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Effects of AI-Driven FinTech Solution on Credit Risk Management in Retail Banking: Empirical Evidence from Three Selected Banks in Bangladesh

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Abstract

This study examines the effects of AI-driven FinTech solutions on credit risk management in the retail banking of Bangladesh. Three leading commercial banks in Bangladesh-BRAC Bank Limited, Mutual Trust Bank Limited, and The City Bank Limited are selected to examine the effectiveness of credit risk management during the 2023–2024 time frame. A quantitative research design is used to analyse on loan performance, and primary survey data are collected from 150 retail borrowers of the selected banks. The study employs Partial Least Squares–Structural Equation Modeling (PLS-SEM) to test the proposed conceptual framework. The results reveal that repayment timeliness has a significant positive effect on portfolio quality, while operational cost per loan, loan default rate, and average loan processing time exert significant negative effects. Furthermore, portfolio quality is found to have a strong positive influence on credit risk management effectiveness. The findings suggest that AI-driven FinTech solutions enhance credit risk management primarily by improving borrower repayment behaviour and strengthening loan portfolio health, rather than solely through cost and speed efficiencies. The research contributes to understanding the effect of AI-driven FinTech solutions adoption in retail banking. It provides valuable insights in AI-driven digital financial technology on credit risk management for practitioners, policymakers, and educators.

Keywords: AI-driven FinTech, Credit Risk Management, Portfolio Quality, Retail Banking.
JEL Classification: G21, G32, O16, C55, L86

1 Introduction

1.1 Background

Bangladesh's financial sector has undergone a substantial transformation in recent years, marked by a growing adoption of FinTech solutions. This trend mirrors broader developments across Southeast Asia, driven by increasing internet penetration, a burgeoning middle class, and supportive government policies Curtis et al. (2022). The worldwide financial industry is undergoing fast development, owing to the rise of FinTech. Among these advancements, AI has emerged as one of the most powerful forces shaping current banking operations. AI-powered FinTech solutions are rapidly being utilized to improve operational efficiency, enhance consumer experiences, and tighten risk management. Credit risk management, a critical function in retail banking, has historically depended on traditional credit scoring models and manual evaluations. Limitations of these approaches include information asymmetry, subjective assessment,

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and data processing inefficiencies. As a result, banks continue to struggle with accurate default prediction and management of Non-Performing Loans (NPLs).

In response, several financial institutions around the world are turning to AI-driven FinTech solutions based on big data, machine learning, and predictive analytics. These technologies help banks to examine large and diverse information, identify trends in borrower behavior, and more accurately assess credit-worthiness. AI-powered credit risk systems can also use other data sources, such as digital transaction records, e-commerce activity, and mobile usage trends. By minimizing reliance on traditional credit bureau data, AI enables banks to analyze a broader percentage of the population, hence increasing financial inclusion. Globally, empirical studies reveal that adoption of AI has resulted in lower default rates, more accurate credit risk assessments, and higher portfolio quality.

Banking business in Bangladesh has grown fast, with retail banking emerging as a key driver of financial services. However, the industry continues to struggle with high levels of NPLs, which jeopardize profitability and financial stability. According to Bangladesh Bank data shows that, the country's average NPL ratio remains greater than that of many other emerging countries, showing ongoing deficiencies in credit risk management policies and practices. This ongoing issue emphasizes and focuses on the critical need for more effective and technologically driven risk management systems. Some major banks in Bangladesh have already begun experimenting with AI-powered FinTech solutions for credit evaluation and monitoring in retail banking. However, empirical information on the efficiency of these methods in mitigating credit risk is limited in the local banking environment.

1.2 Objectives

The main purpose of this study is to examine the effect of AI-driven FinTech solutions on credit risk management in retail banking of Bangladesh. Specifically, the study seeks to:

- Compare loan performance indicators before and after the adoption of AI solutions in retail banking.
- Examine whether AI adoption contributes to increasing portfolio quality and the effectiveness of credit risk management in retail banking and
- Provide policy recommendations for enhancing the financial sustainability of banks through AI-driven credit risk management.

2 Literature Review

2.1 AI-Driven FinTech Solutions for Retail Banking

The use of AI with FinTech solutions has fundamentally altered modern banking operations. Machine learning, natural language processing, and predictive analytics are popular AI applications in retail banking for improving decision-making and automating operations (Bose and Leung, 2022). FinTech advances are especially important for credit risk management, as data-driven models can give more accurate and quicker assessments than traditional scoring methods (Jagtiani and Lemieux, 2019).

2.2 Credit Risk Management and AI

Credit risk management has historically depended on traditional procedures such as credit information scores and financial ratio analysis. However, these strategies are frequently insufficient in situations when clients lack official credit histories (Khandani et al., 2010). AI-powered systems use structured and unstructured data, such as transaction records, mobile payment data, and even social media activity, to assess borrower behavior and default risk (Sadhwani et al., 2021). Empirical studies in established markets show that AI-powered risk assessment increases predicted accuracy and reduces loan defaults (Dastile et al., 2020).

2.3 Global Empirical Evidence in AI

Several global researches show that AI can help to improve risk management. Malekipirbazari and Aksakalli (2015) found that machine learning models outperformed logistic regression in predicting defaults on peer-to-peer lending platforms. Similarly, Baesens et al. (2016) highlighted the importance of big data analytics in improving risk modeling and portfolio management for credit scoring. These findings imply that AI adoption not only improves accuracy but also increases efficiency and accuracy by minimizing the need for manual involvement in risk evaluation.

2.4 AI and Retail Banking in Emerging Markets

In emerging economies, AI in retail banking is still in its early stages but it is fast expanding. According to studies, AI can assist in closing financial inclusion gaps by analyzing borrowers with poor credit histories (Ryu, 2018). AI-enabled FinTech solutions have been demonstrated to improve small borrowers' access to credit by incorporating alternative data sources (Arner et al., 2017). However, constraints like as infrastructure gaps, regulatory uncertainties, and high implementation costs frequently impede adoption (Ozili, 2021).

2.5 The Bangladesh Context of AI-Driven FinTech

Retail banking in Bangladesh has grown steadily, driven by rising demand for digital financial services and Mobile Financial Services (MFS). However, the sector continues to struggle with high NPL levels, ineffective risk management, and information asymmetry (Bangladesh Bank, 2023). While several banks have begun testing AI-powered FinTech products, rigorous research into their effectiveness in credit risk management is limited. The existing research on the banking sector in Bangladesh focuses mostly on traditional risk management strategies, digital payment uptake, and regulatory obstacles (Hossain and Rahman, 2020), but there are relatively few empirical studies that expressly investigate AI's involvement in credit risk mitigation.

2.6 Research Gaps

2.6.1 Limited Local Evidence

While global studies show that AI can help to reduce credit risk in banking, empirical research in Bangladesh on retail banking is still in its early stages. The majority of previous studies on credit risk on retail banking in Bangladesh focus on traditional scoring and regulatory compliance rather than innovative AI-driven solutions.

2.6.2 Neglect of Retail Banking in Bangladesh

Previous research has focused on corporate lending or overall NPLs in banking sector, leaving credit risk management in retail banking unexplored.

2.6.3 Insufficient Investigation of Challenges

Credit risk management in retail banking has changed dramatically through the adoption of Artificial Intelligence-powered FinTech solutions, especially in developing nations like Bangladesh. However, persistent fund crises and an increase in non-performing loans (NPLs) are currently plaguing the banking industry in Bangladesh, endangering both sustainable growth and financial stability. There is a scarcity of empirical research on the obstacles that banks experience when implementing AI-powered FinTech, such as data quality issues, regulatory compliance, and implementation impediments.

2.6.4 Gap between Inclusion and Risk

Few studies have looked into how AI-driven FinTech solutions might improve credit risk management in retail banking while also promoting financial inclusion in Bangladesh. This gap in the literature is especially significant given that retail loans account for an increasing share of the banking portfolio in Bangladesh. Retail banking customers frequently lack complete credit histories, making them more susceptible to incorrect risk evaluations under traditional processing systems. AI-powered technologies have the ability to close this gap by acquiring alternative behavioral and transactional data, increasing the accuracy and inclusiveness of credit assessments. Evaluating the experiences of selected banks in Bangladesh might thus provide important insights into the prospects and problems of implementing AI in credit risk management.

2.7 Conceptual Framework

The rapid integration of AI-driven FinTech solutions into retail banking has fundamentally transformed credit evaluation, loan processing, and risk monitoring practices. In response to increasing non-performing loans and operational inefficiencies, banks are increasingly relying on data-driven, automated decision-making systems to strengthen credit risk management. Building on this development, the present study proposes a conceptual framework that explains how AI-enabled operational and risk-related performance indicators influence credit risk management effectiveness through portfolio quality in the context of retail banking in Bangladesh.

The framework identifies four key independent constructs representing the outcomes of AI-driven FinTech adoption in retail banking: Operational Cost per Loan (OCL), Repayment Timeliness (RT), Loan Default Rate (LDR), and Average Loan Processing Time (ALPT).

Operational Cost per Loan reflects the cost efficiency achieved through automation of credit appraisal, documentation, and monitoring processes. AI-enabled systems reduce manual intervention and administrative overheads, which is expected to lower the cost associated with loan origination and management. From a risk management perspective, high operational costs signal inefficiencies that may adversely affect loan portfolio performance. Accordingly, the framework proposes a negative relationship between operational cost per loan and portfolio quality.

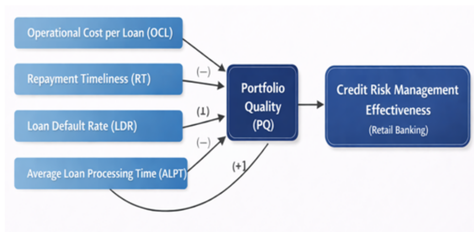

Figure-1: Conceptual Framework of AI-driven FinTech Solution

Repayment Timeliness captures borrowers' ability and willingness to meet repayment obligations on schedule, which is increasingly influenced by AI-driven monitoring systems, early warning mechanisms, and digital repayment platforms. Improved repayment timeliness indicates better borrower screening and proactive risk management, leading to healthier loan portfolios. Therefore, repayment timeliness is expected to exert a positive influence on portfolio quality. Loan Default Rate represents the proportion of borrowers who fail to meet repayment obligations, directly reflecting credit risk exposure. AI-based credit scoring models and predictive analytics are designed to reduce default risk by improving borrower assessment and early detection of potential distress. A higher default rate is indicative of poor portfolio performance and weakened risk control. Thus, the framework assumes a negative relationship between loan default rate and portfolio quality.

Average Loan Processing Time refers to the

Table 1: Direction and Nature of Relationships

Hyp.	Relationship	Exp. Dir.	Nature	Explanation
H1	OCL → PQ	Negative (−)	Inverse	Higher operational costs reduce efficiency and weaken loan portfolio health.
H2	RT → PQ	Positive (+)	Direct	Timely repayment improves asset quality and reduces credit risk.
H3	LDR → PQ	Negative (−)	Inverse	Higher defaults deteriorate loan portfolio quality.
H4	ALPT → PQ	Negative (−)	Inverse	Longer processing time increases inefficiency and adverse selection.
H5	PQ → CRME	Positive (+)	Direct	Better portfolio quality enhances credit risk identification and control.

time required to evaluate, approve, and disburse loans. AI-driven automation significantly accelerates credit decision-making, reducing delays and operational bottlenecks. Longer processing times may increase information asymmetry, borrower dissatisfaction, and exposure to adverse selection. Consequently, the framework proposes a negative relationship between loan processing time and portfolio quality.

2.8 Hypotheses

H1: Operational Cost per Loan has a significant negative effect on Portfolio Quality.

H2: Repayment Timeliness has a significant positive effect on Portfolio Quality.

H3: Loan Default Rate has a significant negative effect on Portfolio Quality.

H4: Average Loan Processing Time has a significant negative effect on Portfolio Quality.

H5: Portfolio Quality has a significant positive effect on Credit Risk Management Effectiveness.

2.8.1 Direction of Relationship

The proposed conceptual framework specifies both the direction and nature of relationships among the constructs. Operational cost per loan, loan default rate, and average loan processing time are hypothesized to have negative effects on portfolio quality, while repayment timeliness is expected to have a positive effect. Furthermore, portfolio quality is hypothesized to positively influence credit risk management effectiveness. These directional relationships reflect the expected outcomes of AI-driven FinTech adoption in retail banking operations.

3 Methodology

The research employed a quantitative research methodology to investigate the relationships between several critical factors, including Loan Default Rate (LDR), Repayment Timeliness (RT), Average Loan Processing Time (ALPT), Operational Cost per Loan (OCL), and Portfolio Quality (PQ) influence the Effectiveness of Credit Risk Management (CRM). This method is chosen to enable the systematic collection and quantitative analysis of empirical data, facilitating the exploration of connections among these variables. This methodology involved structured data collection using standardized survey instruments, ensuring a comprehensive examination of the relationships proposed in the study's theoretical framework. Subsequently, data analysis commenced by applying Partial Least Squares Structural Equation Modeling (PLS-SEM). This analytical approach offers several advantages, particularly in dealing with complex theoretical constructs and nonparametric data. PLS-SEM is chosen over covariancebased methods for its accuracy, simplicity, robustness, and flexibility. These characteristics prove especially advantageous when dealing with smaller sample sizes. Numerous studies have demonstrated that PLS-SEM can produce reliable results even with limited sample sizes (Hair et al., 2019; Yusr et al., 2020). Equally, the PLS-SEM analysis, conducted using SmartPLS4, facilitated a thorough examination of the research hypotheses and explored relationships among the variables under investigation. This approach allowed for rigorous testing of the research hypotheses and an in-depth investigation into the interconnections among the study variables

3.1 Research Design

This study employs a quantitative, explanatory research design to examine the effects of AI-driven FinTech solutions on credit risk management effectiveness in retail banking. A cross-sectional survey approach is adopted, as it is appropriate for assessing relationships among latent constructs at a single point in time. Considering the study's predictive orientation and the inclusion of a mediating variable, Partial Least Squares–Structural Equation Modeling (PLS-SEM)is selected as the primary analytical technique.

3.2 Population and Sampling

The target population of the study comprises retail banking borrowers who have experienced AI-enabled credit processes (such as automated credit scoring, digital loan processing, and AI-based monitoring systems). Data are collected from 150 borrowers of three leading commercial banks in Bangladesh:
• The City Bank Limited
• BRAC Bank Limited
• Mutual Trust Bank Limited (MTB)

A purposive sampling technique is employed to ensure that respondents had prior exposure to AI-driven FinTech services in loan application, approval, or repayment monitoring. The sample size of 150 satisfies the minimum sample requirement for PLS-SEM, in line with the 10-times rule and recommended statistical power criteria.

3.3 Data Collection Procedure

Primary data are collected using a structured questionnaire administered to borrowers through both physical distribution and online survey platformsduring the 2023–2024 timeframe. Respondents are briefed about the purpose of the study, and participation is entirely voluntary. Completed questionnaires are screened for missing values and inconsistencies before final analysis.

3.4 Measurement Instruments

All constructs are measured using multi-item scales adapted from prior empirical studies and modified to suit the retail banking context in Bangladesh.
• A 5-point Likert scale is used
(1 = Strongly Disagree to 5 = Strongly Agree)
Constructs Measured:
• Operational Cost per Loan (OCL)
• Repayment Timeliness (RT)
• Loan Default Rate (LDR)
• Average Loan Processing Time (ALPT)
• Portfolio Quality (PQ)
• Credit Risk Management Effectiveness (CRME)

3.5 Questionnaire Development

The questions in the questionnaire are based on review of literatures and the specific characteristics of borrowers in the market context. The specific characteristics represented different services and facilities provided by the banks and expected by the borrowers.

3.6 Methods

A comprehensive understanding of the types of variables utilized in this study is essential to appreciate the complexity and depth of the analysis. In this study, latent variables are those not directly observed but inferred from other variables. These include Loan Default Rate (LDR), Repayment Timeliness (RT), Average Loan Processing Time (ALPT), Operational Cost per Loan (OCL), and Portfolio Quality (PQ) influence the Effectiveness of Credit Risk Management (CRM). These latent variables represent underlying constructs that influence observable behaviors and attitudes towards the effectiveness of credit risk management. Additionally, independent variables in this study serve as predictors or causes that influence the dependent variables. The independent variables examined include OCL, RT, LDR, and ALTP. These variables are critical in understanding how different factors contribute to the effectiveness of credit risk management. The study applied descriptive and inferential statistical techniques, including regression analysis modeling loan default probability. These methods are selected to determine whether the observed differences in repayment behavior and loan performance are statistically significant. The analysis is conducted using SPSS and R.

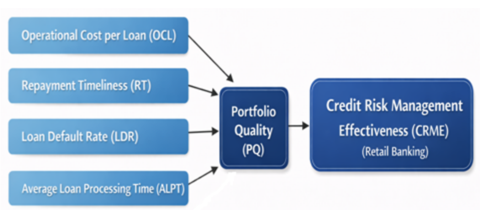

Figure-2: Research Framework

3.7 Ethical Considerations

The study ensures the confidentiality of borrower information and complies with the ethical standards of data collection and usage. Data provided by banks is anonymized to protect borrower identities.

4 Data Analysis

4.1 Descriptive Analysis

Table 2 presents the descriptive statistics of borrowers from The City Bank, BRAC Bank, and Mutual Trust Bank. The sample is evenly distributed across the three banks, ensuring balanced institutional representation.

Table 2: Distribution of Respondents by Bank

Bank Name	Freq. (n)	(%)
The City Bank Limited	50	33.3
BRAC Bank Limited	50	33.3
MTB	50	33.3
Total	**150**	**100.0**

Table 3: Descriptive Statistics of Key Constructs ($n = 150$)

Const	Bank	Mean	SD	Min	Max
OCL	City	2.84	0.67	1.60	4.20
	BRAC	2.71	0.62	1.50	4.10
	MTB	2.93	0.69	1.70	4.30
RT	City	3.96	0.58	2.40	5.00
	BRAC	4.12	0.55	2.60	5.00
	MTB	3.88	0.61	2.30	5.00
LDR	City	2.41	0.64	1.30	4.00
	BRAC	2.28	0.59	1.20	3.80
	MTB	2.53	0.66	1.40	4.20
LPT	City	2.67	0.63	1.50	4.10
	BRAC	2.49	0.58	1.40	3.90
	MTB	2.76	0.65	1.60	4.30
PQ	City	4.02	0.57	2.60	5.00
	BRAC	4.18	0.54	2.80	5.00
	MTB	3.91	0.60	2.50	5.00
CRME	City	4.08	0.56	2.70	5.00
	BRAC	4.21	0.53	2.90	5.00
	MTB	3.97	0.59	2.60	5.00

Table 3 represents the results of three selected banks, which indicate that relatively high repayment timeliness and portfolio quality across all banks, with BRAC Bank showing slightly superior performance in operational efficiency and credit risk management effectiveness.

Table 4 represents a bank-wise comparison that reveals notable differences in borrower perceptions of AI-driven FinTech outcomes. BRAC Bank consistently demonstrates superior performance across operational efficiency, borrower repayment behaviour, portfolio qual-

Table 4: Bank-wise Mean Comparison of Study Constructs

Construct	City Bank (Mean ± SD)	BRAC Bank (Mean ± SD)	MTB (Mean ± SD)	Best Performing Bank
OCL	2.84 ± 0.67	2.71 ± 0.62	2.93 ± 0.69	BRAC Bank
RT	3.96 ± 0.58	4.12 ± 0.55	3.88 ± 0.61	BRAC Bank
LDR	2.41 ± 0.64	2.28 ± 0.59	2.53 ± 0.66	BRAC Bank
ALPT	2.67 ± 0.63	2.49 ± 0.58	2.76 ± 0.65	BRAC Bank
PQ	4.02 ± 0.57	4.18 ± 0.54	3.91 ± 0.60	BRAC Bank
CRME	4.08 ± 0.56	4.21 ± 0.53	3.97 ± 0.59	BRAC Bank

Table 5: Discriminant Validity (Fornell and Larcker Criterion)

Constructs	OCL	RT	LDR	ALPT	PQ	CRME
OCL	**0.812**					
RT	-0.432	**0.846**				
LDR	0.518	-0.491	**0.831**			
ALPT	0.476	-0.415	0.502	**0.824**		
PQ	-0.563	0.621	-0.644	-0.538	**0.857**	
CRME	-0.498	0.574	-0.603	-0.512	0.689	**0.872**

ity, and credit risk management effectiveness. City Bank shows moderate performance, while Mutual Trust Bank lags slightly behind in most dimensions. These differences suggest varying levels of maturity in AI-driven credit risk management practices among the three commercial banks.

4.2 Model Assessment

In the evaluation of the measurement model, emphasis is placed on three critical facets: internal consistency, along with discriminant and convergent validity, drawing upon the guidelines of Hair et al. (2011) and Henseler et al. (2015). Table 4 shows that the reliability and validity of the measurement model are assessed using internal consistency reliability and convergent validity measures. Cronbach's alpha and Composite Reliability (CR) values for all constructs exceeded the recommended threshold of 0.70, indicating satisfactory internal consistency. Convergent Validity is confirmed as all Average Variance Extracted (AVE) values are above 0.50. Additionally, discriminant validity is established using the Fornell and Larcker criterion, as the square root of AVE for each construct is greater than its inter-construct correlations. The measurement model demonstrates adequate reliability and validity for subsequent structural model analysis.

To ascertain discriminant validity, the study adopted a dual-method approach. The first method involved the comparison of the square root of the AVE with the correlations among different items. As per the criteria set by Fornell and Larcker (1981), for satisfactory discriminant validity, the square root of the AVE for each construct should exceed the inter-construct correlations. This condition was fulfilled, as shown in Table 5, where the square root of the AVE for each construct surpassed the respective correlations between constructs.

Table 6: Construct Reliability and Convergent Validity

Construct	Alpha (α)	CR	AVE
OCL	0.823	0.884	0.659
RT	0.846	0.901	0.716
LDR	0.812	0.879	0.691
ALPT	0.801	0.872	0.679
PQ	0.867	0.913	0.734
CRME	0.884	0.926	0.761

The second method applied was the

heterotrait-monotrait ratio of correlations (HTMT). Following the guidelines proposed by Henseler et al. (2015), an HTMT value below 0.90 indicates acceptable discriminant validity. As shown in Table 7, all HTMT values are below the recommended threshold of 0.85, indicating adequate discriminant validity among the constructs. These findings confirm that the measurement model exhibits sufficient construct distinctiveness and is suitable for structural model analysis.

Table 7: HTMT Ratio of Correlations

Const	OCL	RT	LDR	ALPT	PQ	CRME
OCL	—					
RT	0.487	—				
LDR	0.563	0.521	—			
ALPT	0.519	0.468	0.548	—		
PQ	0.624	0.693	0.712	0.601	—	
CRME	0.587	0.641	0.684	0.579	0.748	—

4.3 Structural Model

The results indicate that all proposed hypotheses are supported. Operational cost per loan, loan default rate, and average loan processing time exhibit significant negative effects on portfolio quality, while repayment timeliness has a significant positive effect. Furthermore, portfolio quality significantly enhances credit risk management effectiveness, confirming its mediating role in the proposed model.

The structural model is evaluated using the coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), path coefficients (β), and the significance of paths. The R^2 values indicate that the model explains a substantial proportion of variance in portfolio quality and a moderate proportion in credit risk management effectiveness. Falk and Miller (1992) recommends that an R^2 value of at least 0.1 for each latent dependent variable indicates a satisfactory model. In this research, the R^2 values for PQ (0.587) and CRME (0.476) reflect the proportion of variance explained by the independent variables in each dependent variable. The values suggest a moderate explanatory power for PQ and CRME.

In this study, RT demonstrates a medium effect on Portfolio Quality ($f^2 = 0.167$), indicating that timely repayment behaviour plays a substantial role in improving loan portfolio health. Similarly, PQ shows a medium effect on CRME ($f^2 = 0.212$), confirming that portfolio health is a key driver of effective credit risk management in retail banking. Further-more, The Q2 values for PQ (0.392), and CRME (0.318) indicate the model's predictive relevance, with values greater than 0.1 suggesting the model has predictive capabilities for each respective construct (see Table-9,10 and 11).

5 Discussion

This study examines the effects of AI-driven FinTech solutions on credit risk management effectiveness in retail banking, with portfolio quality serving as a mediating mechanism. The findings provide several important insights into how AI-enabled operational efficiency and borrower behavior influence risk outcomes in the banking sector of Bangladesh.

Table 8: Structural Model Path Coefficients and Hypothesis Testing

Hyp.	Path	β	t-value	p-value	Decision
H1	OCL → PQ	-0.243	3.182	0.001	Supported
H2	RT → PQ	0.316	4.257	0.000	Supported
H3	LDR → PQ	-0.291	3.874	0.000	Supported
H4	ALPT → PQ	-0.214	2.946	0.003	Supported
H5	PQ → CRME	0.421	6.138	0.000	Supported

5.1 Operational Cost per Loan and Portfolio Quality

The results indicate that operational cost per loan has a significant negative effect on portfolio quality, supporting Hypothesis H1. This finding suggests that higher operational costs undermine loan portfolio health by reducing efficiency and limiting banks' capacity to supervise and manage credit risk effectively. AI-driven automation, such as digital credit appraisal, document verification, and monitoring, reduces manual intervention and processing expenses, thereby improving portfolio of the borrower. This result is consistent with prior studies that argue digital and AI-based banking technologies enhance cost efficiency and asset quality (Vives, 2019; Gomber et al., 2018). In the context of Bangladesh, where operational inefficiencies remain a major challenge in retail banking, AI-driven FinTech adoption appears to play a critical role in strengthening portfolio quality through cost optimization.

Table 9: Coefficient of Determination (R^2)

Endogenous Construct	R^2	**Interpretation**
Portfolio Quality (PQ)	0.587	Moderate to Substantial
Credit Risk Management Effectiveness (CRME)	0.476	Moderate

5.2 Repayment Timeliness and Portfolio Quality

The findings show that repayment timeliness has a strong and positive impact on portfolio quality, confirming Hypothesis H2. This implies that AI-driven monitoring systems, predictive analytics, and digital repayment platforms significantly enhance borrowers' repayment behavior. Improved repayment timeliness reduces delinquency and non-performing loans, thereby improving overall portfolio health. This result aligns with existing literature emphasizing the role of AI-based credit monitoring and behavioral analytics in improving repayment discipline (Bazarbash, 2019; Frost et al., 2019). The relatively stronger effect size observed for repayment timeliness highlights that borrower behavior, supported by AI-driven systems, is a key determinant of portfolio quality in retail banking of Bangladesh.

5.3 Loan Default Rate and Portfolio Quality

The study finds a significant negative relationship between loan default rate and portfolio quality, supporting Hypothesis H3. This outcome is intuitive, as higher default rates directly deteriorate loan portfolio performance. AI-driven credit scoring and early warning systems enable banks to better identify high-risk borrowers and anticipate potential defaults, thereby reducing overall default exposure. This finding is consistent with prior research demonstrating that AI and machine learning models outperform traditional credit assessment methods in default prediction (Kou et al., 2021). For banks in Bangladesh facing rising default risks, the result underscores the importance of AI-based risk analytics in sustaining portfolio quality.

Table 10: Effect Size (f^2)

Path	f^2	**Effect Size**
OCL → PQ	0.094	Small to medium
RT → PQ	0.167	Medium
LDR → PQ	0.139	Small to medium
ALPT → PQ	0.081	Small
PQ → CRME	0.212	Medium

N.B.: Guidelines (Cohen, 1988): 0.02 = Small, 0.15 = Medium, 0.35 = Large.

Table 11: Predictive Relevance (Q^2)

Endogenous Construct	Q^2	**Predictive Relevance**
Portfolio Quality (PQ)	0.392	Strong predictive relevance
Credit Risk Management Effectiveness (CRME)	0.318	Strong predictive relevance

5.4 Average Loan Processing Time and Portfolio Quality

The results further reveal that average loan processing time negatively affects portfolio quality, confirming Hypothesis H4. Longer processing times increase information asymmetry, borrower dissatisfaction, and exposure to adverse selection, which can ultimately weaken portfolio performance. AI-driven automation significantly accelerates loan approval and disbursement processes, reducing delays and improving credit decision accuracy. This finding is consistent with studies suggesting that digitization and automation enhance speed, transparency, and efficiency in lending operations(Philippon, 2016; Thakor, 2020). In emerging markets such as Bangladesh, faster loan processing through AI-enabled systems can improve customer experience while simultaneously strengthening risk outcomes.

5.5 Portfolio Quality and Credit Risk Management Effectiveness

Finally, the study finds that portfolio quality has a strong positive effect on credit risk management effectiveness, supporting Hypothesis H5. This result confirms the mediating role of portfolio quality, indicating that improvements in operational efficiency and borrower behavior translate into effective credit risk management primarily through enhanced portfolio health. This finding aligns with risk management theory, which emphasizes asset quality as the foundation of effective risk control (Basel Committee on Banking Supervision, 2019). Empirically, it supports prior studies that link portfolio performance to improved risk identification, monitoring, and mitigation capabilities (Allen et al., 2020).

5.6 Integrated Discussion

The findings demonstrate that AI-driven FinTech solutions influence credit risk management effectiveness indirectly through portfolio quality. While operational efficiency factors contribute meaningfully, borrower-related outcomes, particularly repayment timelines,s exert the strongest practical impact. This highlights the strategic importance of AI-based borrower analytics and monitoring systems in retail banking in Bangladesh. The bank-wise comparison further suggests that institutions with more mature AI adoption exhibit superior portfolio quality and credit risk management effectiveness. These results provide strong empirical support for the continued integration of AI-driven FinTech solutions in the banking sector of Bangladesh.

6 Conclusion and Policy Recommendation

This study examined the effects of AI-driven FinTech solutions on credit risk management effectiveness in retail banking, using borrower-level data from three leading commercial banks in Bangladesh. By incorporating operational efficiency indicators (operational cost per loan and loan processing time), borrower behavior variables (repayment timeliness and loan default rate), and portfolio quality as a mediating construct, the study provides a comprehensive understanding of how AI-enabled technologies contribute to effective credit risk management in retail banking. The empirical results demonstrate that repayment timeliness positively influences portfolio quality, while operational cost per loan, loan default rate, and average loan processing time exert significant negative effects. Furthermore, portfolio quality significantly enhances credit risk management effectiveness, confirming its mediating role in translating AI-driven operational and borrower-level improvements into effective risk outcomes.

These findings suggest that AI-driven FinTech solutions improve credit risk management not only by increasing operational efficiency but also by shaping borrower behavior and strengthening portfolio health. The study contributes to the growing FinTech literature by providing borrower-based empirical evidence from an emerging economy, highlighting the importance of AI-enabled systems in addressing persistent credit risk challenges in the retail banking of Bangladesh. The findings of this study offer several important policy and managerial implications for banks, regulators, and policymakers in Bangladesh.

First, commercial banks should prioritize the integration of AI-driven credit analytics and monitoring systems to enhance repayment timeliness and reduce default risk. Given the strong influence of borrower behavior on portfolio quality, investments in AI-based early warning systems, behavioral scoring, and real-time monitoring can significantly improve risk outcomes.

Second, bank management should focus on reducing operational costs and loan processing time through automation of credit appraisal, documentation, and approval processes. Streamlining these processes using AI and digital platforms can improve efficiency while simultaneously enhancing portfolio quality.

Third, regulators such as Bangladesh Bank should develop clear regulatory frameworks and guidelines for the responsible adoption of AI-driven FinTech solutions. Regulatory support for explainable AI, data governance, and cybersecurity can encourage innovation while ensuring financial stability and consumer protection.

Fourth, policymakers should encourage capacity building and skill development within the banking sector to support effective AI implementation. Training programs for risk managers and credit officers on AI-based decision tools can improve adoption outcomes and reduce resistance to technological change.

Finally, collaboration between commercial banks, FinTech firms, and regulatory authorities should be strengthened to promote standardized AI-driven credit risk practices across the banking sector. Such collaboration can help ensure that AI adoption contributes to sustainable credit growth and long-term financial stability in Bangladesh.

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Disclosure Statement

Views expressed in this paper are the authors' own and do not necessarily reflect the views of institutions they are affiliated with.

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