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(Research Article)

Artificial intelligence and credit access among microfinance institutions in developing economies

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Abstract

This paper develops a conceptual framework to examine the effect of artificial intelligence (AI)–enabled credit scoring on credit access in microfinance institutions within emerging economies. Traditional credit assessment methods often exclude low-income individuals due to limited financial histories, thereby constraining financial inclusion. AI-enabled credit scoring leverages alternative data and machine learning techniques to evaluate creditworthiness more inclusively and efficiently. This paper argues that AI-driven credit scoring enhances credit access by reducing information asymmetry and improving risk assessment accuracy. It further identifies key mediating mechanisms and moderating conditions influencing this relationship. The study contributes to the literature by proposing a theoretically grounded model that links AI adoption in microfinance to financial inclusion outcomes and highlights critical policy considerations.

Keywords: Artificial Intelligence; Credit Access; Microfinance Institutions

1. Introduction

Access to credit is a fundamental driver of economic development, yet remains limited in many emerging economies. A significant proportion of low-income individuals and small-scale entrepreneurs remain excluded from formal financial systems due to the absence of reliable credit histories, collateral requirements, and high transaction costs. Microfinance institutions (MFIs) were established to address this gap; however, their continued reliance on traditional credit assessment methods limits their ability to effectively reach financially excluded populations.

The emergence of artificial intelligence (AI) in financial services presents a transformative opportunity. AI-enabled credit scoring systems utilize alternative data—such as mobile phone usage, transaction patterns, and behavioral indicators—to assess creditworthiness. This innovation has the potential to redefine lending practices in microfinance institutions by expanding access to credit.

Despite the growing adoption of AI in financial services, the existing literature remains fragmented, with limited conceptual integration of how AI influences credit access within the microfinance context. Most studies focus either on technological efficiency or financial inclusion outcomes, with insufficient attention to the underlying mechanisms linking AI adoption to credit accessibility, particularly in developing economies. This lack of a coherent theoretical and conceptual framework represents a significant gap in the literature.

Against this background, the objective of this paper is to systematically review and synthesize existing literature to examine the relationship between Artificial Intelligence and credit access among MFIs in developing economies.

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Specifically, the paper aims to develop a conceptual framework that explains how AI-enabled credit scoring influences credit access, while identifying key mediating and moderating factors shaping this relationship.

2. Literature review

2.1. Credit Access in Microfinance

Credit access refers to the ability of individuals, households, or enterprises to obtain financial resources from formal or semi-formal financial institutions for productive or consumption purposes. In development finance literature, it is widely recognized as a critical enabler of entrepreneurship, poverty reduction, and inclusive economic growth, particularly in developing economies where large segments of the population remain financially excluded.

Microfinance institutions (MFIs) were established to address this exclusion by providing small-scale financial services to low-income populations who are typically underserved by conventional banking systems. These institutions emerged as an innovative response to structural credit market failures, particularly the inability of traditional banks to serve clients lacking collateral, formal income records, or established credit histories. However, despite their expansion, MFIs continue to face persistent constraints in expanding effective credit access.

A central limitation identified in the literature is information asymmetry between borrowers and lenders. Because MFIs often operate in environments with weak credit bureaus and limited financial data infrastructure, they rely on imperfect proxies such as group lending mechanisms, social collateral, or simplified screening tools. While these mechanisms partially mitigate risk, they do not fully eliminate uncertainty in borrower evaluation, often resulting in conservative lending behavior and credit rationing. Classical theoretical foundations by Stiglitz and Weiss (1981) remain highly relevant in explaining these persistent market inefficiencies in microfinance contexts.

Recent empirical literature further demonstrates that credit access in microfinance is shaped by a combination of borrower-specific and institutional factors. On the demand side, variables such as income stability, education level, financial literacy, gender, and entrepreneurial experience significantly influence the likelihood of loan approval. On the supply side, institutional lending policies, interest rate structures, risk appetite, and regulatory environments determine the extent to which MFIs can extend credit to underserved populations. Recent studies in development finance confirm that these factors jointly shape access disparities across regions and demographic groups in developing economies.

More recent research highlights an emerging and increasingly important constraint: the exclusion of “credit-invisible” populations. A significant proportion of individuals in developing economies operate within informal sectors and therefore lack formal financial records necessary for traditional credit scoring systems. This structural gap reinforces financial exclusion even among economically active individuals with viable repayment capacity. Consequently, traditional credit scoring approaches used by MFIs are increasingly viewed as inadequate for capturing the full spectrum of borrower risk profiles.

In response to these limitations, recent literature has begun to emphasize the role of financial technology innovations in reshaping credit access mechanisms. Digital lending platforms and alternative data-driven credit assessment approaches are increasingly being adopted to supplement or replace traditional evaluation methods. These approaches incorporate non-traditional data sources such as mobile phone usage patterns, digital transaction histories, and behavioral data to improve borrower assessment and reduce reliance on formal financial records.

Recent conceptual and empirical studies further suggest that these innovations significantly improve credit inclusion by expanding the pool of assessable borrowers and reducing screening costs for lenders. By enabling more accurate and data-rich assessments of borrower behavior, these systems reduce uncertainty in lending decisions and increase the likelihood of credit approval for previously excluded individuals. However, the literature also acknowledges that these gains are uneven and context-dependent, particularly in environments with weak digital infrastructure.

Despite these advances, significant concerns remain regarding fairness, transparency, and systemic bias in modern credit assessment systems. Recent studies highlight that algorithmic decision-making, if not properly designed and regulated, may reinforce existing inequalities through biased training data or uneven digital representation. Additionally, issues related to data privacy, regulatory oversight, and explainability of automated credit decisions continue to pose important challenges for financial institutions and policymakers.

Overall, the literature indicates that while microfinance has significantly improved access to financial services in developing economies, structural constraints—particularly information asymmetry and exclusion of informal borrowers—continue to limit its effectiveness. These persistent challenges provide the foundation for exploring emerging technological solutions, particularly artificial intelligence, as a potential mechanism for enhancing credit access and improving financial inclusion outcomes

2.2. Artificial Intelligence–Enabled Credit Scoring

Artificial Intelligence (AI)–enabled credit scoring refers to the application of machine learning algorithms and advanced analytics to assess borrower creditworthiness using both traditional financial data and alternative data sources. Unlike conventional credit scoring models that rely primarily on historical financial records, income statements, and collateral-based indicators, AI-driven systems integrate large and diverse datasets to generate more dynamic and predictive assessments of credit risk.

Recent literature highlights that AI-based credit scoring systems utilize supervised and unsupervised learning techniques to identify patterns in borrower behavior that are often invisible to traditional statistical models. These systems process structured and unstructured data, including mobile phone usage patterns, digital transaction histories, social and behavioral indicators, and real-time financial activity, to construct more comprehensive credit profiles. By leveraging these heterogeneous data sources, AI models improve predictive accuracy in assessing default risk and repayment capacity.

A key advantage of AI-enabled credit scoring lies in its adaptive learning capability. Unlike traditional econometric models, which are typically static and based on predefined assumptions, machine learning algorithms continuously improve as new data becomes available. This dynamic learning process enables financial institutions to refine credit decisions over time, thereby enhancing the precision of risk classification and reducing uncertainty in lending decisions.

Furthermore, recent studies emphasize that AI systems significantly reduce information asymmetry in credit markets. By incorporating alternative data, AI expands the informational base available to lenders, particularly in environments where formal credit histories are weak or non-existent. This is especially relevant in microfinance contexts, where a large proportion of borrowers are "credit invisible" due to informal economic activity. As a result, AI-enabled systems have been increasingly recognized as a transformative tool for improving financial inclusion and expanding credit access.

Empirical and conceptual research in fintech also suggests that AI-based credit scoring enhances operational efficiency in lending processes. Automated decision-making reduces the time and cost associated with manual credit evaluation, allowing microfinance institutions to scale lending operations more efficiently. This efficiency gain is particularly important in developing economies, where financial institutions often operate under resource constraints and high transaction costs.

However, the literature also identifies important limitations and risks associated with AI-enabled credit scoring. Concerns have been raised regarding algorithmic bias, lack of transparency, and explainability of machine learning models. If training data reflects historical inequalities, AI systems may inadvertently reproduce or even amplify existing disparities in credit allocation. Additionally, the use of sensitive alternative data raises ethical and regulatory concerns related to privacy and data protection.

Overall, the literature positions AI-enabled credit scoring as a significant innovation in credit risk assessment, with the potential to transform lending practices in microfinance institutions. By combining enhanced predictive capabilities with alternative data integration, AI systems offer a more inclusive and efficient approach to credit evaluation, while also introducing new governance and ethical challenges that require careful consideration.

2.3. Linking Artificial Intelligence to Credit Access

Artificial Intelligence (AI)–enabled credit scoring systems are increasingly recognized as a transformative mechanism influencing credit access in microfinance institutions. The relationship between AI adoption and credit access can be understood through several interconnected mechanisms that collectively reshape lending decisions and financial inclusion outcomes.

First, AI systems expand the pool of assessable borrowers by incorporating alternative data sources beyond traditional credit histories. In many developing economies, a significant proportion of individuals lack formal financial records, rendering them "credit invisible" under conventional scoring systems. By leveraging digital footprints such as mobile usage patterns, transaction histories, and behavioral data, AI enables financial institutions to evaluate previously excluded individuals. This broadens the borrower base and directly enhances credit access.

Second, AI adoption contributes to a reduction in screening and transaction costs associated with credit evaluation. Traditional credit assessment processes are often manual, time-consuming, and resource-intensive, particularly in microfinance settings where client volumes are high and financial infrastructure is limited. Machine learning algorithms automate data processing and credit decisioning, thereby increasing operational efficiency. This cost reduction enables microfinance institutions to process more loan applications and extend credit to a wider segment of the population.

Third, AI systems improve the accuracy of repayment prediction and risk classification. By analyzing large and complex datasets, machine learning models identify patterns of borrower behavior that are not captured by conventional statistical methods. This improved predictive capability reduces uncertainty in lending decisions, lowers default risk, and enhances lenders' confidence in extending credit to previously underserved clients. As a result, institutions are more willing to approve loans for borrowers who would otherwise be considered high-risk under traditional models.

Collectively, these mechanisms suggest that AI-enabled credit scoring has a positive and reinforcing effect on credit access in microfinance institutions. By reducing information asymmetry, improving risk assessment accuracy, and lowering operational costs, AI systems enhance both the supply and efficiency of credit delivery. Consequently, the adoption of AI in credit scoring is theoretically expected to expand financial inclusion and improve access to credit among underserved populations in developing economies.

3. Theoretical framework

This study is anchored on three complementary theoretical perspectives—Information Asymmetry Theory, Financial Inclusion Theory, and the Technology Acceptance Model (TAM)—which collectively explain how Artificial Intelligence (AI)–enabled credit scoring influences credit access in microfinance institutions.

Information Asymmetry Theory, originally advanced by Akerlof (1970) and further developed in credit market analysis by Stiglitz and Weiss (1981), posits that lending markets are characterized by unequal distribution of information between borrowers and lenders. This imbalance creates adverse selection and moral hazard problems, leading financial institutions to ration credit or impose strict lending conditions.

In microfinance contexts, information asymmetry is particularly pronounced due to the absence of formal credit histories and reliable financial documentation for a large proportion of borrowers. AI-enabled credit scoring systems address this limitation by integrating diverse alternative data sources such as digital transactions, mobile usage patterns, and behavioral indicators. By expanding the informational base available to lenders, AI reduces uncertainty in credit assessment, thereby improving lending efficiency and expanding credit access.

3.1. Financial Inclusion Theory

Financial Inclusion Theory emphasizes the importance of ensuring that individuals and enterprises have access to affordable, timely, and appropriate financial services. It views access to credit as a key driver of inclusive economic growth, poverty reduction, and entrepreneurial development, particularly in developing economies.

Within this framework, AI-enabled credit scoring serves as an enabling innovation that enhances financial inclusion by lowering barriers to credit access. By allowing previously excluded or "credit-invisible" individuals to be assessed using alternative data, AI systems extend financial services to underserved populations. This aligns with the broader objective of inclusive finance, which seeks to integrate marginalized groups into formal financial systems and improve their economic participation.

3.2. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis (1989), explains users' acceptance and adoption of new technologies based primarily on perceived usefulness and perceived ease of use. In the context of microfinance institutions, the adoption of AI-enabled credit scoring systems depends on whether decision-makers perceive the technology as improving lending efficiency and simplifying credit assessment processes.

Perceived usefulness is reflected in the ability of AI systems to enhance risk prediction accuracy, reduce default rates, and expand credit portfolios. Perceived ease of use relates to the integration of AI tools into existing lending systems without excessive complexity or operational burden. Accordingly, TAM provides a behavioral explanation for why microfinance institutions adopt or resist AI-based credit scoring technologies.

Collectively, these three theories provide a comprehensive explanation of the relationship between AI-enabled credit scoring and credit access. Information Asymmetry Theory explains the problem AI addresses, Financial Inclusion Theory explains the developmental objective it supports, and TAM explains the institutional adoption process. Together, they establish a strong conceptual foundation for understanding how AI influences credit access in microfinance institutions.

3.3. Conceptual Framework and Propositions

This study is anchored on a conceptual framework that examines the relationship between AI-Enabled Credit Scoring and Credit Access in the microfinance sector. AI-Enabled Credit Scoring serves as the independent variable, while Credit Access is the dependent variable. The framework proposes that the adoption of artificial intelligence in credit scoring improves borrowers' access to credit by enabling faster, more accurate, and data-driven lending decisions. Risk Assessment Accuracy is introduced as a mediating variable because AI systems enhance the precision of evaluating borrowers' creditworthiness, thereby reducing information asymmetry and lending risks. This improved accuracy strengthens the ability of microfinance institutions to extend credit to underserved populations. In addition, Digital Infrastructure is considered as a moderating variable because the availability of reliable internet connectivity, digital payment systems, and technological readiness influences the effectiveness of AI-driven credit scoring systems. Where digital infrastructure is strong, the positive relationship between AI-Enabled Credit Scoring and Credit Access becomes more significant. Therefore, the framework suggests that AI adoption, supported by accurate risk assessment and strong digital infrastructure, can significantly improve financial inclusion through expanded credit access.

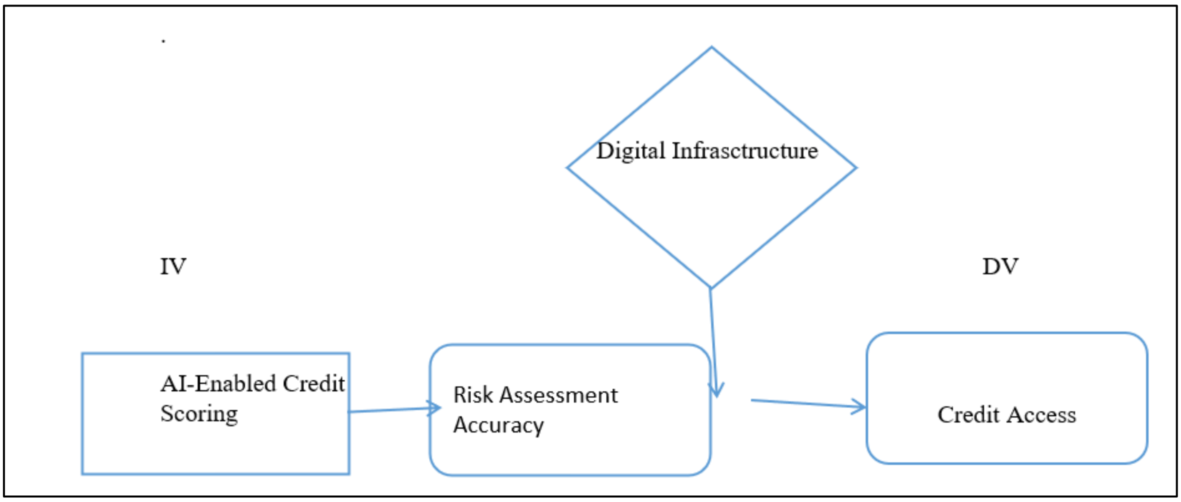

Figure 1 Research Conceptual framework

4. Discussion

The conceptual model developed in this study highlights the transformative role of Artificial Intelligence (AI)–enabled credit scoring in enhancing credit access within microfinance institutions. By reducing information asymmetry and improving data-driven decision-making, AI has the potential to significantly expand the reach and efficiency of credit delivery, particularly for underserved populations in developing economies. However, the effectiveness of this transformation is not automatic, as it depends strongly on enabling conditions such as regulatory support, institutional capacity, and the level of digital infrastructure available in the operating environment.

The framework also draws attention to important risks and limitations associated with AI adoption in credit markets. These include algorithmic bias, where historical inequalities embedded in training data may be reproduced in lending decisions, as well as the potential exclusion of individuals with limited or no digital footprints. These concerns highlight the need for careful governance, ethical safeguards, and inclusive design in the deployment of AI-based credit scoring systems.

From a theoretical perspective, this study contributes to the financial inclusion and technology adoption literature by positioning AI as a central mechanism for improving credit access in microfinance contexts. It integrates insights from information asymmetry and technology adoption theories to explain how AI reshapes lending decisions and extends credit to previously excluded populations. This enriches existing frameworks by introducing a technology-driven pathway to financial inclusion.

From a policy perspective, the study underscores the importance of developing robust AI governance frameworks to regulate the use of algorithmic credit scoring systems. It also emphasizes the need for investments in digital infrastructure to support data collection and processing, as well as the promotion of inclusive data practices that ensure marginalized groups are not excluded from digital financial systems. Strengthening financial literacy is also essential to enable borrowers to effectively engage with AI-enabled financial services.

5. Conclusion

Overall, this paper provides a conceptual foundation for understanding the relationship between AI-enabled credit scoring and credit access in microfinance institutions. It proposes a structured model that can guide both future empirical research and policy formulation. While AI presents significant opportunities for improving financial inclusion, its impact is ultimately contingent on supportive institutional, technological, and regulatory environments.

Future research should focus on empirically testing the proposed relationships using quantitative methods, as well as conducting cross-country comparative studies to assess contextual differences in AI adoption. Further studies should also examine ethical and regulatory challenges in greater depth, particularly issues related to fairness, transparency, and data privacy. In addition, future research may integrate gender, rural finance, and vulnerability perspectives to better understand how AI-enabled credit systems affect different population groups.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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