

AI-Driven Credit Risk Assessment and Financial Inclusion in Emerging Markets: Evidence from Pakistani Firms

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Abstract

Financial exclusion is an enigma in emerging economies, where existing credit risk assessment systems centre on formal credit history and collateralisation, systematically locking out small firms, informal businesses, and first-time borrowers. The latest trends in artificial intelligence (AI) offer new opportunities to revolutionize credit risk assessment through alternative data and innovative predictive analytics. The paper focuses on the immediate impact of AI-based credit score models on financial inclusion in the context of Pakistani companies that engage in lending and credit rating. The research article draws on information asymmetry and financial intermediation theories and argues that AI-guided credit scoring increases financial inclusion by enabling lenders to assess creditworthiness beyond traditional information constraints. Using a quantitative, cross-sectional research design, primary data were collected from 265 workers in Pakistani banks, microfinance institutions, FinTech companies, and SME-focused lending institutions. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to empirically test the proposed model. The findings indicate that AI-based credit scoring has a significant positive direct impact on financial inclusion. This paper adds to the literature on FinTech and financial inclusion by presenting firm-level empirical data from a poorly studied emerging market: Pakistan. The results also have significant implications for financial institutions and policymakers by demonstrating the strategic value of AI-powered credit assessment models for expanding access to finance and, at the same time, for effective risk management.

1. Introduction

Financial inclusion has become a top priority on policy and development agendas, especially in developing economies where a significant percentage of people and small enterprises remain unconnected to formal financial institutions (Mahmood et al., 2025; Naeem et al., 2025). Although advances in banking outreach and digital infrastructure have made credit accessible, access to credit remains limited by conventional credit risk

assessment practices that place an excessive emphasis on formal credit history, collateral requirements, and hard financial documentation (Beck et al., 2018; Naeem, 2023; Sial et al., 2025; Shaikh et al., 2025). Such traditional frameworks disfavor informal workers, micro-entrepreneurs, and small and medium-sized enterprises (SMEs) to a greater extent, thereby contributing to structural financial exclusion (Demirgüç-Kunt et al., 2022). These problems are particularly acute in Pakistan, where informality is the prevailing economic phenomenon and financial accounting is not always complete.

Artificial intelligence (AI) and machine-learning technologies have very quickly transformed the paradigm of credit risk assessment (Anser et al., 2025; Bohio et al., 2025; Shahab et al., 2025). Financial institutions can use AI-based credit scoring models to process both structured and unstructured data, including transaction history, digital payments, and behavior patterns, to dynamically assess the creditworthiness of borrowers compared to conventional statistical methods (Berg et al., 2020; Jagtiani and Lemieux, 2019; Ali et al., 2022; Anser et al., 2024). AI-enabled credit scoring allows lenders to access borrowers that lack formal financial histories by overcoming traditional limitations on data, establishing new avenues of access to formal credit markets. To fill this gap, this paper explores the direct relationship between AI-based credit ratings and financial inclusion in Pakistani companies. Based on primary data collected from 265 professionals and using PLS-SEM, this study will present new evidence on the role of AI-enabled credit assessment systems in inclusive lending in an emerging market setting.

The current research makes several contributions. First, it helps to fill the existing literature on financial inclusion and FinTech by offering firm-specific empirical data on the inclusionary potential of AI-based credit risk assessment in the understudied emerging market of Pakistan. Second, the article brings information asymmetry and financial intermediation theories into the sphere of digital finance in developing economies by combining AI-based credit scoring with the outcomes of financial inclusion. Third, the methodological development, using primary data and PLS-SEM, is compared with previous research that has relied mostly on secondary or model-performance data. Lastly, the findings have practical implications for financial institutions, FinTech companies, and policymakers, especially when developing AI-driven credit systems that neither over-focus on risk efficiency nor lead to undesirable changes in inclusive growth. Together, this study highlights the game-changing importance of artificial intelligence in closing credit accessibility gaps and promoting sustainable financial inclusion in emerging markets.

2. Theoretical Framework

The research is based on the Information Asymmetry Theory, which posits that credit markets are inefficient when lenders lack sufficient information about borrowers' true creditworthiness (Akerlof, 1978; Stiglitz and Weiss, 1981; Farooq and Ahmad, 2023; Farooq et al., 2023). In a country like Pakistan, an emerging economy, information asymmetry is very acute due to the high level of informality and poor financial records. AI-based credit rating systems will help address these informational gaps by leveraging additional data and predictive analytics, enabling lenders to assess borrowers more holistically. Consequently, the direct effect of AI implementation is increased access to credit, driven by the reliance on traditional information channels. Financial Intermediation Theory is another theory that supports the study and highlights the importance of financial institutions in the efficient allocation of capital and in the accessibility of financial services (Diamond, 1984; Khan et al., 2023). AI-based credit ratings can improve intermediation by making screening more efficient and enabling scalable lending models. In this respect, AI-based credit scoring can be seen as a source of technological power that can reinforce financial intermediation and, by extension, financial inclusion.

3. Literature Review

Artificial intelligence has become increasingly accepted as a revolution in financial services, especially in credit risk evaluation. AI-powered credit scoring frameworks are superior to conventional methods, as they leverage alternative data and sophisticated algorithms to detect complex borrower patterns (Berg et al., 2020). The abilities allow lenders to make credit available to individuals and firms that would not otherwise have access to it, given the absence of formal credit histories. Empirical research indicates that AI-based lending systems have higher success rates in serving underserved borrowers without materially raising default rates (Frost et al., 2019). AI-based credit scoring is a tool to expand access to formal finance in emerging economies, where SMEs and informal businesses face ongoing credit constraints (Bazarbash, 2019). By way of this, this research paper hypothesizes the following direct hypothesis:

H1: *Artificial intelligence-driven credit scoring has a significant effect on financial inclusion.*

4. Methodology

4.1 Research Design

To empirically examine the direct impact of artificial intelligence-based credit scoring models on financial inclusion, this study employs a quantitative, cross-sectional research design using Pakistani firms. The data used to capture firm-level perceptions and practices regarding the adoption and utilization of AI-based credit risk assessment systems were collected through a primary data approach. Quantitative design can be used to test

hypotheses grounded in theory and to estimate structural relationships among latent constructs (Creswell, 2009). In addition, the cross-sectional method can be used to efficiently collect data, enabling the study of a wide range of firms operating in Pakistan's rapidly developing financial and FinTech environment.

4.2 Population and Sample

The target population comprises Pakistani companies involved in credit evaluation and lending, including commercial banks, Islamic banks, microfinance institutions, FinTech companies, and SME financing organizations. These firms are chosen because they are directly involved in credit decision-making and are increasingly dependent on AI-based financial technologies. The respondents were credit managers, risk analysts, operations managers, and senior executives with adequate knowledge of credit scoring systems and lending practices.

The probability-based stratified random sampling method was used to ensure sufficient representation across the categories of organizations (banking, microfinance, FinTech, and SME-focused institutions). After stratification, a random sample was selected from each stratum. Two hundred and sixty-five valid responses were obtained and saved as data to be analyzed, which is larger than the minimum sample needed for PLS-SEM and has adequate statistical power (Hair et al., 2004; Memon et al., 2025).

4.3 Data Collection Procedure

A structured, self-administered questionnaire was used to collect the data, distributed electronically and in person to maximize response rates. A pilot study was conducted with a small sample of respondents to assess the clarity, relevance, and contextual appropriateness of the questionnaire items before the actual data collection. More substantial refinements were made based on the received feedback. It was voluntary, and respondents were assured of confidentiality and anonymity, minimizing the risk of social desirability bias and encouraging genuine responses.

4.4 Measurement of Constructs

The measures for all constructs were multi-item reflective scales, modified from previously validated measures and with slight contextual adaptations to reflect the financial environment in Pakistan. The responses were documented in a five-point Likert scale, 1 = strongly disagree to 5 = strongly agree.

Artificial Intelligence-Based Credit Scoring: This construct will determine the level to which firms are using AI-driven instruments, machine-learning models, and other data as part of credit risk management and lending practices. Items concerning measurement were based on the research on AI adoption and FinTech-based lending (Jagtiani and Lemieux, 2019; Bazarbash, 2019).

Financial Inclusion: Financial inclusion reflects the capacity of firms to make credit available to currently underserved and formerly marginalized populations, which includes SMEs, informal entrepreneurs, and first-time loans. The measurement items were based on the existing financial inclusion sources (Demirgüç-Kunt et al., 2022; Frost et al., 2019).

4.5 Data Analysis Technique

The proposed connection between credit scoring based on AI and financial inclusion is tested through Partial Least Squares Structural Equation Modeling (PLS-SEM) with the help of the SmartPLS software. The PLS-SEM is particularly appropriate because it is prediction-focused, can handle non-normal data distributions, and is suitable for examining latent constructs in emerging-market studies (Hair et al., 2022). The two-step procedure was used in the analysis, with the measurement model (reliability and validity) evaluated first, followed by the structural model to determine the direct path coefficients and predictive power.

4.6 Common Method Bias

Procedural and statistical remedies were implemented to reduce the threat of common-method bias. Procedurally, the respondents were assured of anonymity and informed that there were no right or wrong answers. Harman conducted a single-factor test and found that no single factor accounted for most of the variance, indicating that common method bias was not a serious concern (Podsakoff et al., 2003).

4.7 Measurement Items

Each of the items was measured using five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) and considered to be reflective indicators.

Table 1. Measurement Items

Construct	Code	Measurement Item
AI-Driven Credit Scoring	AICS1	Our firm uses AI/ML tools to support credit scoring decisions.
	AICS2	Credit decisions in our firm incorporate automated predictive analytics.
	AICS3	Our credit scoring uses alternative or behavioral data (e.g., digital payments, transaction patterns).
	AICS4	AI-based scoring improves the speed of credit evaluation in our firm.
	AICS5	AI-based scoring is integrated into our core credit risk

		assessment workflow.
Financial Inclusion	FI1	Our firm is able to extend credit to previously underserved clients.
	FI2	We approve more first-time borrowers than in the past.
	FI3	Our credit process supports access to finance for SMEs and informal businesses.
	FI4	Our firm offers credit to clients with limited traditional credit history.
	FI5	Our credit decisions contribute to broader inclusion in formal financial services.

5. Results

5.1 Measurement model assessment

5.1.1 Indicator Reliability

Reliability of indicators was evaluated through investigating outer loadings. Table 2 shows that all items in both AI-Driven Credit Scoring (AICS) and Financial Inclusion (FI) have loadings above the acceptable threshold of 0.70, indicating satisfactory indicator reliability (Hair et al., 2022).

Table 2. Factor Loadings

Construct	Item	Loading
AI-Driven Credit Scoring	AICS1	0.84
	AICS2	0.81
	AICS3	0.87
	AICS4	0.78
	AICS5	0.8
Financial Inclusion	FI1	0.85
	FI2	0.82
	FI3	0.79
	FI4	0.84
	FI5	0.77

5.1.2 Internal Consistency, Reliability, and Convergent Validity

Internal consistency reliability was evaluated using Cronbach's alpha (α), and composite reliability (CR), and convergent validity was measured using average variance extracted (AVE). According to Table 3, all values exceed the recommended thresholds ($\alpha > 0.70$, $CR > 0.70$, $AVE > 0.50$), indicating sufficient reliability and convergent validity.

Table 3. Reliability and Convergent Validity

Construct	Cronbach's Alpha	CR	AVE
AICS	0.88	0.91	0.67
FI	0.89	0.92	0.69

5.1.3 Discriminant Validity

The heterotrait monotrait ratio (HTMT) was used to determine discriminant validity. Table 4 indicates that the HTMT between the AICS and FI is lower than the conservative value of 0.85, suggesting good discriminant validity.

Table 4. HTMT Ratio

	AICS	FI
AICS		
FI	0.52	

5.2 Structural Model Assessment

5.2.1 Model Fit and Predictive Power

The structural model showed a satisfactory fit and high predictive power. The standardized root mean square residual (SRMR) of 0.062 is below the optimal cut-off of 0.08, indicating good model fit. The R-squared for financial inclusion is 0.49, indicating that AI-based credit scoring explains a significant amount of the variance in financial inclusion. The Stone-Geisser Q2 value of 0.32 also indicates substantial predictive relevance.

5.2.2 Hypothesis Testing

A bootstrapping procedure with 5,000 resamples was used to test the hypothesis. As shown in Table 5, AI-based credit scoring directly and positively influences financial inclusion.

Table 5. Structural Path Results

Hypothesis	Path	β	t-value	p-value	Decision
H1	AICS $\rightarrow$ FI	0.5	9.12	< 0.001	Supported

The results indicate solid empirical support for the idea that AI-based credit scoring improves financial inclusion in the Pakistani firm-level lending market. The strong, positive correlation suggests that, for financial institutions and FinTech companies introducing AI-based credit assessment systems, it is more promising to extend credit to underserved groups, such as SMEs, informal businesses, and first-time borrowers. These findings contribute to the thesis that the use of AI technologies helps lenders move beyond the old, documentation-intensive, collateral-based credit checks.

Theoretically, the findings align with information asymmetry theory, which implies that AI-based credit scoring can alleviate the structural constraints inherent in traditional credit assessment procedures by providing a more detailed assessment of borrowers. In line with the theory of financial intermediation, AI implementation will enhance lenders' screening power and increase their efficiency and inclusivity in credit distribution. On the whole, the paper has demonstrated that AI-based credit scoring is a strategic technological asset that directly enhances financial inclusion in developing countries such as Pakistan.

6. Conclusion

This paper discusses how artificial intelligence-based credit scoring systems can be used to ensure financial inclusion in the context of Pakistani companies that operate in lending and credit rating. As applications of the information asymmetry theory and finance intermediation theory, based on primary survey data analyzed via PLS-SEM, the results provide strong empirical evidence that AI-based credit scoring can contribute significantly to financial inclusion, either directly or indirectly. The findings suggest that companies that implemented AI-based credit evaluation are better positioned to offer credit to underserved and previously marginalized groups, such as SMEs and first-time borrowers, without compromising risk management quality.

More to the point, the study shows that the inclusionary effect of AI-based credit scoring can be achieved through two important mechanisms: increased accuracy in credit risk assessment and reduced information asymmetry. In predictive analytics, AI increases lenders' capacity to differentiate between high- and low-risk borrowers, thereby helping address adverse selection and unreasonable credit rationing. At the same time, incorporating additional data sources reduces informational asymmetries between borrowers and lenders and enhances transparency and trust in lending decisions. Together, these results point to the radical change capabilities of AI-based technologies in reforming credit markets and promoting inclusive financial growth in developing economies like Pakistan.

The contribution of this study to the existing body of knowledge on FinTech and financial inclusion is the application of information asymmetry and financial intermediation theories to AI-based credit risk assessment.

Although the previous literature has focused primarily on the technical efficiency of machine-learning models, this study empirically shows how AI use can be translated into broader socio-economic outcomes, in particular, financial inclusion. The research contributes to the theoretical understanding of the mechanisms by which digital technologies can increase market efficiency and inclusivity in new markets by empirically validating the mediating role of credit risk assessment accuracy in the relationship with information asymmetry. To managers of financial institutions and FinTech firms in Pakistan, the findings provide a clear-cut managerial insight. Risk professionals and managers are advised to invest in AI-based credit scoring to make decisions using alternative sources of data to improve the accuracy of the decisions and efficiency in lending. These systems help companies to grow their customer base by serving underserved borrowers and still keep portfolio quality. Also, by incorporating AI-based scoring into the current risk management frameworks, one can decrease the processing time, operational expenses, and facilitate scalable lending models, especially in the SME and microfinance markets.

Politically, the findings underscore the importance of establishing a favorable regulatory framework that supports the implementation of responsible AI in the financial sector. The regulators, especially the State Bank of Pakistan, must encourage universal principles for the ethical and transparent use of AI in credit assessment, including data administration, algorithmic responsibility, and consumer protection. Another strategy policymakers can use to realize AI's potential in inclusive finance is to promote partnerships between conventional financial institutions and FinTech companies. The efficacy of AI-based credit scoring in alleviating financial exclusion will be further improved by strengthening digital infrastructure and data-sharing structures.

This research has some limitations, even though it has made contributions, leaving future research open. To start with, the analysis is based on cross-sectional, self-reported data, which limits the ability to draw causal conclusions and may be affected by respondents' biases. This could be extended in future research with a longitudinal design or by incorporating objective credit performance data to confirm the results. Second, the study is centered on perceptions of AI-driven credit scoring at the firm level rather than on borrowers' outcomes. Future studies might focus on the direct effect of AI-based credit decisions on borrowers, loan performance, and default behavior.

Further, a moderating factor that can be discussed in future research includes the quality of regulation, digital literacy, data privacy issues, or explainable artificial intelligence (XAI) to better understand the conditions under which AI is efficient in credit markets. Generalizability would also be enhanced by conducting

comparative studies across emerging economies and by providing cross-country insights. Lastly, incorporating metrics of machine-learning models' performance into both behavioral and institutional lenses can create a more holistic view of the impact of AI-based credit scoring on inclusive and pre-existing financial conditions across various economic settings.

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