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ADOPTION OF AI-ENABLED FINTECH SOLUTIONS IN BANKS AND ITS EFFECTS ON CREDIT RISK MANAGEMENT

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ABSTRACT

This paper examines how banking sectors in Bangladesh uses AI and FinTech to deal with credit risk management. Among the three commercial banks in Bangladesh (Dutch-Bangla Bank, Prime Bank and Trust Bank) has been conducted a study to find out the effectiveness of their respective credit risk management processes for the year 2023 and 2024. A study of the effects of bank's loan advances on the financial status of customers is based on statistical data. This study involved 150 customers who got loans from retail banks. Using Partial Least Squares Structural Equation Modeling (PLS SEM), this study tested the proposed conceptual framework.

It was observed that loan repayments in a timely manner result in a better quality of loans. Conversely, high operational costs per loan, high loan default rates, and long loan processing times are all detrimental to loan quality. The company's entire asset allocation is closely tied to risk management. There is significant evidence that portfolio management assists and facilitates risk management techniques. Throughout the recruitment process a high standard portfolio is necessary. In the financial industry, credit risk management can be improved with the use of AI driven technologies. The main cause of the benefits is the influence they have on debtors who are paying back their loans and the financial well-being of the loan companies rather than merely trimming costs and the swift handling of transactions.

This study provides insights on how artificial intelligence is adopted by the retail banking sector in Bangladesh, focusing particularly on its practical applications in that country. In addition, the study provides practical guidance to educators, banking professionals and those responsible for making financial policy on the use of artificial intelligence in the banking sector. The research project focuses on whether or not computer systems can make more accurate judgments on clients' creditworthiness.

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

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1. INTRODUCTION

1.1 Background

The recent dramatic changes in the domestic financial sector are down to the growing popularity of new financial technologies. The growing blogging trend in Malaysia mirrors developments in other South East Asian countries (**Curtis *et al.* 2022**). These countries are seeing increased internet penetration along with a developing middle class and supportive laws. FinTech has over the past few years made rapid progress across the globe, impacting the banking sector by employing new technologies such as AI. The trend in mobile payments has brought about significant alterations to the traditional banking industry's business strategies.

Financial institutions are now employing artificial intelligence to increase the speed and efficiency of their processes, to offer enhanced customer service and to reduce the risk involved in banking (**Ghandour, 2021**). The key challenge which such financial institutions will face is credit risk management (**Khandani *et al.* 2010**). Generally, banks assess credit risk by conventional methods involving a manual process. In these the assessment of a loan applicant's creditworthiness may be prejudiced by differing levels of information available to lenders and borrowers. This traditional system can also involve subjective decisions. Credit risk assessment has been complicated by a variety of issues.

Using big data, predictive analytics and machine learning, lenders are starting to adopt AI-based credit scoring models globally (**Berg *et al.* 2020; Leo *et al.* 2019**). Innovative data analysis methods used by the financial services sector enables it to study large amounts of data, to identify potential risks linked with specific customers and thus make lending decisions with more knowledge. Artificial intelligence systems are able to assess the creditworthiness of individuals by taking into account a large volume of data (**Lin, 2019**). This data could include details of previous transactions, mobile phone use and digital payment records. The use of artificial intelligence technology by banks worldwide has been found to produce improved credit assessment and evaluation, in addition to lower default rates and improved loan portfolios.

In Bangladesh there has been significant growth in retail banking and it is one of the major drivers of the expansion of banking. Significant numbers of bad loans within the banking sector remain a threat to the financial stability and potential future profitability of banks. It has been observed that Bangladesh's non-performing loans ratio is higher compared to many other emerging markets. This could imply that there are weaknesses in the credit system of the country. The current global situation highlights the need for more effective risk management systems which incorporate advanced technology. There is at present limited empirical evidence as regards the effectiveness of recently introduced in Bangladesh AI driven retail credit products of some commercial banks particularly from borrowers' perspective. This research aims at a bridging of this knowledge gap.

1.2 Objectives of the Study

This research is an attempt to investigate the impact of the Artificial Intelligence (AI) based FinTech tools on credit risk management in the retail banking sector of Bangladesh. The research objectives are as follows:

1. Analyze changes in key loan performance indicators associated with the adoption of AI-enabled FinTech solutions in retail banking.
2. Examine whether AI adoption contributes to improvements in portfolio quality and credit risk management effectiveness.
3. Provide policy-relevant recommendations to enhance the financial sustainability and risk management capacity of commercial banks through AI-enabled credit assessment systems.

2. LITERATURE REVIEW

2.1 AI-enabled FinTech Solutions for Retail Banking

Advanced AI technologies have dramatically impacted the development of FinTech, resulting in a complete overhaul of banking systems (**Mhlanga, 2024**). Increasingly retail banking is making use of technologies like predictive analytics, natural language processing and machine learning in order to increase efficiency in operational processes and to help make automatic decisions (**Jagtiani & Lemieux, 2019**). In the field of credit risk, specifically, big data technologies are making it possible to carry out credit assessments more quickly and with greater accuracy. This is compared to the older credit scoring methods. Digital banking operations are experiencing a significant increase in their online presence, and banking technology firms that use artificial intelligence are assisting banks in handling large volumes of data. These results are being able to adapt to changing risk more effectively.

2.2 Credit Risk Management and the Role of AI

For a number of years, the general approach taken by credit managers when assessing the risk that a borrower might default on a loan has been based on certain key ratios of the borrower's financial situation, a view of any security being given and a credit report on the borrower. In certain situations, credit scoring models are successful, they however often fail when the applicant has no formal credit record or when their credit score needs to be revised in real time. By using both structured and unstructured data such as transaction histories and payment records from mobile phones the risk that a borrower may default is assessed more thoroughly. Studies into credit decision systems within developed economies have discovered that they are more effective at forecasting credit worthiness and result in reduced levels of bad debt (**Dastile *et al.* 2020**).

2.3 Global Empirical Evidence on AI-based Credit Risk Assessment

Research from around the world shows that the application of AI in the assessment of credit risk has its benefits. In a study published in 2015, F**lorez-Lopez and Ramon-Jeronimo** compared machine learning with the more traditional logistic regression method, and found that machine learning models were better at predicting loan defaults. Similarly, **Baesens (2014)** and **Bello (2024)** argued that financial institutions can benefit from the use of big data analytics as it allows them to integrate a broader set of information into their risk management and credit scoring processes. The overall evidence implies that the use of AI can lead to better predictions as well as decrease the requirement for manual processing intervention, resulting in enhanced operational efficiency within lending evaluation processes.

2.4 AI Adoption in Retail Banking within Emerging Markets

The early but rapidly developing adoption of FinTech with artificial intelligence in retail banking is seen in newly industrialising countries (**Ediagbonya & Tioluwani, 2023**). Previous studies have shown that the adoption of artificial intelligence in banking systems can increase access to credit for those in developing countries by allowing lenders to assess individuals with little or no credit history. Innovative methods of obtaining information have made it possible for computer algorithms to lend to people who are small and lack access to credit (**Arner *et al.* 2017**). Despite the benefits, the uptake of mobile banking is being hindered by several issues including high setup costs, a lack of suitable digital networks and uncertainty over the regulatory framework.

2.5 AI-enabled FinTech and the Bangladesh Banking Context

There has been a continuous rise in retail banking in Bangladesh largely because of a strong demand for the services of digital banking and an expanding mobile banking market. The sector still suffers from difficulties with non-performing loans, inefficient systems for credit risk assessment and a lack of information; these issues are ongoing (**Bangladesh Bank, 2023**). Limited research exists into the efficacy of AI in FinTech when used by commercial banks in the evaluation and monitoring of credit. Studies concerning the Bangladeshi banking industry have mainly been concentrated on issues like traditional risk management, the implementation of digital payment, and regulations in the sector (**Rahman *et al.* 2025**), with an area yet to be studied being the application of artificial intelligence in credit risk assessment.

2.6 Research Gaps

2.6.1 Limited Empirical Evidence in Bangladesh

Research in various countries indicates that the application of artificial intelligence decreases the risk associated with loans, however, the Bangladesh retail banking market is still in need of detailed analysis in this area. Only a small number of studies have considered the implementation of AI in the context of finance.

2.6.2 Underrepresentation of Retail Banking

In Bangladesh, most academic research tends to look at the lending to companies or the trend of bad loans at a general level; however, research in retail banking has been relatively less looked into especially when it comes to managing the risk to the bank's loans. There is a considerable research deficit in retail credit.

2.6.3 Insufficient Analysis of Implementation Challenges

Bangladesh's banks are currently experiencing some problems such as low data quality, difficulties in implementing regulatory requirements, integrating their systems and being operationally ready. These studies are rare in the field, concerning the use of systems of artificial intelligence in assessing the risk of borrowers.

2.6.4 Gap between Financial Inclusion and Risk Management

Only a few studies examine how Bangladeshi AI-FinTech, which uses AI, can improve financial services for the poor at the same time as cutting credit risks. Borrowers from the retail sector often do not have a good credit history which makes them prone to being classified wrongly by the usual credit scoring systems. By using AI techniques, lenders can access and integrate data that is not in the traditional credit history, such as the consumer's payment records on their mobile phone bill.

2.7 Conceptual Framework

As banking more increasingly adopts AI systems, it is using them to automatically evaluate credit and process loan applications. This new system also monitors risks more effectively. As banks encounter growing numbers of non-performing loans and become less efficient in their operations, there is a trend for them to introduce computer-based decision-making tools to help them in credit. In the Bangladesh retail banking sector, this paper develops a conceptual framework to demonstrate how the quality of a bank's loan portfolio can be affected by artificial intelligence in credit risk management.

Key outcomes from the adoption of AI-driven financial technologies include Loan Default Rate (LDR), Average Loan Processing Time (ALPT), Repayment Timeliness (RT) and cost per loan. The operational cost per loan is a measure of the efficiency gains resulting from the automation of credit appraisal and monitoring processes. Since a lender's operational costs are a significant portion of its expenses, inefficient operations can decrease portfolio performance. Hence a negative correlation is expected between operational cost per loan and the quality of the loan portfolio. The repayment history of a borrower is measured by their ability to make repayments on time. The use of automated monitoring techniques and warning signals has been shown to enhance borrowers' repayment habits, which in turn results in better credit portfolios. It is reasonable to expect borrowers who keep to their repayment schedules to have a positive effect on the overall quality of a portfolio.

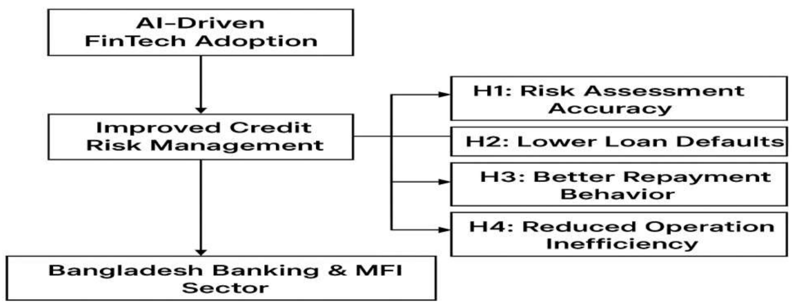

Fig.-1: Conceptual Framework of AI-enabled FinTech Solution

Credit risk exposure is directly captured by loan default rate. Advanced AI predictive models can help lower the default rate on loans by refining the borrower profile and financial condition and early warning signs of potential insolvency. The expectation is thus that a higher default rate will reduce the quality of a portfolio. The time a loan takes to be approved and disbursed is known as the average loan processing time. Automation, by virtue of its artificial intelligence component, minimizes processing delays. Conversely, any delays in processing can have the effect of increasing both inefficiency and adverse selection. There appears to be a relationship where the quality of a portfolio is negatively affected by the time spent in processing loans.

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 model structure clearly indicates the type and direction of relationships between variables in the theory. Three variables, namely average loan processing time, the loan default rate and the operational cost per loan, are hypothesised to negatively affect portfolio quality. It is also hypothesised that the timely repayment of loans will have a positive effect on the quality of a portfolio. Portfolio quality is considered likely to enhance the effectiveness of the organisation's credit risk management strategy. This AI-enhanced FinTech adoption in retail banking operations will bring about these impacts and associations.

Table-1: Direction and Nature of Relationships

Hypothesis	Relationship	Expected Direction	Nature of Effect	Explanation
H1	Operational Cost per Loan (OCL) → Portfolio Quality (PQ)	Negative (–)	Inverse	Higher operational costs reduce efficiency and weaken loan portfolio health
H2	Repayment Timeliness (RT) → Portfolio Quality (PQ)	Positive (+)	Direct	Timely repayment improves asset quality and reduces credit risk

Hypothesis	Relationship	Expected Direction	Nature of Effect	Explanation
H3	Loan Default Rate (LDR) → Portfolio Quality (PQ)	Negative (–)	Inverse	Higher defaults deteriorate loan portfolio quality
H4	Average Loan Processing Time (ALPT) → Portfolio Quality (PQ)	Negative (–)	Inverse	Longer processing time increases inefficiency and adverse selection
H5	Portfolio Quality (PQ) → Credit Risk Management Effectiveness (CRME)	Positive (+)	Direct	Better portfolio quality enhances credit risk identification and control

3. METHODOLOGY

Using a quantitative research approach, this study investigates how selected variables affect the performance of retail banking's credit risk management systems. These variables include the operational cost per loan, the average loan processing time, the loan default rate, the portfolio quality and the timeliness of repayments. The quantitative research method allows for the objective examination of the relationships between a variety of variables by means of the statistical analysis of numerical data.

Data are gathered using standardised survey techniques to guarantee consistency and comparability in the answers provided by respondents. Using a Partial Least Squares-Structural Equation Modeling (PLS-SEM) framework allows for the assessment of the relationships between various variables at the same time. PLS-SEM looks at how unobserved latent variables, which are the underlying concepts we are measuring, influence one another.

Because PLS-SEM is more suitable for predictive research and can handle mediating relationships in complex models than are traditional covariance-based SEM techniques, the latter are often selected over the former. Additionally, PLS-SEM is robust in the context of smaller sample sizes. Numerous earlier studies have found that using partial least squares structural equation modelling PLS SEM results in highly reliable and consistent outcomes even in situations with very small sample sizes. The study by **Hair *et al.* (2011)** employed PLS-SEM to investigate the research hypothesis. The analysis was conducted by SmartPLS 4 and it tested both measurement and structural model.

3.1 Research Design

This study aims to explore how FinTech enabled by Artificially Intelligent systems influences the effectiveness of credit risk management in Bangladesh's retail banking sector through a quantitative analysis of existing data. The use of a cross-sectional study design is appropriate here as it enables the investigation of the associations among variables at a single time point. The research takes a predictive approach and has a mediator (portfolio quality) so the PLS-SEM methodology was chosen for this study to test the framework and hypotheses presented.

3.2 Population and Sampling

Individuals familiar with AI in credit services are the target audience; this consists of retail banking customers who have used services which include automated assessment of credit worthiness, computerised loans processing and AI systems used to monitor repayment. The primary data have been gathered from 150 borrowers of three prominent commercial banks of Bangladesh.

- Trust Bank Limited

- Dutch Bangla Bank Ltd. is one of the prominent private commercial banks in Bangladesh.
- Prime Bank Limited

The study specifically targeted individuals who have used technology with Artificial Intelligence (AI) in the finance sector for loans, such as applications, approvals or tracking loans. This sample size of 150 is sufficient for PLS-SEM analysis, meeting the ten times rule of the number of items used for the structural model and also statistical power guidelines.

3.3 Data Collection Procedure

Information was collected during the 2023-2024 periods using questionnaires which had been structured and were given to people in two different ways. Participation in this study is entirely voluntary and only those who have been informed of the academic purpose of the research will be involved. Before undergoing any data analysis the completed questionnaires undergo checks to make certain that they are complete, free from incorrect information and contain no outlying data.

3.4 Measurement Instrument

The constructs in this study were measured by multi-item scales that were adapted from earlier research studies and have been modified to suit the context of retail banking 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

In light of existing literature, the questionnaire was formulated to ensure that it is specific to the characteristics of borrowers in retail banking in Bangladesh. The tool gives lenders insight into the perception of their customers towards the bank's assessment methods, how customers repay their debts, how efficiently loans are being used and portfolio performance with AI systems in place.

3.6 Analytical Methods

In this research, core variables are regarded as unobserved, multivariate latent constructs. The values of these variables are to be inferred from the multiple observed indicators. The external factors considered in this model include loan operational cost per loan unit, loan repayment timeliness, loan default percentage and loan processing time. Portfolio Quality is a mediating variable in this model where Credit Risk Management Effectiveness is the dependent variable. A connection diagram illustrating the connections between several units is shown below. This study applied partial least squares structural equation modelling (PLS SEM) in two stages. Before using the measuring instrument, its validity and reliability must be checked. This can be done by determining the internal consistency, convergent validity and discriminant validity. A structural model's appropriateness is judged by the path coefficients, the R^2, effect size and the predictive fit. The analysis was carried out by employing the statistical programme SPSS to provide descriptive statistics, and SmartPLS version 3 was utilised to assess the structural model and the hypotheses put forward.

3.7 Ethical Considerations

This study was done according to the principles of the current Declaration of Tokyo. Everything said or done at our meetings, events or through our services is treated as strictly confidential and is protected by law. The identities of the banks and borrowers in this study have been anonymised to guarantee confidentiality. The data was gathered with the full cooperation of all the parties involved. To commence, a description is given of the survey's parameters.

4. DATA ANALYSIS

4.1 Descriptive Analysis

The data summarised in Table 2 provides descriptive statistics for borrowers with loans from the Trust Bank, Dutch-Bangla Bank and Prime Bank. In order to ensure that there is a balanced representation of institutions from each of the three banks, the sample was distributed evenly across them. The table 3 displays the results of the three banks in question, indicating that generally high repayment timeliness and portfolio quality across all banks, though Dutch-Bangla Bank displayed a slight superiority in operational efficiency and credit risk management.

Table-2: Distribution of Respondents by Bank

Bank Name	Frequency (n)	Percentage (%)
Trust Bank Limited	50	33.3
Dutch-Bangla Bank Limited	50	33.3
Prime Bank Limited	50	33.3
Total	150	100.0

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

Construct	Bank	Mean	SD	Minimum	Maximum
OCL	Trust Bank	2.84	0.67	1.60	4.20

Construct	Bank	Mean	SD	Minimum	Maximum
	Dutch-Bangla Bank	2.71	0.62	1.50	4.10
	Prime Bank	2.93	0.69	1.70	4.30
RT	Trust Bank	3.96	0.58	2.40	5.00
	Dutch-Bangla Bank	4.12	0.55	2.60	5.00
	Prime Bank	3.88	0.61	2.30	5.00
LDR	Trust Bank	2.41	0.64	1.30	4.00
	Dutch-Bangla Bank	2.28	0.59	1.20	3.80
	Prime Bank	2.53	0.66	1.40	4.20
ALPT	Trust Bank	2.67	0.63	1.50	4.10
	Dutch-Bangla Bank	2.49	0.58	1.40	3.90
	Prime Bank	2.76	0.65	1.60	4.30
PQ	Trust Bank	4.02	0.57	2.60	5.00
	Dutch-Bangla Bank	4.18	0.54	2.80	5.00
	Prime Bank	3.91	0.60	2.50	5.00
CRME	Trust Bank	4.08	0.56	2.70	5.00
	Dutch-Bangla Bank	4.21	0.53	2.90	5.00

Construct	Bank	Mean	SD	Minimum	Maximum
	Prime Bank	3.97	0.59	2.60	5.00

As shown in Table 4, comparison at the bank level highlights notable differences in borrower perception of the benefits of AI in FinTech. In the light of operational efficiency, borrower repayment behaviour, credit risk management and portfolio quality, the Dutch-Bangla Bank have achieved very good performance. Trust Bank performed fairly over the last year, in comparison with Prime Bank who trailed slightly across several areas. The differing approaches suggest varying levels of maturity in credit risk management using AI technology in these three commercial banks.

Table-4: Bank-wise Mean Comparison of Study Constructs

Construct	Trust Bank (Mean ± SD)	Dutch-Bangla Bank (Mean ± SD)	Prime Bank (Mean ± SD)	Best Performing Bank
OCL	2.84 ± 0.67	2.71 ± 0.62	2.93 ± 0.69	Dutch-Bangla Bank
RT	3.96 ± 0.58	4.12 ± 0.55	3.88 ± 0.61	Dutch-Bangla Bank
LDR	2.41 ± 0.64	2.28 ± 0.59	2.53 ± 0.66	Dutch-Bangla Bank
ALPT	2.67 ± 0.63	2.49 ± 0.58	2.76 ± 0.65	Dutch-Bangla Bank
PQ	4.02 ± 0.57	4.18 ± 0.54	3.91 ± 0.60	Dutch-Bangla Bank

Construct	Trust Bank (Mean ± SD)	Dutch-Bangla Bank (Mean ± SD)	Prime Bank (Mean ± SD)	Best Performing Bank
CRME	4.08 ± 0.56	4.21 ± 0.53	3.97 ± 0.59	Dutch-Bangla Bank

4.2 Model assessment

The evaluation of the scale's measurement model places importance on internal consistency and the discriminant and convergent validity. **Hair *et al.* (2011)** provide the framework for this process. 2011, 2016) and **Henseler *et al.* (2015)** (In Table 5, internal consistency reliability and convergent validity are used to assess the reliability and validity of the proposed measurement model (Cronbach's alpha = 0.897, composite reliability = 0.900 and average variance extracted = 0.533). The results showed that all the scales had high levels of internal consistency as evidenced by the Cronbach alpha coefficients which were 0.70 or greater for every scale. Similarly, the composite reliability values were greater than 0.70 for all the measures. The convergent validity is demonstrated with all AVES being above 0.50. This study demonstrates that the correlations between each pair of constructs are lower than the construct reliabilities, i.e. the correlations between each pair of the four constructs are lower than their respective square roots of AVE. The subsequent analysis of the structural model is supported by the reliability and validity of the measurement model.

Table-5: Construct Reliability and Convergent Validity

Construct	Cronbach's Alpha (α)	Composite Reliability (CR)	AVE
OCL	0.823	0.884	0.659

Construct	Cronbach's Alpha (α)	Composite Reliability (CR)	AVE
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

To check for discriminant validity the research employed a dual-method approach. The initial procedure entailed a comparison of the square root of the average variance extracted with correlations between variables. Discriminant validity should be at a satisfactory level if the square root of the AVE for each variable is greater than the correlation between the variable and any other variable. As shown in table 6, the square root of the AVE for each factor was greater than the correlation between the factor and all other factors.

Table-6: Discriminant Validity Using Fornell and Larcker (1981) 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

The second of these tests used was the heterotrait-monotrait ratio of correlations (HTMT) method. Following the guidelines proposed by **Henseler *et al.* (2015).** a correlation of 0.90 or higher suggests that a HTMT value of 0.90 would be a reasonable threshold for acceptable discriminant validity. The discriminant validity was confirmed by HTMT, where all the HTMT values were below 0.85 as shown in table 7. Our results show that the measurement model has sufficient construct distinctiveness to allow structural model analysis.

Table-7: HTMT Ratio of Correlations

Constructs	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 findings confirm that the proposed hypotheses are supported by the data. Three key variables which have a negative impact on a bank's loan portfolio are the cost of running the loan, the rate at which loans are defaulted upon and the length of time it takes to process a loan. Loans that are repaid on time have a positive effect. Portfolio quality also has a significant positive effect on the credit risk management effectiveness, thereby confirming its mediating role within the model proposed here.

Table-8: Structural Model Path Coefficients and Hypothesis Testing

Hypothesis	Path	β (Path Coefficient)	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

The performance of the structural model is judged by the R^2 coefficient of determination, effect size (f^2) and predictive fit (Q^2), path coefficients (beta) and the significance of the paths within it. While the R^2 values indicate that a significant proportion of the variance in portfolio quality is explained by the model, only a moderate proportion of the variance in the effectiveness of credit risk management is explained by the model's parameters. According to **Falk and Miller (1992)**, a model is satisfactory if each latent variable has an R-square of 0.1 or greater. The R2 values for PQ (0.587) and for CRME (0.476) represent the proportion of the variance in the data which is explained by the variables of the model. This study shows moderate explanatory power for the Proportional and Quadratic (PQ) and Constrained and Regulated Maximum Entropy (CRME) DCMs.

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

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

The results from the research show that timely repayments significantly enhance the quality of a loan portfolio ($f^2 = 0.167$). A moderate impact is evident from the PQ on the CRME ($f^2 = 0.212$) indicating that the state of a portfolio is indeed a crucial factor in banks for effective credit management. In addition, the Q2 values of 0.392 for the performance of the company model and 0.318 for the research and development model indicate the models are significant in forecasting future outcomes. This is due to the values being higher than 0.1.

5. DISCUSSION

In this study we looked at how new financial technology, which uses artificial intelligence, affects the way banks evaluate the risk that borrowers pose. Portfolio quality acted as a middle link in the process. This research offers new insights into the ways in which banking technology is associated with risk in retail banking in Bangladesh. While the outcomes reveal that improvements to the operational efficiency and the way that borrowers behave in repaying loans, both enabled by AI, greatly help in reducing the risk associated with bad loans, this results in a better overall credit management system.

5.1 Operational Cost per Loan and Portfolio Quality

The findings indicate that a strong negative correlation exists between operating expense per loan and the quality of the loan portfolio, which validates hypothesis 1. The research implies that higher operating costs damage the quality of a bank's assets by stopping them from efficiently assessing, monitoring and managing risks connected to retail lending. Where automation technologies that are AI powered are used in credit, this results in less human intervention and consequently reduced paperwork and a decrease in potential errors. As operational costs fall banks can devote more of their budget to proactive risk management, which in turn has a positive effect on overall loan portfolio health. The findings of this research are in line with studies which have demonstrated the part digital and AI-based technologies have to play in banking operations improving cost efficiency and asset quality (**Gomber *et al.* 2015**). The context in Bangladesh indicates that with retail banking operations often being plagued by process inefficiencies and high servicing costs, AI-driven fintech may contribute to reducing costs and therefore to a higher quality portfolio.

5.2 Repayment Timeliness and Portfolio Quality

Our findings demonstrate that a loan's repayment history has a notably positive impact on its overall quality. This finding supports hypothesis two. Key findings include the crucial influence of borrower repayments on the performance of loan products. With the help of predictive analytics, digital repayment platforms and AI-driven monitoring tools loan providers can quickly detect any repayment issues that may arise and respond accordingly. Their inclusion also helps to enhance payment habits, lower the rate of customers failing to meet payments and reduce the total value of loans which are not being repaid as agreed. The use of technology for monitoring credit behaviour and the analysis of consumer behaviour both have been proven to assist in lowering default rates according to studies done previously (**Frost *et al.* 2019**; **Bazarbash, 2019**). In Bangladesh, it was noted in 2019 that repayment timeliness had a stronger effect. It appears that in retail banking AI-driven borrower centred outcomes may have a greater impact on the quality of a bank's portfolio than measures aimed at improving operational efficiency.

5.3 Loan Default Rate and Portfolio Quality

This study found a negative correlation between the rates of loan defaults and the quality of a loan portfolio, which confirms hypothesis three. In the first instance this is obvious because the higher the defaults in a loan portfolio will be the worse the returns on the investment will be. Banks are able to assess the risk associated with borrowers more effectively with the aid of credit scoring systems that are enabled by AI. Furthermore, banks can now anticipate loan defaults occurring through the use of warning systems. These systems make use of predictive techniques and diverse data sources to improve the accuracy of default assessments when compared with traditional methods of assessment. The performance of the AI and machine learning models was consistent with findings from previous studies indicating that these types of models generally perform better than traditional models in predicting corporate credit defaults (**Bello, 2023**). The research in 2020 points out that the ongoing problem of defaults in Bangladesh's banking industry highlights the benefits of employing advanced statistical methods in assessing and improving the quality of loans and in reducing the risk of default.

5.4 Average Loan Processing Time and Portfolio Quality

This outcome strongly suggests that the longer it takes to originate a loan, the lower the credit score of the loans being made, thus supporting hypothesis H4. As processing times lengthen, it is likely that the disparity in information between lenders and borrowers increases, dissatisfaction amongst borrowers grows and the possibilities of adverse selection enhance. Automation of loan assessments with the use of AI speeds up loan assessment and disbursement procedures. This consequently cuts down delays in lending decisions and increases the precision of such decisions. A more rapid processing of loan applications will have the added advantage of giving customers a better deal but also lowers the risk of making decisions based on old or incomplete details of the borrower. Past research has suggested digitalisation and automation bring about efficiency and transparency improvements in lending (**Philippon, 2016**). In Bangladesh and other growing economies, lengthy loan processing is often a problem which an AI enabled system could potentially reduce. This time saving could be important in maintaining a high-quality portfolio.

5.5 Portfolio Quality and Credit Risk Management Effectiveness

The findings support the conclusion that the quality of the loan portfolio is significantly associated with the credit risk management process, thereby supporting hypothesis five. The quality of assets held within a bank's portfolio is crucial in the translation of operational efficiency and borrower actions into effective management of risk to the bank's loans. Good portfolio quality enables a bank to assess and keep track of its risks more effectively which in turn improves its overall risk management. In accordance with established risk management practices, asset quality is a fundamental factor in the effective management of credit risk. This is in line with the views of the **Basel Committee on Banking Supervision (2019)**. Research carried out previously has provided further evidence in support of the argument that portfolio performance is closely tied to the implementation of better risk management methods (**Vučinić, 2020**).

5.6 Integrated Discussion

It appears that FinTech products and services powered by AI enhance the way in which credit risk is managed, mainly through an improvement in the overall quality of a loan portfolio. In fact, the most significant factors in determining the performance of a portfolio are not necessarily the cost reductions and faster processing that can be achieved through operational efficiency. Instead, these tend to be borrower-related performance indicators. These include how promptly borrowers repay their loans. Banks which have employed AI-based credit processes to a greater extent are found to have stronger loan portfolios and to better manage risks in the process. Research carried out here shows the benefits of a holistic approach that incorporates AI technology with FinTech in Bangladeshi retail banking especially when tackling loan repayments which have not been honoured and operational inefficiencies.

6. CONCLUSION AND POLICY RECOMMENDATIONS

Research has been conducted into the ways in which retail banking in Bangladesh can utilize AI technology to better manage credit risk. The study made use of data from three major commercial banks of Bangladesh. The effects of banking systems which are driven by modern technology on the risk that the borrowers will not repay their loans is examined in this study. The variables of the quality of the lending portfolio and the behaviour of the borrowers and the efficiency of banking operations were used as middle variables.

This study examined operational efficiency indicators such as operational cost per loan and the time taken to process loans. Such models also considered borrower behaviour factors like how promptly borrowers repay loans and the rate at which they default on those loans. A relationship existed between a company's portfolio quality and the risk that the company's credit posed.

The study shows that a high quality of the portfolio has a beneficial effect on the repayment rates of the borrowers. Conversely, operational costs per loan are negatively influenced by the loan portfolio quality, as are the default rates of loans and the time it takes to process a loan. Portfolio quality significantly affects credit risk management as the latter appears to be significantly enhanced when portfolio quality is high. The key findings suggest that stronger bank balance sheets are mainly a result of successful management of credit risk. This is largely due to a combination of better operational efficiency and improved lending standards.

In reality technology based financial products contribute significantly to credit risk management by having a positive impact on borrowers' repayment habits as well as healthier loan books. This research contributes to the literature on the issues of credit risk in retail banking in an emerging economy, Bangladesh. It draws on data about borrowers, to offer insights into the operation of banks in this country.

6.1 Policy and Managerial Implications

This study has a number of significant implications for bank management, for bank regulators and also for those concerned with financial policy.

These lenders should reinforce their systems for checking on borrowers and loan recovery. Due to the considerable influence that timely repayments have on the quality of a portfolio, the use of advanced credit monitoring tools, early warning signs, and credit scoring systems will result in better credit risk management.

Bank management should focus on eliminating operational inefficiencies by streamlining the appraisal, loan documentation and approval process. By streamlining operations, institutions can reduce operational costs and decrease loan processing times. This should help improve loan portfolios and the management of risk.

Financial institutions in Bangladesh need to have regulatory systems in place which encourage the responsible use of new technology for risk management in credit. Technologies such as cloud computing, distributed ledger technology and machine learning are nurtured by consumer protection, transparency, data governance and the provision of clear explanations.

The government should also implement policies that improve the banking system's operational capability. Lenders themselves will benefit from training in the operation and capabilities of the automated appraisal systems. Such training programs could help to ensure that the tools are used properly and to their full effect. This in turn may lead to the successful implementation of these new technologies and reduce resistance to change within institutions.

For the future, a close working relationship between regulators, banks and innovative financial businesses is necessary for standardised and coherent risk management techniques to emerge. Collaboration between these two parties can facilitate the sharing of knowledge and best practices that will help ensure that the adoption of technology supports the long-term financial security of Bangladesh.

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