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THE ROLE OF ARTIFICIAL INTELLIGENCE IN ENHANCING FINANCIAL INCLUSION IN MICROFINANCE LENDING IN NIGERIA

Saidu Ibrahim Halidu[1], Abdullahi Ya'u Usman[1] and Amina Ahmed Umar[2]
[1]ANAN University Kwall, Nigeria
[2]Department of Accounting, Nuhu Bamalli Polytechnic, Zaria, Kaduna, Nigeria

Corresponding Email Address: saiduh.anuk@gmail.com

Abstract

This study investigates the transformative potential of artificial intelligence (AI) in enhancing financial inclusion through microfinance lending in Nigeria, where 40% of adults remain financially excluded. Employing a sequential explanatory mixed-methods design, the research analyzed responses from 720 microfinance stakeholders out of 840 reached (85.72% response rate) and conducted in-depth interviews with 15 key informants (100% response rate). Findings reveal a tiered adoption pattern, with fraud detection systems (mean=3.12) showing higher implementation than customer-facing AI applications (mean=1.57), reflecting infrastructural and cultural barriers. Structural equation modeling demonstrated AI's significant positive impact on loan approval rates ($\beta=0.38$, $p<0.001$) and default reduction ($\beta=-0.21$, $p<0.001$), though processing time improvements were moderate ($\beta=0.29$). Regional analysis uncovered stark disparities, with South West institutions (mean=3.78) outperforming North East MFBs (mean=2.15) due to uneven digital infrastructure. The study makes three key contributions: (1) extending the Technology Acceptance Model to incorporate infrastructural mediators, (2) documenting Nigeria's unique "security-first" AI adoption pathway in microfinance, and (3) providing empirical evidence of AI's inclusion benefits in an emerging market context. Practical recommendations emphasize phased implementation, hybrid human-AI decision systems, and zonal regulatory sandboxes to address implementation challenges while maximizing financial inclusion outcomes.

Keywords: *Artificial Intelligence; Microfinance; Financial Inclusion; Nigeria; Credit Scoring; Digital Lending*

INTRODUCTION

Financial inclusion remains a critical driver of economic growth, poverty reduction, and social development. Despite global advancements in banking technology, millions of people - particularly in developing economies—still lack access to formal financial services. Microfinance institutions (MFIs) have long served as a bridge for the unbanked, offering small loans, savings accounts, and insurance to low-income individuals and small businesses. However, traditional lending methods face inefficiencies, including high operational costs, subjective credit assessments, and limited scalability.

Artificial intelligence (AI) presents a transformative opportunity to address these challenges. By automating credit scoring, improving risk assessment, and enhancing customer engagement, AI can expand financial access while reducing costs for microfinance banks (MFBs). This study examines how AI-driven solutions can optimize microfinance lending in Nigeria, fostering greater financial inclusion. Financial exclusion persists as a global challenge, with approximately 1.4 billion adults remaining unbanked, according to the World Bank (Adelaja et al., 2024). Traditional banking systems often exclude low-income populations due to stringent requirements, such as collateral and formal credit history. In response, fintech innovations - particularly AI - have emerged as game-changers. AI-powered credit scoring models leverage alternative data, such as mobile transactions and utility payments, to assess borrowers without conventional banking records. Countries like India and Kenya have demonstrated success with AI-driven lending platforms, significantly increasing loan approvals for previously excluded groups.

Africa faces a unique financial inclusion paradox: while mobile money adoption is high, formal credit access remains limited. The continent accounts for nearly 45% of the world's mobile money transactions, yet only 23% of African adults have access to formal loans. Microfinance institutions play a crucial role, but manual processes hinder efficiency. AI adoption in lending is gradually gaining traction, with fintech startups in Kenya, South Africa, and Nigeria using machine learning to assess creditworthiness. However, challenges such as data privacy concerns, infrastructure gaps, and regulatory uncertainty slow widespread implementation.

Nigeria, Africa's largest economy, has over 40% of its adult population excluded from formal financial services. The Central Bank of Nigeria (CBN) has prioritized financial inclusion, targeting 95% inclusion by 2024 through initiatives like the National Financial Inclusion Strategy (NFIS) on which real data is needed to evaluate performance. Despite progress, microfinance lending remains constrained by inefficiencies. Loan officers rely on subjective judgment, leading to inconsistent approvals and high default rates. AI presents a viable solution, yet adoption among Nigerian MFBs remains low due to limited technical expertise, funding constraints, and mistrust in automated systems. Despite the potential of AI to enhance financial inclusion, Nigerian microfinance banks continue to rely on outdated lending practices. Manual credit assessments are slow, prone to bias, and inefficient in evaluating borrowers without formal credit histories. Many deserving applicants - particularly small business owners, women, and rural dwellers - are denied loans due to rigid evaluation criteria.

Existing AI solutions in Nigeria's financial sector primarily focus on fraud detection and digital banking, with limited application in microfinance lending. Where AI is used, challenges such as poor data quality, lack of regulatory clarity, and resistance from loan officers hinder effectiveness. Without optimized AI models, MFBs struggle to expand their reach, leaving millions of Nigerians financially excluded.

Most current studies focs on traditional lending models, collateral subtitudes or human based risk assessment. Conse, loan, loan monitoringand repayment prediction in the context of of quently few studies examine AI driven credit assessment, fraud detection, loan monitoring and repayment prediction in the context of micro finance institutions, especially in developing economies. Therefore, this study explores how AI can revolutionize microfinance lending in Nigeria, ensuring faster, fairer, and more scalable financial access for underserved populations.

This study investigates the gap between AI's potential and its actual deployment in Nigeria's microfinance sector. It identifies key barriers and proposes strategies to integrate AI-driven lending tools effectively. The primary objective of this study is to assess the impact of AI on financial inclusion through microfinance lending in Nigeria. The specific objectives include are to evaluate the effectiveness of AI-based credit scoring in expanding loan approvals for unbanked Nigerians, identify key obstacles - technological, regulatory, and cultural - limiting AI adoption in MFBs, analyze how AI reduces human bias in loan approval processes and recommend policy and operational strategies for scaling AI-driven lending in Nigeria's microfinance sector.

LITERATURE REVIEW

2.1 Conceptual Framework

The conceptual framework of this study examines the intersection of artificial intelligence (AI) and financial inclusion within microfinance lending. It identifies three core dimensions: AI-driven lending tools, financial inclusion outcomes, and moderating factors influencing adoption.

First, AI-driven lending tools encompass alternative credit scoring, predictive risk modeling, and automated customer engagement systems. Alternative credit scoring leverages non-traditional data - such as mobile money transactions, utility payments, and social media activity - to assess borrowers without formal credit histories (Demirgüç-Kunt et al., 2018). Predictive risk modeling employs machine learning to forecast loan defaults, enabling dynamic pricing and risk-based lending (Bazarbash, 2019). Automated systems, including chatbots and digital loan officers, streamline application processes and improve financial literacy among underserved populations (Gabor & Brooks, 2017).

Second, financial inclusion outcomes measure the effectiveness of AI in expanding access to credit. Key indicators include loan approval rates for previously excluded groups, reduction in processing time, and borrower satisfaction (Sahay et al., 2020). Studies suggest AI can lower operational costs for microfinance institutions (MFIs), allowing them to serve low-income clients profitably (Chen et al., 2021).

Third, moderating factors influence AI adoption in microfinance. These include regulatory policies, data infrastructure, and institutional readiness. For instance, countries with clear fintech regulations see faster AI integration in lending (Arner et al., 2020). Data infrastructure, particularly digital identity systems and interoperable payment platforms, determines the quality of inputs for AI models (GPFI, 2020). Institutional readiness—measured by management support, staff training, and IT capabilities - affects implementation success (Manyika et al., 2019).

This framework positions AI as an enabler of financial inclusion, contingent on supportive ecosystems. The next section reviews empirical evidence supporting these relationships.

2.2 Review of Empirical Studies

A critical examination of empirical research on AI in microfinance lending reveals both the transformative potential of these technologies and significant methodological limitations that justify the present study.

Studies from major emerging markets showcase AI's capacity to expand credit access, though methodological constraints temper their generalizability. Research on Indian platforms like KreditBee (Banerjee et al., 2021) and Kenyan lender Tala (Barboni et al., 2021) demonstrates impressive gains in loan approval rates (30% increases reported) through alternative data analysis. However, these studies predominantly rely on proprietary data from single fintech providers, raising concerns about selection bias and lack of independent verification. The focus

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on urban, digitally-active populations in these studies leaves unanswered whether similar results could be achieved among truly marginalized, offline communities - a critical gap this study addresses through its inclusion of rural Nigerian MFBs.

The bias identification research by Berg et al. (2020) presents more rigorous methodology through randomized audit studies, yet their focus on traditional banking systems limits direct applicability to microfinance contexts. While Mehrabi et al.'s (2021) proposed fairness-aware algorithms show theoretical promise, there remains a striking absence of field implementations in African microfinance - a gap this study begins to address through its examination of bias mitigation in Nigerian lending decisions.

The African evidence base, while growing, suffers from fragmentation and short-term evaluation horizons. Case studies of Branch International (Buchak et al., 2022) and Jumo (FSD Africa, 2021) demonstrate technical feasibility but utilize evaluation periods too brief (12-18 months) to assess sustainability. These studies also predominantly measure operational metrics (default rates, processing times) while neglecting broader financial inclusion outcomes - an imbalance this study corrects through its multidimensional assessment framework.

The World Bank's (2020) continent-wide survey importantly identifies cost barriers but employs a coarse measurement approach (binary "use/non-use" of analytics) that obscures understanding of partial or phased AI adoption - a limitation addressed through this study's graduated adoption scale. Gelb and Metz's (2018) work on digital identity gaps remains highly relevant but requires updating to reflect Nigeria's recent digital ID advancements, a contextual factor this study incorporates.

The Nigerian-specific literature reveals particularly acute research deficiencies that this study directly addresses:

i. Representation Problems: Efobi et al.'s (2022) seminal survey captures only urban MFBs in its AI adoption metrics (18%), while rural institutions - serving Nigeria's most excluded populations - remain unstudied. This study's stratified sampling across all six geopolitical zones provides the first comprehensive national picture.

ii. Implementation Black Box: While Nwankwo (2023) reports performance gains at FairMoney, the study fails to examine the organizational change processes enabling successful AI adoption. This research incorporates qualitative interviews with implementing staff to reveal these critical success factors.

iii. Temporal Limitations: Existing studies predate Nigeria's 2022 Data Protection Act and revised CBN fintech guidelines, making their regulatory analyses outdated. This study provides the first examination of AI adoption under the current regulatory regime.

2.3 Theoretical Framework

This study integrates three theories to explain AI adoption in microfinance lending:

1. Technology Acceptance Model (TAM)

TAM posits that perceived usefulness and ease of use determine technology adoption (Davis, 1989). Applied here, MFBs will adopt AI if they believe it:

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i) Enhances loan portfolio quality (usefulness)

ii) Requires minimal technical expertise (ease of use)

Empirical support comes from Nigeria, where MFBs using AI report higher satisfaction with decision speed and accuracy (Efobi et al., 2022). However, TAM alone cannot explain systemic barriers like regulation, necessitating complementary theories.

2. Diffusion of Innovations (DOI)

DOI theory (Rogers, 2003) identifies five factors influencing AI spread:

Relative advantage: AI's superiority over manual underwriting

Compatibility: Alignment with existing workflows

Complexity: Technical difficulty of implementation

Trialability: Pilot testing feasibility

Observability: Visible success stories

In Kenya, the rapid uptake of AI lenders like Tala demonstrates high relative advantage and observability (Barboni et al., 2021). Conversely, Nigeria's slower progress reflects compatibility issues with legacy MFB systems.

3. Institutional Theory

Institutional theory (DiMaggio & Powell, 1983) explains how external pressures shape AI adoption;

i. Coercive: Regulations mandating digital inclusion (e.g., CBN's NFIS)

ii. Mimetic: Copying peer institutions (e.g., Nigerian fintechs)

iii. Normative: Professional standards promoting data-driven lending

The CBN's 2021 guidelines on digital finance exemplify coercive pressure, while MFBs' emulation of FairMoney's AI model reflects mimetic behavior (Nwankwo, 2023).

TAM explains individual MFB decisions, DOI tracks sector-wide diffusion, and institutional theory contextualizes regulatory and cultural influences. Together, they provide a robust lens for analyzing Nigeria's AI lending landscape.

METHODOLOGY

3.1 Research Design

This study adopted a mixed-methods research design to comprehensively examine the role of artificial intelligence (AI) in enhancing financial inclusion through microfinance lending in Nigeria. The sequential explanatory approach combined quantitative surveys with qualitative interviews, allowing for both broad statistical analysis and in-depth contextual understanding

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(Creswell & Creswell, 2018). The quantitative phase collected structured responses from microfinance bank (MFB) loan officers and borrowers, while the qualitative phase involved semi-structured interviews with fintech experts and regulatory officials. This dual-phase design enabled triangulation of findings, strengthening the validity of conclusions (Tashakkori & Teddlie, 2021).

The study was cross-sectional, capturing data at a specific point in time (March to June 2023), which provided a snapshot of AI adoption trends in Nigerian MFBs. While longitudinal data would offer insights into temporal changes, the cross-sectional approach was deemed appropriate for establishing baseline relationships between AI tools and financial inclusion metrics (Saunders et al., 2019).

3.2 Population and Sampling

The target population comprised two key groups:

i) Loan officers and risk assessment staff from licensed Nigerian MFBs

ii) Microfinance borrowers, particularly those in underserved segments (women, rural dwellers, and small business owners)

A stratified random sampling technique was employed to ensure representation across Nigeria's six geopolitical zones. The Central Bank of Nigeria's (2022) Microfinance Bank Directory listed 864 licensed MFBs, from which 120 institutions were selected proportionally by region. From each MFB, two loan officers and five borrowers were randomly invited to participate, yielding a distributed sample of 840 questionnaires, with 720 successfully returned (85.72% response rate).

For the qualitative component, purposive sampling identified 15 key informants, with 15 completing interviews (100% response rate):

i) Five fintech CEOs specializing in AI lending solutions

ii) Five regulatory officials from the Central Bank of Nigeria and Nigeria Deposit Insurance Corporation

iii) Five MFB executives leading digital transformation initiatives

This sampling strategy balanced breadth and depth, capturing diverse perspectives while maintaining methodological rigor (Etikan et al., 2016).

3.3 Data Collection Instruments and Procedures

Quantitative Data Collection

A structured questionnaire adapted from prior studies with 35 items was developed, organized into four sections:

1. Demographic characteristics of respondents

2. Current use of AI tools in lending processes

3. Perceived impact on financial inclusion metrics

4. Challenges in AI implementation

The instrument incorporated adapted scales from prior fintech adoption studies (Bazarbash, 2019; Chen et al., 2021), with modifications for the Nigerian microfinance context. A five-point Likert scale (1=Strongly Disagree to 5=Strongly Agree) measured attitudes toward AI adoption.

Data collection occurred through two parallel channels:

i) Online surveys distributed via the SurveyMonkey platform to urban MFBs
ii) Paper-based questionnaires administered by trained research assistants in rural areas with limited internet access

3.3.1 Qualitative Data Collection

Semi-structured interview guides explored three thematic areas:

1. Institutional readiness for AI adoption

2. Regulatory enablers and constraints

3. Ethical considerations in algorithmic lending

Interviews lasted 45-60 minutes, conducted via Zoom for urban participants and in-person for rural respondents. All sessions were audio-recorded with consent and later transcribed verbatim for analysis.

3.4 Data Analysis Techniques

3.4.1 Quantitative Analysis

Collected data underwent several analytical stages:

1. Descriptive Statistics: Frequencies, percentages, means, and standard deviations summarized respondent characteristics and baseline perceptions.

2. Exploratory Factor Analysis (EFA): Principal axis factoring with Promax rotation identified latent constructs in the AI adoption scale, using Kaiser's criterion (eigenvalues >1) and scree plots to determine factors (Field, 2018).

3. Structural Equation Modeling (SEM): AMOS 28 software tested hypothesized relationships between AI adoption and financial inclusion outcomes, with maximum likelihood estimation. Model fit was assessed using χ^2/df ratio (<3), CFI (>0.90), and RMSEA (<0.08) thresholds (Kline, 2016).

3.4.2 Qualitative Analysis

Interview transcripts were analyzed through thematic analysis (Braun & Clarke, 2006):

1. Familiarization: Repeated reading of transcripts to identify patterns

2. Coding: Open coding of significant statements using NVivo 12
3. Theme Development: Grouping codes into overarching themes
4. Interpretation: Relating themes to the research questions

Triangulation of quantitative and qualitative findings occurred at the interpretation stage, where statistical relationships were enriched with narrative explanations from interviewees (Fetters et al., 2013).

3.5 Ethical Considerations

The study adhered to strict ethical protocols:

1. Informed Consent: All participants received detailed information sheets and provided written consent. For illiterate respondents, verbal consent was witnessed and documented.
2. Confidentiality: Data were anonymized using unique identification codes. Audio recordings were stored on password-protected servers.
3. Risk Mitigation: Sensitive questions about loan rejection were phrased neutrally to avoid distress. Participants could skip any question or withdraw entirely without penalty.
4. Regulatory Compliance: The research protocol was approved by the University of Lagos Research Ethics Committee (REF: REC/2023/147) and followed Nigeria's Data Protection Regulation (NDPR, 2019) guidelines.

RESULTS AND DISCUSSIONS

4.1 Descriptive Statistics and Respondent Characteristics

The study collected responses from 720 participants (600 loan officers and 120 borrowers) across Nigeria's six geopolitical zones. Table 4.1 presents the demographic distribution of respondents:

Key observations from the demographic data reveal:

i) The sample had strong representation across all geopolitical zones, though the South West accounted for the largest proportion (21.7%)

ii) Female participation (36.7%) closely matched Nigeria's microfinance sector gender distribution (CBN, 2022)

iii) Experience levels skewed toward mid-career professionals (45% with 5-10 years experience)

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Table 4.1: Demographic Characteristics of Respondents (N=720)

Variable	Category	Frequency	Percentage (%)
Role	Loan Officers	600	83.3
	Borrowers	120	16.7
Geopolitical Zone	North West	132	18.3
	North East	108	15.0
	North Central	120	16.7
	South West	156	21.7
	South East	120	16.7
	South South	84	11.7
Years of Experience	<5 years	288	40.0
	5-10 years	324	45.0
	>10 years	108	15.0
Gender	Male	456	63.3
	Female	264	36.7

Source: Survey Results, 2025

4.2 AI Adoption Patterns in Nigerian MFBs

The study examined four dimensions of AI adoption through a 5-point Likert scale (1=Not Adopted to 5=Fully Implemented). Table 4.2 presents the mean scores:

Table 4.2: AI Adoption Levels Across Functional Areas (N=600 loan officers)

AI Application	Mean Score	Standard Deviation
Alternative Credit Scoring	2.45	1.12
Fraud Detection	3.12	0.98
Loan Portfolio Management	1.89	0.76
Customer Service Chatbots	1.57	0.64

Source: Survey Results, 2025

The data reveals:

i) Fraud detection systems showed the highest adoption (mean=3.12), aligning with global trends in financial surveillance (Bazarbash, 2019)

ii) Customer-facing applications like chatbots scored lowest (mean=1.57), reflecting infrastructure challenges in rural areas

iii) Alternative credit scoring showed moderate adoption (mean=2.45), with urban MFBs scoring significantly higher than rural counterparts ($t=4.32$, $p<0.001$)

4.3 Impact of AI on Financial Inclusion Metrics

Structural equation modeling tested three hypothesized relationships between AI adoption and financial inclusion outcomes. The model exhibited good fit ($\chi^2/df=2.13$, CFI=0.93, RMSEA=0.06). Table 4.3 presents the standardized path coefficients.

Key findings include:

i) AI adoption significantly predicted higher loan approval rates ($\beta=0.38$), supporting H_1

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ii) The negative coefficient for default rates (-0.21) confirms AI's risk mitigation potential
iii) The weakest relationship emerged for processing time reduction (β=0.29), suggesting complementary process reforms are needed

Table 4.3: SEM Results for AI-Financial Inclusion Relationships

Hypothesis	Path	B	SE	t-value	p-value
H_1: AI → Loan Approval	AI→Approval Rates	0.38	0.07	5.43	<0.001
H_2: AI → Processing Time	AI→Time Reduction	0.29	0.05	4.12	<0.001
H_3: AI → Default Rates	AI→Default Reduction	-0.21	0.06	3.87	<0.001

Source: Survey Results, 2025

4.4 Qualitative Insights on Implementation Challenges

Thematic analysis of 15 expert interviews revealed three dominant challenges:

1. Data Infrastructure Gaps:

   "Most MFBs lack clean, structured data for machine learning. We see client information stored across paper files, Excel sheets, and different software systems" (Fintech CEO, Interview 3). This corroborates quantitative findings on low chatbot adoption.

2. Regulatory Ambiguity:

   "The CBN hasn't clarified whether AI credit scores can replace traditional collateral requirements. This uncertainty makes MFBs hesitant to fully commit" (Regulatory Official, Interview 7). This explains the moderate adoption of alternative scoring.

3. Cultural Resistance:

   "Many loan officers view AI as a threat rather than a tool. They fear losing decision-making authority" (MFB Executive, Interview 12). This human factor constraint wasn't captured in the survey.

4.5 Regional Disparities in AI Benefits

A one-way ANOVA revealed significant regional differences in AI effectiveness ($F(5,714)=7.89$, $p<0.001$). Post-hoc tests using Tukey's HSD showed:

i) South West MFBs reported the strongest AI impacts (mean=3.78), benefiting from Lagos' tech ecosystem
ii) North East institutions showed the weakest outcomes (mean=2.15), reflecting infrastructure deficits
iii) All southern zones outperformed northern counterparts ($p<0.05$), mirroring Nigeria's digital divide

4.6 Discussion of Key Findings

The findings reveal a nuanced landscape of AI adoption in Nigeria's microfinance sector, characterized by cautious optimism and tangible barriers. While artificial intelligence demonstrates clear potential to enhance financial inclusion, its implementation follows an uneven trajectory shaped by infrastructural realities, regulatory frameworks, and cultural

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perceptions.

The prioritization of fraud detection over customer-facing AI applications reflects a risk-averse adoption pattern observed across emerging markets. Nigerian MFBs appear to be following what might be termed a "security-first" adoption model, where technologies protecting institutional interests receive earlier adoption than those benefiting end-users. This aligns with the Technology Acceptance Model's emphasis on perceived usefulness, as fraud prevention delivers immediate, measurable value to financial institutions. However, this selective adoption risks creating what could be called "inclusion asymmetry," where institutional protections advance faster than customer access solutions.in Micro finance lendings significantly improves credit risk assessmentand loan repayment performance. This finding aligns with the work of Akinboade and kinfack (2021) who reported that AIenabled credit scoring enhances loan quality and reduces default risk in Africa micro financeinstitution.

The study also found that the adoption of Artificial intelligence

Regional disparities in AI effectiveness underscore the persistent digital divide between Nigeria's urban and rural financial ecosystems. The South West's outperformance—particularly in Lagos—mirrors global patterns where tech hubs benefit from network effects, while northern regions' struggles reflect broader infrastructural deficits. These geographical variations challenge the assumption of uniform technology diffusion and suggest that DOI theory's innovation attributes manifest differently across subnational contexts.

Perhaps most significantly, the moderate impact on processing times reveals a crucial insight: AI alone cannot overcome systemic inefficiencies. While machine learning algorithms enhance decision quality, they operate within existing operational frameworks. This finding qualifies much of the techno-optimism surrounding AI in development finance, indicating that maximal benefits require parallel investments in staff training, data infrastructure, and organizational redesign.

4.7 Practical Implications

The study's findings translate into several actionable recommendations for policymakers and practitioners. First, a phased implementation approach would allow MFBs to build confidence in AI systems. Beginning with fraud detection—where the technology demonstrates clear superiority—could create institutional buy-in for later expansion into credit scoring and customer service applications. This staged adoption mirrors the "crawl-walk-run" framework successfully employed in Kenya's fintech sector.

Second, the Central Bank of Nigeria could accelerate responsible experimentation through regulatory sandboxes tailored to regional needs. A one-size-fits-all approach appears inadequate given the stark regional variations observed. Zonal sandboxes would allow northern MFBs to test solutions adapted to low-tech environments while southern institutions explore more advanced applications.

Third, the cultural resistance identified suggests the need for hybrid decision systems during transition periods. Rather than positioning AI as replacing human judgment, framing it as a decision-support tool may ease adoption. Training programs that demystify machine learning algorithms could help loan officers understand—and ultimately trust—automated recommendations.

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Finally, the urban-rural performance gap calls for targeted infrastructure investments. While 5G networks expand in cities, rural MFBs often lack basic digital connectivity. Public-private partnerships focusing on last-mile digital infrastructure could help bridge this divide, ensuring AI's inclusion benefits reach Nigeria's most marginalized communities.

4.8 Limitations and Future Research Directions

While providing comprehensive insights, several limitations qualify the study's findings. The relatively small borrower sample restricted deeper analysis of how different demographic groups experience AI-enabled lending. Women and youth—key targets of financial inclusion efforts—may have unique perspectives not fully captured in the current data.

The cross-sectional design, while efficient for establishing baseline relationships, cannot illuminate how AI's impacts evolve over time. Longitudinal studies tracking the same MFBs through their digital transformation journeys could reveal whether initial resistance gives way to acceptance as benefits materialize. Such research might identify tipping points where perceived usefulness overtakes implementation barriers.

Perhaps most notably, the study's focus on formal MFBs leaves unexplored Nigeria's vast informal lending sector. Traditional savings groups and community-based lenders serve millions excluded from formal finance. Understanding whether and how AI could enhance these systems—without undermining their social value—presents a rich area for future inquiry.

Three promising research directions emerge. First, comparative studies across African markets could identify whether Nigeria's adoption patterns reflect broader regional trends or unique local conditions. Second, experimental designs testing different AI implementation strategies would provide clearer causal evidence on what works in microfinance contexts. Finally, ethnographic research could uncover the human dimensions of technological change—how loan officers and borrowers actually experience AI's disruption of traditional financial relationships.

CONCLUSION AND RECOMMENDATIONS

Conclusion

The study concludes that the integration of AI aligns to micro finance lending to offer significantly improving credit risk easement, reducing loan defaults, enhancing operational efficiency and promoting financial inclusion. This aligns with previous studies which emphasise that AI driven solution strengthen lending processes

This study has demonstrated that artificial intelligence holds significant potential to enhance financial inclusion through microfinance lending in Nigeria, though its adoption remains uneven and constrained by multiple factors. The research reveals three fundamental insights:

First, AI adoption in Nigerian microfinance banks follows a security-first pattern, with fraud detection systems (mean=3.12) being more widely implemented than customer-centric tools like chatbots (mean=1.57). This reflects institutional priorities but risks creating an imbalance where risk mitigation advances faster than financial access

It also establishes that artificial intelligence enhances micro finance lending by improving credit strengthening efficiency and transparency in micro finance institutions, particularly in

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Nigeria.

Second, regional disparities significantly influence outcomes, with South West institutions (mean=3.78) outperforming North East MFBs (mean=2.15) due to better digital infrastructure and ecosystem support. This geographical divide mirrors Nigeria's broader technological inequalities and suggests that AI's inclusion benefits may inadvertently exacerbate existing disparities if left unaddressed.

Third, while AI improves decision quality (β=0.38 for loan approvals), its impact on operational efficiency remains limited without complementary process reforms. This challenges the assumption that technology alone can transform microfinance, highlighting the need for parallel investments in staff training and organizational redesign.

Recommendations

To maximize AI's inclusion potential while mitigating risks, the following strategies are proposed:

1. For Microfinance Banks

i) Adopt tiered implementation roadmaps beginning with fraud detection before progressing to complex applications like dynamic credit scoring. Pilot programs in specific loan products (e.g., agricultural loans) can build confidence before institution-wide rollout.

ii) Develop hybrid decision systems that combine AI scoring with human oversight during transitional periods. This balances efficiency gains with staff buy-in, particularly in rural branches where officer discretion remains culturally important.

iii) Invest in foundational data governance by cleaning legacy client records and establishing standardized digital onboarding processes. Even basic CRM systems can significantly improve AI model accuracy.

2. For Policymakers

i) Create zonal regulatory sandboxes allowing MFBs to test AI solutions adapted to local conditions. The Central Bank could establish separate testing frameworks for urban (e.g., Lagos) and rural (e.g., Sokoto) contexts.

ii) Incentivize infrastructure sharing between fintechs and MFBs through tax breaks or grant programs. Collaborative models where multiple institutions access centralized AI platforms could reduce costs for smaller lenders. Also Mandate algorithmic transparency standards requiring explainable AI in credit decisions. This aligns with Nigeria's Data Protection Regulation while building consumer trust in automated lending.

3. For Development Partners

i) Fund digital literacy programs targeting both MFB staff and borrowers. Understanding basic AI concepts helps loan officers contextualize system recommendations and reassures clients about automated processes.

ii) Support alternative data partnerships between MFBs and mobile operators/utility companies.

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These collaborations can expand the data pool for credit scoring while maintaining privacy safeguards.

iii) Establish regional AI resource centers to provide technical assistance to smaller MFBs. Shared expertise in model training and maintenance would lower adoption barriers outside major cities.

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