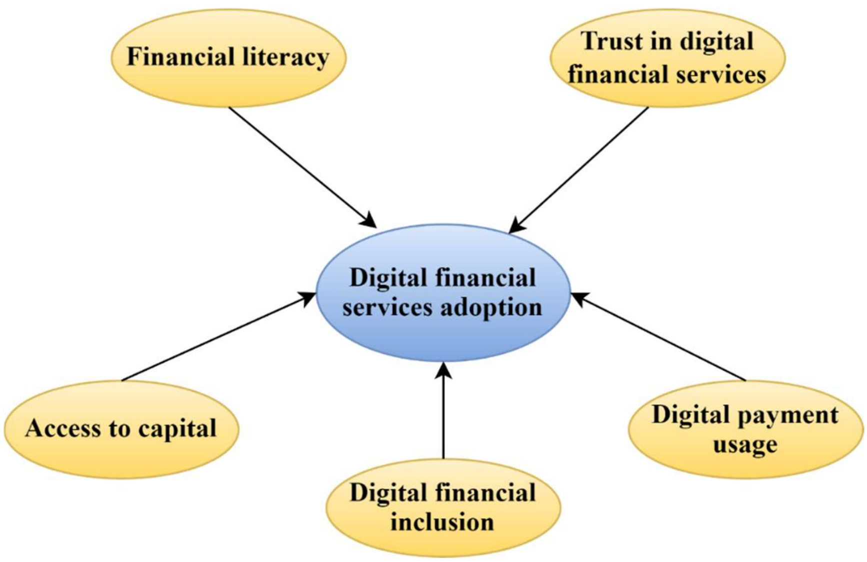

Figure 1. Conceptual framework (Author's construction).

Additionally, digital financial inclusion serves as an important context in the TAM framework, as it addresses the barriers to access, such as affordability, geographic constraints, and lack of infrastructure, which can influence perceived ease of use and usefulness [47]. By improving access to capital and promoting policies that support digital financial inclusion, more individuals are able to perceive DFS as useful and easy to use, thus increasing adoption rates. Based on the literature review and theoretical understanding of the Technology Acceptance Model, the following conceptual framework is developed in Figure 1.

3. Methodology

3.1. Data and Sample

The study targeted five key groups as its population: digital financial service users, providers, practitioners at banks, NGOs, and government officials, all based in Dhaka city. A convenience sampling method was employed to select participants. Following Hair et al. [48] and Rahman et al. [49], the required sample size was set at a minimum of ten times the number of questionnaire items, necessitating at least 180 respondents. To ensure sufficient data for analysis, 400 questionnaires were distributed. Data collection spanned from April 30, 2024, to June 1, 2024, utilizing a structured questionnaire. Out of the 400 questionnaires, 340 valid and complete responses were received and included in the analysis. The study strictly adhered to the ethical standards outlined by the BIGM Institutional Review Board, ensuring participant anonymity throughout the research process.

Table 1. Demographic profile of the respondents.

Demographic Variable	Category	n=340	%
Gender	Male	200	58.8
	Female	140	41.2
Age	18–25	80	23.5
	26–35	120	35.3
	36–45	90	26.5
	46–55	30	8.8
	56+	20	5.9
Education	Non-formal	10	2.9
	Diploma	40	11.8
	Secondary	70	20.6
	Higher Secondary	60	17.6
	Bachelor	100	29.4
	Master	50	14.7
	Others	10	2.9

Table 1 provides a detailed demographic breakdown of the study's respondents (n=340). Regarding gender, the majority were male, comprising 58.8% (n=200) of the sample, while females accounted for 41.2% (n=140). In terms of age distribution, the largest proportion of respondents fell within the 26–35 age group, representing 35.3% (n=120). This was followed by the 36–45 age group at 26.5% (n=90), and the 18–25 age group at 23.5% (n=80). Respondents aged 46–55 accounted for 8.8% (n=30), while those aged 56 and above represented the smallest group at 5.9% (n=20).

When considering educational attainment, a significant portion of the respondents held a bachelor's degree, making up 29.4% (n=100) of the sample. This was followed by secondary education at 20.6% (n=70) and higher secondary education at 17.6% (n=60). Respondents with master's degrees accounted for 14.7% (n=50), while those with diplomas comprised 11.8% (n=40). A small percentage of respondents reported having non-formal education or other forms of education, each representing 2.9% (n=10). This demographic profile highlights a diverse sample in terms of gender, age, and education, with a significant representation of young and middle-aged individuals as well as varying levels of educational attainment.

3.2. Operationalization of Measurement Scales

The study incorporates six latent variables: "Financial Literacy," "Trust in Digital Financial Service," "Access to Capital," "Digital Payment Use," "Digital Financial Inclusion," and "Digital Financial Service Adoption." These variables represent key constructs designed to capture various dimensions of digital financial service within the research framework. Each variable plays a distinct role in examining the relationships and impacts relevant to the study's objectives. Following Rahman and Sadik [16], each of the variable is constructed using 3 items in this study.

Financial literacy (FL) is evaluated by analyzing individuals' ability to acquire and apply financial knowledge and skills effectively. This involves examining the extent to which respondents actively seek financial knowledge and skills to make informed decisions (FL1), their familiarity with various digital financial services (FL2), and their awareness of the critical role financial literacy plays in achieving financial stability (FL3). Collectively, these metrics provide a comprehensive overview of financial literacy and its contribution to informed financial behaviors.

Trust in digital financial services (TDFS) is assessed by capturing users' perceptions of the reliability and security of these platforms. The evaluation includes whether respondents trust the security of their personal information when using these services (TDFS1), perceive providers as reliable and trustworthy (TDFS2), and feel confident in the accuracy and efficiency of transaction processing (TDFS3). These items collectively measure the confidence users place in digital financial services, influencing their adoption and continued use.

Access to capital (AC) is measured through respondents' perceptions of and experiences with financial resources. This assessment considers whether individuals believe financial institutions are willing to provide loans or credit when needed (AC1), recognize the importance of access to capital in achieving financial goals (AC2), and find the process of obtaining financial resources through digital platforms to be straightforward and user-friendly (AC3). These metrics highlight how accessibility to capital affects financial empowerment.

Digital payment usage (DPU) focuses on understanding the frequency and user perceptions of digital payment methods. It evaluates whether respondents frequently use digital payment systems like mobile wallets and online banking (DPU1), perceive these methods as more convenient than traditional cash transactions (DPU2), and believe digital payments improve expense tracking (DPU3). These factors reflect how digital payment solutions streamline financial transactions for users.

Digital financial inclusion (DFI) is analyzed by exploring respondents' access to and perceptions of digital financial services. This includes assessing whether respondents have easy access to digital services like mobile or Internet banking (DFI1), feel included in the financial system with access to tailored products (DFI2), and perceive these services as equitable, providing opportunities irrespective of socioeconomic status (DFI3). Together, these items, rated on a Likert scale, offer insights into the breadth and equity of digital financial inclusion.

Lastly, digital financial service adoption (DFSA) is measured through individuals' usage experiences and perceptions. This involves determining whether respondents find digital financial services convenient for transactions (DFSA1), believe these services have improved their financial management efficiency (DFSA2), and recognize their positive impact on financial activities (DFSA3). These indicators collectively represent the extent to which users have embraced digital financial platforms in their financial practices.

Each item, evaluated on a 5-point Likert scale, offers a detailed assessment of digital financial service adoption and the various factors that influence it. The 5-point scale provides a clear and structured way to capture varying degrees of agreement or disagreement, allowing for a more nuanced understanding of respondents' attitudes and perceptions.

3.3. Analysis Approaches

This study adopts a multi-method approach, combining PLS-SEM with ANN to rigorously test the proposed hypotheses [50]. PLS-SEM is preferred over Covariance-Based SEM (CB-SEM) due to its suitability for exploratory research, especially when the model is complex and the sample size is limited, as in this study [51-53]. PLS-SEM effectively handles non-normal data distributions and can assess both reflective and formative constructs, making it ideal for exploring the complex relationships between variables in sustainability research [51, 54]. Following PLS-SEM, ANN is used to further strengthen the analysis by identifying non-linear relationships and interactions that traditional linear models might overlook. ANN's capacity to capture complex patterns and interactions provides a powerful framework to validate the results from PLS-SEM, offering a comprehensive understanding of the factors that influence DFS [55].

3.4. Common Method Bias

For ensuring the reliability and validity of the results, this study took comprehensive measures to address potential common method bias (CMB). It is a concern when the same data collection method is used for multiple variables. Two primary strategies were implemented to detect and minimize CMB. First, Harman's single-factor test was conducted, as suggested by Karatepe [56], to determine whether a single factor dominated the variance in the data. The analysis showed that the largest factor accounted for only 34.27% of the total variance, which is significantly below the 50% threshold commonly accepted in the literature [57], indicating that CMB was not a major issue. Second, the full collinearity test, recommended by Kock [58], was employed to calculate the variance inflation factors (VIFs) for the latent variables. All VIF values were below 3.0, further confirming that multicollinearity is absent and CMB did not pose a significant problem in this study.

4. Results and Discussions

4.1. Measurement Modeling

In this study, the PLS-SEM approach was employed to evaluate the relationships between observed indicators and their respective latent variables [51, 59]. A key aspect of this analysis is the measurement model, which serves to validate the reliability and validity of the constructs. The measurement model enables researchers to ensure that the indicators accurately capture the underlying concepts and relationships, facilitating robust structural modeling [60].

The reliability of the constructs was assessed using two metrics: Cronbach's Alpha (CA) and Composite Reliability (CR). These measures ensure internal consistency, verifying that the constructs reliably measure what they are intended to measure. The results, summarized in Table 2, show that all constructs exceed the recommended threshold of 0.70 for both CA and CR, indicating satisfactory reliability [51, 61]. For example, the CR values range from 0.86 for Access to Capital to 0.91 for Digital Financial Service Adoption, while CA values are similarly strong, ranging from 0.79 to 0.87.

Table 2. Measurement model summary.

Constructs	Items	Loadings	CA	CR	AVE
Financial Literacy (FL)	FL1	0.82	0.81	0.88	0.65
	FL2	0.75			
	FL3	0.80			
Trust in Digital Financial Service (TDFS)	TDFS1	0.85	0.84	0.89	0.67
	TDFS2	0.78			
	TDFS3	0.83			
Access to Capital (AC)	AC1	0.76	0.79	0.86	0.61
	AC2	0.80			
	AC3	0.74			
Digital Payment Use (DPU)	DPU1	0.79	0.83	0.89	0.66
	DPU2	0.82			
	DPU3	0.81			
Digital Financial Inclusion (DFI)	DFI1	0.77	0.85	0.90	0.69
	DFI2	0.86			
	DFI3	0.80			
Digital Financial Service Adoption (DFSA)	DFSA1	0.81	0.87	0.91	0.71
	DFSA2	0.84			
	DFSA3	0.89			

Note: CA: Cronbach's Alpha, CR: Composite Reliability, AVE: Average Variance Extracted.

Table 3. Discriminant validity using HTMT.

Constructs	FL	TDFS	AC	DPU	DFI	DFSA
FL						
TDFS	0.56					
AC	0.43	0.41				
DPU	0.61	0.36	0.33			
DFI	0.48	0.66	0.49	0.53		
DFSA	0.37	0.74	0.62	0.57	0.68	

Convergent validity was evaluated through the Average Variance Extracted (AVE), which measures the degree to which a construct explains the variance in its indicators. All constructs in this study achieved AVE values between 0.61 and 0.71, exceeding the minimum acceptable threshold of 0.50, as recommended by Hair et al. [51]. These findings confirm that the constructs are valid and capture the intended theoretical concepts.

Discriminant validity was assessed to ensure that the constructs are distinct and not measuring overlapping concepts. The Heterotrait-Monotrait Ratio (HTMT) criterion was used, which evaluates the degree of correlation between constructs. As shown in Table 3, all HTMT values are below the critical threshold of 0.85, with the highest value being 0.74 between Trust in Digital Financial Services and Digital Financial Service Adoption. This indicates strong discriminant validity, supporting the uniqueness of each construct in the model [51].

4.2. Structural Modeling

In this study, SmartPLS-4 software is used to examine the relationships between variables and test the proposed hypotheses. To ensure the reliability of the results, a bootstrapping technique with 5000 subsamples was applied. This approach allowed for a detailed assessment of the relationships within the model and ensured that the results were robust. Two key metrics were used to evaluate the predictive strength of the model: the R-squared value and the Q-squared value [62].

Table 4 shows that the R-squared value for the dependent variable, Digital Financial Service Adoption, is 0.783. This means that 78.3% of the variance in DFSA can be explained by the independent variables in the model. This high R-squared value indicates that the model has strong predictive power [63]. Additionally, the Adjusted R-squared value, which accounts for the number of predictors, is 0.759. This adjusted value further supports the reliability of the model, showing that the explained variance remains strong even after accounting for the complexity of the model.

Table 4. Model evaluation.

Variable	R-squared	Adjusted R-squared	Q-squared
DFSA	0.783	0.759	0.475

The Q-squared value, which measures the predictive relevance of the model, was found to be 0.475. A positive Q-squared value indicates that the model has substantial predictive significance [64]. In this study, the Q-squared value suggests that the independent variables in the model contribute meaningfully to explaining the dependent variable. These results confirm that the model is capable of making accurate predictions about the relationships between the variables.

The overall fitness of the model was evaluated using several key indicators, as presented in Table 5. One of the main indicators used in PLS-SEM is the SRMR (Standardized Root Mean Square Residual). This value measures the difference between the predicted and observed values in the model [65]. In this study, the SRMR value was found to be 0.058, which is well below the acceptable threshold of 0.08. This low value indicates that the model fits the data very well, with minimal deviations [51].

Table 5. Model fitness.

Measures	Estimated Model
SRMR	0.058
NFI	0.931
d_ULS	0.847
d_G	0.423
Chi-square	627.975

Another important measure of model fit is the NFI (Normed Fit Index). The NFI value for this model was 0.931. Since NFI values closer to 1 indicate better fit, this result suggests that the model performs strongly and aligns well with the observed data [66].

The d_ULS (Unstandardized Leverage Squared) value, which assesses how well the model fits the data, was recorded as 0.847. This value is close to 1, which is the ideal range, indicating that the model fits the data appropriately. Similarly, the d_G (Geodesic Discrepancy) value, which measures how well the model differentiates between significant and non-significant components, was found to be 0.423. This result further supports the model's ability to distinguish meaningful relationships in the data [51].

Finally, the Chi-square ($\chi 2$) value was 627.975. In PLS-SEM, a lower Chi-square value indicates a better fit between the observed and predicted values. The relatively low value in this study suggests that the model has a good fit and that the predicted relationships align closely with the observed data [51].

Thus, the various metrics used to assess the model's fit—such as SRMR, NFI, d_ULS, d_G, and Chi-square—all confirm that the model is robust and well-suited for examining the relationships between the variables. Together with the strong R-squared and Q-squared values, these results provide confidence in the validity and reliability of the study's findings. This comprehensive evaluation ensures that the model can accurately explain and predict the interactions among the constructs under investigation.

Table 6 presents the hypothesis testing results, demonstrating the significant direct effects of the investigated variables on Digital Financial Service Adoption. The findings highlight the positive contributions of each factor, confirming all proposed hypotheses.

Table 6. Hypothesis testing.

Hypothesized relationships	Coefficients	T-value	P-value	Supported
H1: FL→DFSA	0.782	15.64	0.000	Yes
H2: TDFS→DFSA	0.441	7.22	0.000	Yes
H3: AC→DFSA	0.303	5.85	0.000	Yes
H4: DPU→DFSA	0.208	4.22	0.000	Yes
H5: DFI→DFSA	0.578	9.63	0.000	Yes

Specifically, Financial Literacy (FL) exhibits the strongest positive influence on DFSA (coefficient = 0.782, t-value = 15.64, $p < 0.001$), indicating that enhancing individuals' financial literacy significantly promotes the adoption of digital financial services, thereby supporting H1. Similarly, Trust in Digital Financial Services (TDFS) has a notable positive impact (coefficient = 0.441, t-value = 7.22, $p < 0.001$), affirming H2 and emphasizing the critical role of trust in encouraging DFSA.

Access to Capital (AC) also contributes positively to DFSA (coefficient = 0.303, t-value = 5.85, $p < 0.001$), supporting H3 and underscoring the importance of financial resources in driving adoption. Furthermore, Digital Payment Usage (DPU) demonstrates a significant positive effect on DFSA (coefficient = 0.208, t-value = 4.22, $p < 0.001$), aligning with H4 and highlighting the role of payment behavior in fostering service adoption.

Lastly, Digital Financial Inclusion (DFI) has a substantial positive effect on DFSA (coefficient = 0.578, t-value = 9.63, $p < 0.001$), confirming H5 and showcasing the importance of inclusive financial systems in expanding the reach and adoption of digital financial services.

4.3. ANN Modeling

Following the SEM analysis, an Artificial Neural Network approach was applied to validate the results and capture nonlinear relationships among the variables influencing DFSA. This analysis used latent variable scores derived from SEM as input data, ensuring the constructs were well-calibrated for robust predictive modeling. By incorporating these scores, the ANN model leveraged the underlying relationships to provide deeper insights into the adoption process. To enhance the model's reliability and generalizability, a ten-fold cross-validation technique was implemented. This method, widely recommended for ANN analysis, divides the dataset into ten subsets, using 90% of the data for training and 10% for testing in iterative cycles [61]. This process reduces overfitting and ensures consistent predictive performance. The ANN architecture included an input layer with five predictor variables—digital financial inclusion, digital payment usage, financial literacy, trust in digital financial services, and access to capital—and an output layer for DFSA.

Table 7 presents the root mean square error (RMSE) metrics for the training and testing phases of the ANN model. The RMSE values for the training phase ranged between 0.086 and 0.094, while the testing phase exhibited values between 0.057 and 0.083. These results indicate a high level of precision, as all RMSE values fall well below the critical threshold of 0.50 [67, 68]. The proximity of RMSE values between the training and testing phases highlights the model's consistency and reliability in capturing relationships among the variables.

Table 7. ANN-RMSE values.

	Training (90%)			Testing (10%)			Total Samples
Network	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**	**N**	
1	2.336	0.089	296	0.171	0.062	44	340
2	2.580	0.094	293	0.154	0.057	47	340
3	2.276	0.088	292	0.156	0.057	48	340
4	2.271	0.088	295	0.255	0.075	45	340
5	2.386	0.090	297	0.237	0.074	43	340
6	2.384	0.088	305	0.196	0.075	35	340
7	2.611	0.093	303	0.213	0.076	37	340
8	2.150	0.086	288	0.296	0.075	52	340
9	2.463	0.090	306	0.233	0.083	34	340
10	2.316	0.088	297	0.246	0.076	43	340
Mean	2.377	0.089		0.216	0.071		
SD	0.135	0.002		0.044	0.008		

Figure 2 illustrates the RMSE values for both training and testing phases across 10 different ANNs in the study focused on digital financial service adoption. The RMSE is a measure of the model's predictive accuracy, with lower values indicating better performance [69]. In this chart, the orange line represents the RMSE for training, while the gray line shows the RMSE for testing.

From the figure, it can be observed that the RMSE for training data fluctuates around 0.086 to 0.094, suggesting stable performance across most training iterations. The testing RMSE shows more variability, ranging from 0.057 (lowest in ANN 2 and 3) to 0.083 (highest in ANN 9). This difference between training and testing RMSE values indicates how well the models generalize to unseen data. Although there is some variation in the testing RMSE, the results suggest that the ANNs perform consistently without significant overfitting, as the testing RMSE remains reasonably close to the training RMSE for most models.

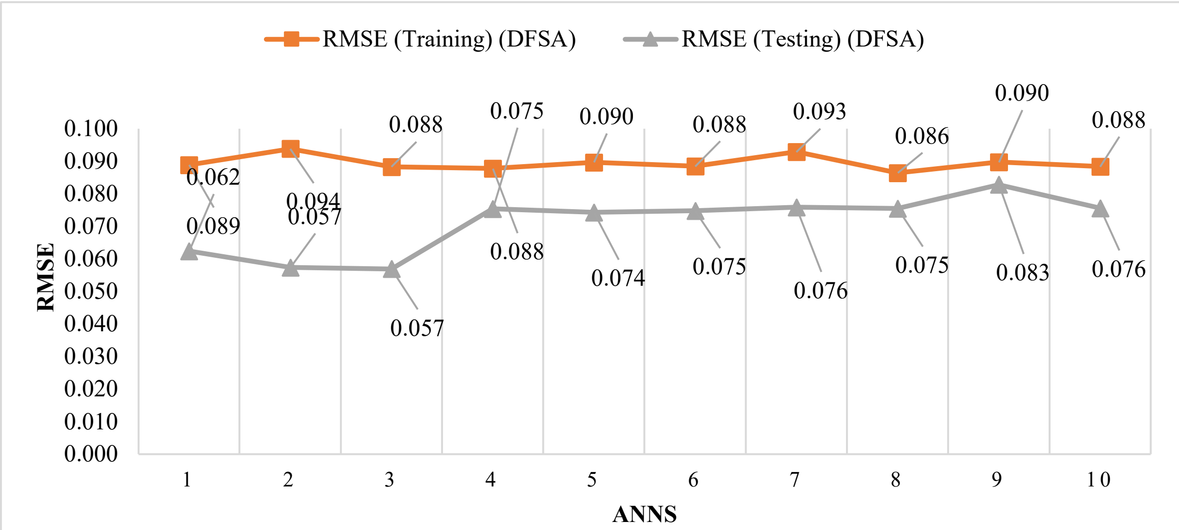

Figure 2. RMSE values for training and testing ANNs.

To identify the most influential factors affecting DFSA, a sensitivity analysis was conducted as part of the ANN approach. This analysis measures the relative importance of each predictor variable in determining the dependent variable. Table 8 summarizes the sensitivity analysis results, presenting both the average and normalized importance of each variable.

Table 8. Sensitivity analysis for ranking.

Network	DFI	DPU	FL	TDFS	AC
1	0.618	0.106	0.850	0.596	0.596
2	0.578	0.217	0.850	0.697	0.697
3	0.669	0.095	0.850	0.456	0.456
4	0.850	0.398	0.622	0.404	0.381
5	0.789	0.394	0.850	0.575	0.406
6	0.787	0.501	0.850	0.583	0.399
7	0.850	0.303	0.571	0.601	0.601
8	0.850	0.397	0.843	0.678	0.499
9	0.850	0.134	0.619	0.596	0.596
10	0.834	0.331	0.850	0.506	0.506
Average Importance	0.767	0.288	0.775	0.569	0.514
Normalized Importance (%)	99%	37%	100%	73%	66%
Ranking	**2**	**5**	**1**	**3**	**4**

The findings reveal that financial literacy is the most critical factor, with a normalized importance of 100%, followed closely by digital financial inclusion at 99%. Trust in digital financial services ranks third with 73%, while access to capital and digital payment usage are ranked fourth and fifth, with normalized importance values of 66% and 37%, respectively. These rankings underscore the hierarchical impact of these factors on DFSA, with financial literacy and inclusion emerging as dominant predictors.

The ANN analysis, supported by sensitivity testing, reinforces the findings from SEM by highlighting the significant and nonlinear contributions of the investigated variables. The robust RMSE values confirm the model's predictive accuracy, while the sensitivity analysis provides actionable insights into prioritizing strategies for promoting digital financial service adoption. These results collectively validate the importance of enhancing financial literacy and inclusion as primary drivers in the adoption process.

4.4. Discussions

This research investigates the factors influencing the adoption of digital financial services in Bangladesh using Structural Equation Modeling and Artificial Neural Networks approaches. The findings underscore the importance of multiple variables, with financial literacy, trust in digital financial platforms, access to capital, digital payment usage, and financial inclusion emerging as significant predictors.

The results reveal that financial literacy is the most critical factor influencing DFS adoption. In Bangladesh, where awareness and knowledge about financial tools and systems remain limited, improving financial literacy can empower users to access and utilize DFS effectively. Financial literacy showed the highest impact in both SEM results and ANN sensitivity analysis, with a normalized importance score of 100%. This highlights the necessity of educational interventions focused on equipping individuals with the skills to navigate digital financial tools. This emphasis on the pivotal role of financial literacy aligns with the conclusions drawn by earlier studies as well [70-72].

Trust plays a vital role in increasing adoption rates. Many users in Bangladesh are apprehensive about the security and reliability of digital platforms, which poses a barrier to widespread adoption. This study confirms that trust significantly influences the willingness to adopt DFS, emphasizing the need for service providers to implement secure systems and ensure transparency to build user confidence [16].

The study also finds that access to financial capital and the frequency of digital payment usage contribute positively to DFS adoption. While access to capital is more directly linked to economic empowerment, the habitual use of digital payments indicates a shift toward financial inclusion and digital literacy. These factors point to the importance of creating an enabling environment where individuals, especially in rural and underserved areas, can access the infrastructure required for DFS.

Financial inclusion significantly impacts the adoption of DFS, aligning with the broader objectives of fostering equitable access to financial services. The study highlights that increased financial inclusion initiatives can bridge the gap between urban and rural populations, ensuring that marginalized groups benefit from digital finance.

Thus, the findings emphasize the interplay between financial literacy, trust, access to capital, digital payment usage, and financial inclusion, enriching the theoretical discourse on technology acceptance and financial behavior. By focusing on Bangladesh, the study fills a significant gap in the literature, offering insights that are highly relevant for other developing economies with similar socio-economic contexts.

This study also identifies several critical priorities for policymakers to consider in order to accelerate the adoption of digital financial services in Bangladesh. Financial literacy emerged as the most influential factor, indicating the need for nationwide educational initiatives focusing on financial awareness and digital competence. Policymakers can collaborate with educational institutions, non-governmental organizations, and financial service providers to implement targeted programs that equip individuals with the knowledge and skills to use DFS effectively. Additionally, improving trust in digital platforms is essential. Ensuring robust cybersecurity measures, transparent policies, and customer-centric services can significantly build user confidence. Regulatory bodies should also focus on creating an inclusive financial environment by extending digital infrastructure to underserved rural areas and promoting equitable access to capital. These initiatives can collectively foster a supportive ecosystem for DFS adoption, aligning with broader goals of financial inclusion and economic empowerment.

5. Conclusions and Implications

This study investigates the determinants of digital financial service adoption in Bangladesh, examining key variables such as financial literacy, trust in digital platforms, access to capital, digital payment usage, and financial inclusion. By employing an integrated methodology combining Structural equation modeling and artificial neural networks, the research provides a detailed understanding of these factors' roles and relative significance. The findings indicate that financial literacy is the most influential factor, followed by digital financial inclusion, trust, access to capital, and digital payment usage. This consistency between SEM and ANN results highlights the critical importance of these elements in facilitating widespread DFS adoption.

The study makes theoretical contributions by emphasizing the interplay among key factors such as financial literacy, trust, and inclusion within DFS adoption frameworks. The prominent role of financial literacy underscores its necessity in fostering digital financial participation, particularly in emerging economies like Bangladesh. The hybrid methodological approach—integrating SEM to identify causal relationships and ANN to rank variable importance—offers a robust framework for future research exploring financial inclusion and DFS adoption. These findings not only validate existing theories but also extend them by integrating advanced analytical tools to uncover both linear and non-linear relationships.

From a practical perspective, the study offers valuable insights for policymakers, financial institutions, and service providers. Targeted educational initiatives are needed to enhance financial literacy, especially in underserved and rural areas, to empower individuals to utilize DFS effectively. Trust in digital platforms must be bolstered by ensuring system security, transparency, and reliability. Policymakers should address infrastructural challenges to promote financial inclusion and equitable access to DFS. Furthermore, facilitating access to financial capital and encouraging habitual use of digital payment systems can drive adoption rates and contribute to economic empowerment.

Methodologically, the study showcases the utility of combining SEM and ANN, offering a comprehensive approach to analyzing both direct and ranked effects of predictors. This dual approach provides a richer understanding of the dynamics influencing DFS adoption, laying a foundation for future research to incorporate additional variables or contexts. Expanding the methodological toolkit enhances the precision and applicability of financial inclusion studies across diverse economic settings.

Despite its contributions, the research has limitations. Its reliance on cross-sectional data restricts the ability to observe long-term adoption trends, and the focus on Bangladesh may limit the generalizability of findings to other regions. Future research should employ longitudinal designs to capture temporal dynamics and explore cultural, technological, and policy factors influencing DFS adoption. Expanding the geographic scope to include comparative studies across different countries could further enrich the global discourse on digital financial inclusion.

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