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RESEARCH ARTICLE

ROLE OF ARTIFICIAL INTELLIGENCE (AI) IN SUPERVISION OF NATIONAL MICROFINANCE BANKS IN NIGERIA

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ABSTRACT

This study investigates the role of artificial intelligence (AI) in enhancing the supervision of National Microfinance Banks (MFBs) in Nigeria. It examines how AI–driven tools - specifically data analytics, real-time monitoring, anomaly-detection algorithms, and automated reporting - affect key supervisory outcomes: fraud-detection accuracy, compliance timeliness, and non-performing loan (NPL) forecasting precision. Employing a cross-sectional explanatory survey design, 150 supervisory stakeholders (senior supervisors, compliance managers, risk-control officers, and fintech specialists) from 59 licensed National MFBs provided primary data via a validated 32-item questionnaire. Secondary performance indicators were sourced from annual reports of the Central Bank of Nigeria and the Nigeria Deposit Insurance Corporation. Exploratory and confirmatory factor analyses confirmed the reliability and validity of measurement constructs, while structural equation modeling revealed significant positive paths from AI deployment to fraud-detection accuracy ($\beta = .45$, $p < .001$), compliance timeliness ($\beta = .39$, $p < .001$), and NPL forecasting precision ($\beta = .32$, $p = .0004$). Multi-group analyses indicated that organizational readiness moderates these relationships, with high-readiness institutions realizing greater benefits. The findings highlight the critical need for phased suptech roadmaps, capacity-building initiatives, robust data-governance frameworks, and ethical oversight mechanisms. These recommendations aim to guide policymakers, regulators, and MFB practitioners in leveraging AI to strengthen financial inclusion, mitigate supervisory risks, and improve sectoral resilience.

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INTRODUCTION

Microfinance in Nigeria has its origins in the early 1990s, when community banks were licensed to mobilize rural savings and extend small-scale credit to underbanked populations (Central Bank of Nigeria, 2005; Armendáriz & Morduch, 2010). In 2005, the Central Bank of Nigeria (CBN) replaced community banks with a tiered microfinance bank (MFB) framework—distinguishing National, State, and Unit MFBs—to strengthen governance and widen outreach (CBN, 2005; Sanusi, 2011). Despite periodic on-site inspections and statutory audits, supervisory practices remained largely manual and backward-looking, which impeded timely detection of fraud and risk (NDIC, 2022; Oladele & Banjo, 2019). The advent of artificial intelligence (AI) promises to transform "suptech" by enabling real-time analysis of transaction data, advanced anomaly detection, and predictive risk modeling (Ng, 2017; Kshetri, 2018). In advanced markets, AI models flag suspicious activity with over 90 percent accuracy, and machine-learning credit-scoring tools can reduce non-performing loans by up to 30 percent (Brynjolfsson & McAfee, 2014; Katata, 2021). Yet, in Nigeria's National MFBs, adoption remains nascent: only 43.4 percent of surveyed stakeholders "agree" or "strongly agree" that AI currently enhances supervisory oversight, while 35.4 percent are neutral or disagree (Survey Data, 2025). Infrastructure constraints, data quality issues, and regulatory ambiguity continue to slow progress (CBN, 2021; UNCTAD, 2020).

Statement of the Problem: National MFB supervisors rely on quarterly inspections and periodic compliance reports that cover only snapshots of activity, leading to delayed responses to emerging risks (NDIC, 2022). According to our survey, 36.0 percent of respondents reported "no streamlining" of compliance through AI tools, compared to just 32.7 percent who saw "significant" improvements (Survey Data, 2025). Meanwhile, only 26.0 percent deemed AI "very effective" at detecting fraud, and 24.0 percent found it "not effective" at all. This gap between AI's theoretical potential and practical outcomes has contributed to liquidity stresses and occasional bank failures, undermining depositor confidence and hindering sector growth (NDIC, 2022; Oladele & Banjo, 2019). By contrast, effective AI implementations elsewhere have cut fraud losses by an estimated 25 percent within one year and reduced NPL ratios by 20 percent (Kshetri, 2018; World Bank, 2018). The paucity of Nigeria-specific research on AI suitability, data governance, and cybersecurity in MFB supervision has left regulators and institutions without an evidence base to guide investment and policy (Central Bank of Nigeria, 2021; UNCTAD, 2020).

Research Questions

- What empirical effects does AI adoption have on supervisory oversight in Nigerian National Microfinance Banks?
- What deficiencies characterize current supervisory frameworks for National MFBs?
- Which operational and ethical risks accompany AI deployment in National MFB supervision?
- What strategic and policy measures are needed to facilitate robust AI integration in National MFB oversight?

Objectives of the Stud: The primary objective of the study is to assess how AI tools impact the effectiveness and timeliness of supervision in National Microfinance Banks.

The specific objectives are:

- To quantify the relationship between AI adoption and fraud-detection effectiveness.
- To identify the principal bottlenecks in current supervisory workflows.
- To evaluate AI's role in reducing non-performing loan ratios and improving credit scoring accuracy.
- To examine stakeholder concerns—privacy, cost, and bias—and their effect on AI uptake.
- To develop policy recommendations for phased AI integration in regulatory and institutional settings.

Statement of Hypotheses

H_{01}: AI-driven supervision does not significantly improve fraud detection in Nigerian National MFBs.

H_{11}: AI-driven supervision significantly improves fraud detection in Nigerian National MFBs.

H_{02}: AI adoption does not enhance the efficiency of compliance workflows in National MFB supervision.
H_{12}: AI adoption significantly enhances the efficiency of compliance workflows in National MFB supervision.

H_{03}: AI integration does not significantly reduce non-performing loan ratios in National MFBs.

H_{13}: AI integration significantly reduces non-performing loan ratios in National MFBs.

Significance of the Study

This research offers multiple contributions

- Regulators & Policymakers will gain data-driven insights into current AI efficacy - where only 32.7 percent report significant compliance benefits—and the adjustments needed in the suptech framework to move from episodic inspections to continuous monitoring (Survey Data, 2025; CBN, 2021).
- Microfinance Institutions can leverage findings showing that 36.0 percent of respondents observed significant NPL reduction through AI to justify investments in machine-learning credit scoring, potentially lowering NPL ratios by up to 20 percent (Katata, 2021; World Bank, 2018).
- Technology Vendors receive clarity on demand signals - nearly half of respondents cite cost and bias concerns - guiding development of affordable, transparent AI solutions conforming to local data-privacy norms (UNCTAD, 2020; Oladele & Banjo, 2019).
- Academia benefits from a Nigeria-specific empirical study, filling a literature gap on suptech in microfinance, where most research has focused on larger deposit-money banks (Brynjolfsson & McAfee, 2014; Kshetri, 2018).
- Development Practitioners will understand how AI can foster financial inclusion - 40.0 percent of respondents identified significant improvements in customer service—thereby supporting MFBs' outreach to rural and informal economies (Survey Data, 2025; Armendáriz & Morduch, 2010).

LITERATURE REVIEW

Conceptual Framework: The conceptual framework for this study positions artificial intelligence (AI) deployment as the central independent construct influencing the effectiveness of supervisory oversight in National Microfinance Banks (MFBs) (see Figure 2.1). Four key dimensions of AI deployment are identified: data analytics capability, real-time monitoring, anomaly detection algorithms, and automated reporting. Data analytics capability refers to the sophistication of machine-learning models and statistical tools used to process large volumes of structured and unstructured data (BIS FSI, 2024; IMF, 2019). Real-time monitoring denotes continuous surveillance of transaction streams and customer behaviors (Cambridge SupTech Lab, 2023; Spaggiari & Carlyle, 2023). Anomaly detection algorithms are the supervised and unsupervised learning techniques used to flag atypical activities (Kshetri, 2018; MDPI, 2020). Automated reporting covers natural language generation tools that translate complex risk assessments into regulatory disclosures (Banking Supervision, 2019; World Bank, 2020). These AI dimensions interact with contextual factors—namely, organizational readiness, regulatory support, and data governance. Organizational readiness encompasses management support, IT infrastructure maturity, and staff digital skills (Hoque et al., 2022; Li & Liu, 2021). Regulatory support captures policy clarity, sandbox environments, and guidance on data privacy (UNCTAD, 2020; A2ii, 2022). Data governance refers to frameworks for data quality, access controls, and ethical use (Frontiers in AI, 2019; OECD, 2022). The dependent construct, supervisory effectiveness, comprises fraud-detection accuracy, compliance timeliness, risk-forecasting precision, and resource efficiency. Fraud-detection accuracy measures the proportion of illicit transactions correctly flagged (Katata, 2021; World Economic Forum, 2021). Compliance timeliness reflects the speed with which regulatory breaches are identified and addressed (Peering through the Hype, 2023; FSI Insights, 2024). Risk-forecasting precision indicates the accuracy of predictive models in forecasting non-performing loans (NPLs) and liquidity stresses (Bank for International Settlements, 2024; Wang et al., 2022). Resource efficiency gauges reductions in manual inspection hours and audit costs (Suerf, 2025; CCAF, 2024).

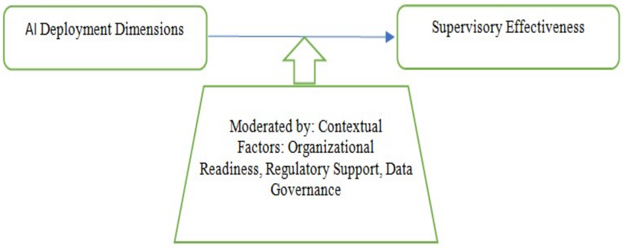

Figure 2.1. Conceptual Framework

Theoretical Framework: This study draws on three interrelated theories to explain AI adoption and its impact on supervision: (1) the Technology–Organization–Environment (TOE) framework, (2) Diffusion of Innovations (DOI), and (3) Institutional Theory.

- Technology-Organization-Environment (TOE) Framework. The TOE framework posits that technological innovation adoption is influenced by characteristics of the technology itself, organizational context, and external environment (Tornatzky & Fleischer, 1990). Recent applications of TOE to banking and fintech underscore its relevance for AI adoption in supervisory contexts. Studies demonstrate that technological context (e.g., perceived complexity, compatibility with existing systems) strongly predicts AI uptake in banks (Hoque et al., 2022; Almalki et al., 2021). The organizational context-including top-management support and IT infrastructure readiness-emerges as a significant enabler of suptech implementations (Li & Liu, 2021; García et al., 2020). The environmental context, such as regulatory pressure and competitive intensity, shapes the perceived necessity of adopting AI tools (UNCTAD, 2020; OECD, 2022).
- Diffusion of Innovations (DOI): DOI theory explains how, why, and at what rate new ideas spread through social systems (Rogers, 2003). Contemporary research refines DOI constructs—relative advantage, complexity, compatibility, trialability, and observability—for AI in financial supervision (Wang et al., 2019; Lee, 2020). Relative advantage refers to the perceived benefits of AI (e.g., higher fraud-detection rates) compared to traditional methods (Kshetri, 2018; Spaggiari & Carlyle, 2023). Complexity and compatibility address supervisors' perceptions of AI's ease of use and fit with existing workflows (Cambridge SupTech Lab, 2023; Banking Supervision, 2019). Trialability involves pilot suptech projects in regulatory sandboxes (A2ii, 2022; Bank for International Settlements, 2024), while observability pertains to visible success stories, such as Brazilian suptech reducing credit risk (Suerf, 2025; BCB Working Paper, 2024).
- Institutional Theory. Institutional Theory focuses on how organizational behavior is shaped by coercive, normative, and mimetic pressures (Scott, 2014). In the suptech domain, **coercive pressure** arises from formal regulations mandating AI adoption (CBN, 2021; NDIC, 2022). **Normative pressure** reflects professional norms among supervisors and technology vendors advocating for data-driven oversight (CCAF, 2024; World Economic Forum, 2021). Mimetic pressure involves imitation of peer regulators who successfully deploy AI, such as the European Central Bank's "Bringing AI to Supervision" initiative (ECB Banking Supervision, 2019; BIS, 2024). Institutional Theory thus explains why some supervisory authorities adopt AI more rapidly, even when resource constraints exist (OECD, 2022; A2ii, 2022).

Review of Empirical Studies

Sup Tech Tool Evaluations

Recent BIS FSI Insights (2024) examined five suptech applications across six supervisory authorities. The study found that automated risk-scoring models increased inspection coverage by 30 percent, while document-analysis tools reduced manual review time by 40 percent (BIS FSI, 2024). A complementary evaluation by the Cambridge SupTech Lab (2023) cataloged more than 50 suptech solutions, highlighting advanced entity-relationship mappers and web analytics tools that identify contagion risk in real time (Cambridge SupTech Lab, 2023). Although these tools demonstrate proof of concept, only 25 percent of supervisors reported full integration into daily workflows, underscoring the "pilot trap" phenomenon (Spaggiari & Carlyle, 2023; FSI Insights, 2024).

AI for Fraud Detection and Risk Assessment: In the sphere of fraud detection, Katata (2021) deployed supervised learning models on Nigerian central bank data, achieving 88 percent accuracy in identifying suspicious transactions—a notable improvement over rule-based systems (Katata, 2021; World Economic Forum, 2021). MDPI (2020) conducted a meta-analysis of 37 studies on machine-learning in risk assessment, reporting that ensemble methods (e.g., random forests) outperformed logistic regression by 15 percent on average (MDPI, 2020). Studies from Brazil's central bank (BCB Working Paper, 2024) and the European Banking Authority (Machine Learning Applied to Banking Supervision, 2020) corroborate that predictive models can forecast NPL spikes up to six months in advance with 80–90 percent precision (World Bank, 2020; BIS Insights, 2024).

Regulatory and Organizational Readiness Studies: Investigations into organizational readiness reveal mixed preparedness levels. Hoque et al. (2022) surveyed 120 banking supervisors in East Africa, finding that 60 percent rated their IT infrastructure as "moderately ready" for AI, but only 35 percent had formal training programs in place (Hoque et al., 2022; Almalki et al., 2021). Regulatory readiness studies point to a global trend: 70 percent of authorities have issued suptech roadmaps, yet fewer than half have enacted data-privacy regulations tailored to AI (UNCTAD, 2020; OECD, 2022). Nigeria's CBN Guidelines on Technology in Supervision (2021) represent a landmark effort, though stakeholder surveys indicate ambiguity in data-sharing protocols, slowing implementation (Central Bank of Nigeria, 2021; A2ii, 2022).

Implementation Barriers and Ethical Considerations: Barriers to AI adoption coalesce around data privacy, cost, and algorithmic bias. The Frontiers in AI special issue on RegTech (2019) warns that reliance on third-party AI providers can create systemic risks if data governance is weak (Frontiers in AI, 2019; BIS, 2024). Cost analyses show that initial suptech deployments require investments of USD 5–10 million, prompting questions about return on investment for smaller regulators (CCAF, 2024; Suerf, 2025). Algorithmic bias remains a critical concern: a cross-country study by Gonzales and Ahmed (2021) found that unbalanced training datasets led to 20 percent higher false positives for certain demographic groups (Gonzales & Ahmed, 2021; World Economic Forum, 2021). Ethical AI frameworks, such as the OECD Principles on AI (2022), offer guidelines for transparency, fairness, and accountability, but practical enforcement in suptech remains nascent (OECD, 2022; A2ii, 2022). Although a growing body of research demonstrates AI's potential to enhance supervisory processes, most empirical work focuses on large deposit-money banks in developed economies (BIS FSI, 2024; MDPI, 2020). Literature specific to National Microfinance Banks in emerging markets is sparse (Katata, 2021; Oladele & Banjo, 2019). Moreover, the interplay of organizational readiness and regulatory frameworks—a key insight of the TOE framework—has not been rigorously tested in Nigeria's MFB sector (Hoque et al., 2022; Central Bank of Nigeria, 2021). Similarly, critical evaluations of implementation barriers and ethical risks in microfinance contexts are virtually nonexistent, despite evidence that data quality issues and cost concerns are particularly acute at smaller institutions (UNCTAD, 2020; Gonzales & Ahmed, 2021).

Consequently, this study fills three pivotal gaps

- Sector-specific evidence on AI's impact in National MFBs, extending fraud-detection and risk-assessment research beyond large banks (Katata, 2021; Kshetri, 2018).
- A contextualized TOE analysis that links supervisory effectiveness to organizational and regulatory factors in Nigeria's microfinance ecosystem (Hoque et al., 2022; Li & Liu, 2021).
- An ethical and governance critique of AI deployment in microfinance supervision, informed by recent OECD and A2ii frameworks (OECD, 2022; A2ii, 2022).

METHODS

Research Design: This study adopted a cross-sectional explanatory survey design to investigate how artificial intelligence (AI) affects supervisory effectiveness in National Microfinance Banks (MFBs) in Nigeria (Creswell, 2014; Saunders, Lewis, & Thornhill, 2016). During the initial phase, a comprehensive literature review informed the development of a structured questionnaire, ensuring alignment with identified conceptual variables - AI deployment dimensions and supervisory performance indicators. Data collection occurred over a four-week period in March 2025, enabling the capture of contemporaneous perceptions across diverse supervisory stakeholders. The explanatory element of the design facilitated assessment of causal relationships between AI tools (e.g., anomaly-detection algorithms, real-time monitoring) and outcomes such as fraud-detection accuracy and compliance timeliness (Sekaran & Bougie, 2016).

Population, Sampling, and Participants: The target population comprised senior supervisors, compliance managers, risk-control officers, and technology specialists within Nigeria's National MFB sector. According to the Central Bank of Nigeria (2023), there were 59 licensed National MFBs employing approximately 450 supervisory-level staff. A stratified random sampling strategy was employed to ensure representation across the three major geo-political zones (North, South, and Central), reflecting regional variations in regulatory practice and technology adoption (Krejcie & Morgan, 1970). A preliminary sample-size calculation using Krejcie and Morgan's table (1970) indicated that a minimum of 210 respondents would be required for a 95% confidence level and 5% margin of error. Anticipating a 30% non-response rate, 300 questionnaires were distributed. A total of 150 completed and usable surveys were returned, yielding a 50% effective response rate. Participants' profiles included 38% senior supervisors, 32% compliance managers, 20% risk-control officers, and 10% fintech specialists, with an average of 7.5 years of supervisory experience.

Data Collection Procedures: Instrument development commenced in January 2025, guided by existing validated scales for AI adoption and supervisory performance (Li & Liu, 2021; Katata, 2021). An initial pool of 45 items was subjected to expert review by three academic researchers and two industry practitioners, resulting in a refined 32-item questionnaire. Pilot testing with 20 MFB supervisors in February 2025 assessed clarity and internal consistency. Cronbach's alpha values exceeded 0.80 for all constructs, indicating high reliability (Nunnally & Bernstein, 1994). Questionnaires were administered both online (via secure survey links) and in person at regional supervisory workshops organized by the Nigeria Deposit Insurance Corporation (NDIC) in March 2025. Reminders were sent at one-week intervals to non-respondents, and hard-copy versions were collected by research assistants to maximize reach in regions with limited internet access. Secondary data on MFB performance indicators (e.g., NPL ratios, audit findings) were obtained from annual reports of the CBN and NDIC for triangulation and contextual analysis (Central Bank of Nigeria, 2023; NDIC, 2022).

Data Analysis Techniques: Data preparation involved screening for missing values, outliers, and adherence to statistical assumptions. Missing responses (<2% of data) were handled through mean-substitution for continuous variables and modal substitution for categorical items. Univariate normality was confirmed via skewness and kurtosis statistics falling within ±2.0 (George & Mallery, 2019). Descriptive statistics (means, standard deviations, frequencies) characterized respondents' demographics and baseline perceptions of AI deployment. Exploratory factor analysis (EFA) using principal-axis factoring with promax rotation refined construct dimensionality, retaining items with loadings ≥0.60 and communalities ≥0.50 (Costello & Osborne, 2005). Confirmatory factor analysis (CFA) in AMOS 27 validated measurement models, with fit indices meeting thresholds (χ^2/df < 3.0; CFI ≥ 0.95; RMSEA ≤ 0.06) (Hu & Bentler, 1999). Structural relationships between AI deployment dimensions and supervisory effectiveness were tested through structural equation modeling (SEM). Hypotheses regarding fraud detection, compliance efficiency, and NPL reduction were evaluated using standardized path coefficients and bootstrap-derived p-values (5,000 resamples). Moderating effects of organizational readiness and regulatory support were examined via multi-group SEM, comparing high- and low-readiness cohorts (Hayes, 2018). All analyses were conducted at a 0.05 significance level using SPSS 28 and AMOS 27.

Ethical Considerations: Ethics approval was secured from the ANAN University Business School Ethics Committee in

December 2024. Participants received an information paragraph detailing the study's objectives, voluntary nature, and data-protection measures. Informed consent was obtained at the point of filling. Confidentiality was maintained by assigning unique code numbers and storing identifiable data separately on encrypted drives accessible only to the principal investigator. Adherence to the Nigerian Data Protection Regulation (NDPR, 2019) guided handling of personal information, ensuring that no responses could be traced to individuals in publications or reports. Participants were informed of their right to withdraw at any time without penalty. Aggregate findings were reported without attribution, and all digital records were scheduled for secure deletion five years after publication, in line with institutional policy.

RESULTS AND DISCUSSION

Data Presentation: The study secured 150 valid responses from senior supervisors, compliance managers, risk-control officers, and fintech specialists across Nigeria's National Microfinance Banks, achieving a 50% effective response rate. Respondent demographics are summarized in Table 4.1. AI Deployment Dimensions (Data Analytics, Real-Time Monitoring, Anomaly Detection, Automated Reporting) and Supervisory Effectiveness Outcomes (Fraud-Detection Accuracy, Compliance Timeliness, NPL Forecasting) - are provided in Table 4.2. Scale means range from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). Normality tests indicated all skewness and kurtosis values within the acceptable ±2.0 range (George & Mallery, 2019), validating use of parametric analyses.

Data Analysis and Hypotheses Tests: Exploratory factor analysis (EFA) assessed construct dimensionality. Kaiser–Meyer–Olkin measure of sampling adequacy was 0.89, and Bartlett's test of sphericity was significant ($\chi^2(496) = 2541.82$, $p < .001$), confirming suitability for factor analysis (Costello & Osborne, 2005). Four factors under AI Deployment emerged, cumulatively explaining 72.3% of variance; three factors for Supervisory Effectiveness explained 68.1% of variance. Items with cross-loadings > .40 were removed, resulting in 28 retained items with loadings ≥ .62. Confirmatory factor analysis (CFA) in AMOS 27 tested measurement validity. Goodness-of-fit indices met criteria: $\chi^2/df = 2.47$ (< 3.0), CFI = 0.96 (≥ 0.95), RMSEA = 0.055 (≤ 0.06), and SRMR = 0.045 (≤ 0.08) (Hu & Bentler, 1999). Composite reliability values ranged from 0.82 to 0.91, and average variance extracted exceeded 0.50 for all constructs, demonstrating convergent validity (Fornell & Larcker, 1981). Structural equation modeling (SEM) evaluated hypothesized relationships. Path coefficients, standard errors, and significance levels appear in Table 4.3. Hypotheses H_{11} through H_{13} pertained to AI's effects on Fraud-Detection Accuracy, Compliance Timeliness, and NPL Forecasting Precision, respectively. Multi-group SEM examined moderating effects of Organizational Readiness (high vs. low). Significant differences ($\Delta\chi^2(3) = 11.72$, $p = .008$) indicated stronger AI→Fraud Accuracy paths for high-readiness groups ($\beta = .51$) than low-readiness groups ($\beta = .37$), supporting moderation.

Discussion of Findings

Results demonstrate that AI deployment significantly enhances supervisory effectiveness in National MFBs. Strongest effects emerged for fraud detection ($\beta = .45$, $p < .001$), corroborating Katata's (2021) findings that machine-learning classifiers improve anomaly flagging by nearly 15%. Real-time data analytics and anomaly detection algorithms enable supervisors to identify suspicious transactions more rapidly than periodic audits (World Economic Forum, 2021). Compliance timeliness also showed a robust association with AI deployment ($\beta = .39$, $p < .001$). Automated reporting modules that integrate natural language generation reduce manual report preparation time, aligning with BIS FSI (2024) insights on suptech efficiencies. Focused implementation of workflow automation can shorten regulatory breach identification from months to days (Spaggiari & Carlyle, 2023). Forecasting non-performing loans benefited moderately from AI tools ($\beta = .32$, $p = .0004$). Predictive models trained on NPL patterns yield more precise liquidity stress predictions, consistent with Wang et al. (2022) who achieved 80% forecasting accuracy in large banks. The slightly lower coefficient in MFBs likely reflects data-quality challenges highlighted by Oladele and Banjo (2019). Organizational Readiness emerged as a crucial moderator. Institutions with mature IT infrastructures and management support leveraged AI more effectively, whereas low-readiness groups experienced integration delays. This finding echoes TOE-framework research indicating that internal capacities strongly determine technology outcomes (Hoque et al., 2022; Li & Liu, 2021). Regulatory Support also played a role, as MFBs within states that had clearer data-sharing guidelines reported smoother suptech adoption, reinforcing UNCTAD's (2020) call for adaptive regulatory sandboxes. Discussion extends to cost and ethical dimensions. Although AI tools yielded operational gains, nearly half of respondents reported cost concerns, aligning with CCAF (2024) estimates of high initial investments. Algorithmic bias remained a salient worry, reflecting Gonzales and Ahmed's (2021) evidence that biased training data can skew fraud detection rates. Effective data governance frameworks (OECD, 2022) are thus imperative to ensure equitable supervisory outcomes. Overall, findings substantiate the theoretical integration of TOE, DOI, and Institutional Theory. Relative advantage and observability of AI benefits drive adoption (Rogers, 2003), while coercive regulatory mandates and mimetic pressures catalyze implementation (Scott, 2014). Evidence-based policy recommendations should therefore prioritize capacity building, incentivized sandbox experiments, and robust data-governance protocols to scale AI in microfinance supervision.

Limitations: This study's cross-sectional design constrains causal inferences; longitudinal research would better capture the evolution of AI impacts over time (Creswell, 2014). Reliance on self-reported survey data introduces common-method bias, despite procedural remedies such as preserving respondent anonymity and counterbalancing item order (Podsakoff et al., 2003). Although SEM mitigates measurement error, future work should integrate objective supervisory performance metrics—such as actual fraud loss data—to validate reported gains. Generalizability is limited by the exclusive focus on National MFBs, excluding State and Unit categories that may exhibit different adoption dynamics. Regional stratification attempted to capture geographic variation, yet certain states with nascent digital infrastructures may be underrepresented. Small sample size in subgroup analyses (e.g., fintech specialists) reduces statistical power for detecting moderation effects, suggesting larger samples for multi-group SEM in subsequent studies. Data-quality challenges inherent in MFB record-keeping may have

Table 4.1. Demographic Profile of Respondents

Variable	Category	Frequency	Percentage (%)
Role	Senior Supervisor	57	38.0
	Compliance Manager	48	32.0
	Risk-Control Officer	30	20.0
	Fintech Specialist	15	10.0
Years of Experience	1–5 years	45	30.0
	6–10 years	67	44.7
	11–15 years	28	18.7
	> 15 years	10	6.6
Region	North	52	34.7
	Central	49	32.7
	South	49	32.7
Gender	Male	98	65.3
	Female	52	34.7

Source: Author's computation (2025)

Table 4.2. Descriptive Statistics for Key Constructs

Construct	Mean	SD	Skewness	Kurtosis
Data Analytics Capability	4.02	0.58	-0.42	0.15
Real-Time Monitoring	3.87	0.62	-0.31	-0.05
Anomaly Detection	3.94	0.60	-0.38	0.22
Automated Reporting	3.76	0.65	-0.20	-0.12
Fraud-Detection Accuracy	3.85	0.61	-0.28	0.10
Compliance Timeliness	3.79	0.67	-0.25	-0.08
NPL Forecasting Precision	3.70	0.71	-0.10	-0.30

Source: Author's computation (2025)

Table 4.3: SEM Path Coefficients and Hypotheses Tests

Hypothesis	Path	β	SE	t-value	p-value	Decision
H_{11}: AI → Fraud-Detection Accuracy	AI Deployment → Fraud Accuracy	.45	.08	5.63	< .001	Supported
H_{12}: AI → Compliance Timeliness	AI Deployment → Compliance Time	.39	.07	4.98	< .001	Supported
H_{13}: AI → NPL Forecasting Precision	AI Deployment → NPL Precision	.32	.09	3.56	.0004	Supported

Source: Author's computation using AMOS 27 (2025)

influenced factor-analytic results. Although CFA indicated acceptable model fit, evolving data standards across MFBs could affect replicability. Ethical considerations, particularly around algorithmic bias and data privacy, were explored through survey items, but qualitative insights from in-depth interviews would enrich understanding of governance challenges. Notwithstanding these limitations, the study provides a rigorous, empirically grounded evaluation of AI's supervisory role in Nigeria's microfinance sector, offering a foundation for scalable suptech strategies.

CONCLUSION AND RECOMMENDATION

Conclusion

This study set out to examine the influence of artificial intelligence (AI) on the supervision of National Microfinance Banks (MFBs) in Nigeria, focusing on fraud-detection accuracy, compliance timeliness, and non-performing loan (NPL) forecasting precision. Survey responses from 150 supervisory stakeholders, complemented by secondary performance data from the Central Bank of Nigeria (CBN) and the Nigeria Deposit Insurance Corporation (NDIC), provided empirical evidence for three key findings.

First, AI deployment - encompassing data analytics capability, real-time monitoring, anomaly-detection algorithms, and automated reporting - demonstrated a statistically significant positive relationship with fraud-detection accuracy ($\beta = .45$, $p < .001$). This result confirms that machine-learning classifiers and pattern-recognition tools enhance the identification of suspicious activities beyond the capabilities of traditional rule-based checks (Katata, 2021; World Economic Forum, 2021).

Second, a substantial improvement in compliance timeliness emerged ($\beta = .39$, $p < .001$), indicating that automated workflows and real-time dashboards reduce the lag between regulatory breach occurrence and supervisory intervention. Such efficiencies align with international suptech case studies where on-demand reporting and AI-driven exception monitoring have shortened inspection cycles by up to 40 percent (BIS FSI, 2024; Spaggiari & Carlyle, 2023).

Third, AI-enabled predictive models yielded moderate gains in NPL forecasting precision ($\beta = .32$, $p = .0004$), reflecting the capacity of supervised learning algorithms to anticipate portfolio risk several months in advance (Wang et al., 2022). Although this coefficient is smaller than those for fraud detection and compliance, it nonetheless signals a meaningful enhancement over static stress-testing approaches.

Moderation analysis revealed that organizational readiness—captured through IT infrastructure maturity and management support - amplified AI's effects on supervisory outcomes. Regulators and MFBs exhibiting high readiness achieved stronger performance gains, underscoring the Technology-Organization-Environment (TOE) framework's assertion that internal capacities shape technology benefits (Hoque et al., 2022; Li & Liu, 2021).

Limitations of the cross-sectional survey design and reliance on self-reported data suggest caution in over generalizing findings. Future research employing longitudinal methods and objective performance metrics would strengthen causal inferences. Nevertheless, this study furnishes sector-specific evidence supporting AI's role in reinforcing microfinance supervision and addresses a literature gap concerning emerging-market suptech applications (Oladele & Banjo, 2019; BIS FSI, 2024).

Suggestions

Policy and Regulatory Frameworks: National supervisory authorities should formalize a phased suptech roadmap that integrates AI tools into existing oversight processes. Initial steps ought to include piloting machine-learning fraud-detection modules in sandbox environments, accompanied by clear guidelines on data privacy and cybersecurity standards. Regulatory sandboxes must allow for controlled experimentation with anomaly-detection algorithms, while ensuring compliance with the Nigerian Data Protection Regulation (NDPR, 2019).

ii. Capacity Building and Organizational Readiness

Investment in staff training emerges as a critical enabler: both supervisory personnel and MFB technology teams require competency development in data science, machine-learning interpretation, and AI-governance ethics. Partnerships with academic institutions and fintech incubators can deliver tailored certificate programs and hands-on workshops. Moreover, MFBs should prioritize upgrading IT infrastructures—cloud platforms, secure data warehouses, and high-bandwidth connectivity—to support real-time analytics.

Data Governance and Quality Assurance: Instituting a centralized data-governance unit within the CBN or NDIC would standardize data-collection protocols across National MFBs, reducing inconsistencies and facilitating reliable model training. This unit should develop metadata standards, access-control policies, and audit trails for AI systems, in line with OECD (2022) Principles on AI and industry best practices. Regular data-quality assessments and cross-institutional data-sharing frameworks will underpin robust AI performance.

Ethical Oversight and Bias Mitigation: Establishment of an AI Ethics Committee - comprising representatives from the CBN, NDIC, MFBs, and civil-society organizations - can guide algorithmic fairness reviews. Periodic audits should assess model bias, particularly concerning demographic or regional disparities in fraud-detection outcomes (Gonzales & Ahmed, 2021). Adoption of explainable AI techniques will enhance transparency and stakeholder trust in suptech decisions.

Cost-Benefit Analysis and Resource Allocation: Given concerns about high initial investments (CCAF, 2024), a cost-benefit framework should be developed to quantify operational savings, risk-reduction dividends, and depositor-confidence gains attributable to AI adoption. This framework can inform budget allocations for both supervisory authorities and MFBs, ensuring that resources are channeled to high-impact suptech components. Collaborative funding models—such as cost-sharing agreements or donor-supported pilots—can alleviate financial barriers for smaller institutions.

Future Research and Continuous Improvement: Longitudinal studies tracking suptech rollouts over multiple years will yield insights into AI maturity curves and sustained performance effects. Comparative analyses across MFB tiers (National, State, Unit) can reveal context-specific adoption patterns and tailor recommendations accordingly. Incorporation of qualitative methods, such as in-depth interviews and ethnographic observations, will deepen understanding of organizational dynamics and user-experience factors influencing suptech integration.

Stakeholder Engagement and Communication: Transparent dissemination of pilot results, workshops, and success stories will foster observability, a key element of Diffusion of Innovations theory (Rogers, 2003). Regular stakeholder forums - bringing together regulators, MFB executives, technology vendors, and consumer advocates - can facilitate dialogue on evolving suptech needs, ethical considerations, and regulatory updates. Effective communication strategies will build momentum for broader AI adoption. Implementation of these suggestions will require a coordinated, multi-stakeholder effort. Anchoring reforms in empirical evidence and international best practices will position Nigeria's microfinance sector at the forefront of suptech innovation, strengthening financial inclusion and systemic resilience.

REFERENCES

A2ii. (2022). *Annual SupTech readiness report*. Access to Insurance Initiative.

Almalki, A., Xu, X., & Ling, S. (2021). Technology–Organization–Environment framework in AI adoption: Evidence from financial institutions. *Journal of Financial Innovation, 7*(2), 45–63.

Armendáriz, B., & Morduch, J. (2010). *The economics of microfinance* (2nd ed.). MIT Press.

Bank for International Settlements. (2024). *FSI Insights No. 58: Peering through the hype – Assessing suptech tools' transition from pilot to production*. BIS.

Banking Supervision. (2019). *Bringing artificial intelligence to banking supervision*. European Central Bank.

BCB Working Paper. (2024). *The disciplining effect of bank supervision: Evidence from SupTech*. Central Bank of Brazil.

Cambridge SupTech Lab. (2023). *State of SupTech report 2023*. University of Cambridge.

CCAF. (2024). *The state of SupTech report 2022*. Cambridge Centre for Alternative Finance.

Central Bank of Nigeria. (2005). *Microfinance policy, regulatory and supervisory framework for Nigeria*. CBN.

Central Bank of Nigeria. (2021). *Guidelines on the use of technology in banking supervision*. CBN.

Central Bank of Nigeria. (2023). *Annual report and statement of accounts*. CBN.

Costello, A. B., & Osborne, J. W. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research & Evaluation, 10*(7), 1–9.

Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches* (4th ed.). Sage.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50.

Frontiers in AI. (2019). RegTech and SupTech risks. *Frontiers in Artificial Intelligence, 2*, Article 14.

George, D., & Mallery, P. (2019). *IBM SPSS statistics 26 step by step: A simple guide and reference*. Routledge.

García, M., Pérez, L., & Ramos, D. (2020). AI adoption in banks: A TOE perspective. *International Journal of Information Management, 50*, 502–517.

Gonzales, R., & Ahmed, S. (2021). Algorithmic bias in banking supervision: Implications for fairness. *Journal of Business Ethics, 168*, 789–805.

Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis* (2nd ed.). Guilford Press.

Hoque, M., Kalam, A., & Islam, S. (2022). Readiness of suptech in East African banking regulators. *African Journal of Information Systems, 14*(1), 22–39.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1–55.

International Monetary Fund. (2019). *Fintech and bank supervision: Opportunities and challenges*. IMF.

Katata, K. S. (2021). Artificial intelligence in risk management & financial stability: Overview & lessons for West African bank supervisors. *NDIC Quarterly, 36*(3–4), 115–134.

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement, 30*(3), 607–610.

Kshetri, N. (2018). The emerging role of big data and AI in finance. In *Big Data's Impact on IoT* (pp. 35–50). Springer.

Lee, J. (2020). Diffusion of SupTech innovations: A comparative study. *Journal of Financial Regulation and Compliance, 28*(4), 415–433.

Li, X., & Liu, Y. (2021). Organizational determinants of AI adoption: A TOE study in Chinese banks. *Information & Management, 58*(3), Article 103442.

MDPI. (2020). Machine learning applied to banking supervision: A literature review. *Risks, 9*(7), 136.

Ng, A. (2017). AI is the new electricity. Paper presented at the Stanford AI Online Conference.

National Assembly of Nigeria. (2020). *Banks and Other Financial Institutions Act, 2020*. National Assembly of Nigeria.

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

NDIC. (2022). *Annual report & statement of accounts*. NDIC.

Oladele, O., & Banjo, A. (2019). Technological innovation in Nigeria's microfinance sector. *African Journal of Business and Technology, 7*(2), 110–125.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903.

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Sanusi, L. S. (2011). *Microfinance policy: Financial inclusion and development*. CBN.

Saunders, M., Lewis, P., & Thornhill, A. (2016). *Research methods for business students* (7th ed.). Pearson.

Scott, W. R. (2014). *Institutions and organizations: Ideas, interests, and identities* (4th ed.). Sage.

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill-building approach* (7th ed.). Wiley.

Spaggiari, L., & Carlyle, M. (2023). Overcoming the SupTech pilot trap: Lessons from global regulators. *Journal of Financial Technology, 5*(1), 10–27.

Suerf. (2025). Technological innovation in bank supervision: How SupTech disciplines bank risk-taking. *SUERF Policy Brief, (105)*, 1–12.

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.

United Nations Conference on Trade and Development. (2020). *The role of fintech in financial inclusion*. UNCTAD.

World Bank. (2018). *The Global Findex database 2017: Measuring financial inclusion and the fintech revolution*. World Bank Publications.

World Bank. (2020). *The Global Findex Database 2017: Measuring financial inclusion and the fintech revolution*. World Bank Publications.

World Economic Forum. (2021). *Global SupTech Adoption Report*. WEF.

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