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Artificial Intelligence and the Future of Digital Banking in Nigeria: A Systematic Review of Emerging Opportunities and Associated Risks

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ABSTRACT

Artificial intelligence (AI) is increasingly embedded in digital banking, yet evidence concerning its actual adoption, operational value, and governance implications in Nigeria remains fragmented. This study provides a PRISMA 2020-guided systematic literature review to examine the emerging opportunities and associated risks of AI-enabled digital banking in Nigeria. Scopus, Web of Science, IEEE Xplore, and Google Scholar were searched for English-language publications issued between 2018 and 2026, supplemented by selected policy and organisational documents. From 3,583 identified records, 1,258 were screened, 236 full texts were assessed, and 89 records were retained. Evidence was appraised using source-sensitive criteria derived from the Mixed Methods Appraisal Tool, AMSTAR 2, and AACODS, and was synthesised through thematic, temporal, technology-use-case, and adoption-maturity analyses. The evidence indicates that AI adoption in Nigerian banking is accelerating but remains uneven and predominantly function-specific. Fraud detection, cybersecurity, customer-service automation, and predictive analytics show the clearest operational uptake, whereas explainable credit scoring, generative AI, and enterprise-wide integration remain emergent. Benefits relating to efficiency, financial inclusion, personalisation, and risk detection are inseparable from data-protection, bias, cybersecurity, model-risk, skills, and infrastructure constraints. The review contributes a Nigeria-specific socio-technical synthesis that links AI capabilities, institutional readiness, adoption maturity, and regulatory safeguards. Sustainable deployment requires privacy-by-design, model validation, human oversight, interoperable digital infrastructure, and coordinated supervision by banking, data-protection, and technology regulators.

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I. Introduction

Artificial intelligence (AI) is reshaping financial intermediation by enabling automated decision-making, real-time risk detection, personalised services, and data-intensive operational optimization. Machine learning, natural language processing, predictive analytics, and intelligent automation are now deployed across fraud detection, credit assessment, customer relationship management, compliance, and cybersecurity. Systematic evidence from the global banking literature associates these applications with improved service responsiveness, operational efficiency, and analytical capability [1], [2]. AI is therefore becoming not just an auxiliary technology but a strategic capability that can alter how banks create value, allocate risk, and compete in increasingly digital financial ecosystems.

Nigeria provides a particularly consequential setting for examining this transformation. The rapid expansion of mobile and internet banking, fintech platforms, electronic payments, digital identity systems, and open-banking arrangements has increased both the volume of machine-readable financial data and the demand for scalable digital services. Nigerian banks and fintech firms are consequently exploring AI-enabled fraud monitoring, chatbots, predictive analytics, customer segmentation, and automated credit assessment [3]-[6]. However, adoption occurs within an environment marked by uneven broadband and power infrastructure, fragmented data systems, limited specialist skills, high implementation costs, and evolving regulatory requirements [7], [8]. These conditions make direct transfer of conclusions from advanced banking markets analytically inadequate.

The existing scholarship is fragmented in three important respects. First, studies frequently examine isolated benefits, such as fraud detection or customer service, without relating those benefits to the privacy, fairness, cybersecurity, and model-risk exposures created by the same data-intensive systems. Second, much of the Nigerian evidence is conceptual, cross-sectional, or based on adoption intentions rather than verified institution-level deployment and longitudinal performance. Third, available reviews are predominantly global or cross-country and do not integrate AI technologies, banking use cases, adoption maturity, institutional type, infrastructure readiness, and Nigeria-specific regulatory conditions within a single analytical framework. As a result, claims that AI is transforming Nigerian banking often exceed the strength of the available empirical evidence.

This review addresses that gap by moving beyond a descriptive inventory of opportunities and risks. Its novelty lies in four interrelated contributions: a PRISMA-guided and reproducible evidence-selection process; a source-sensitive quality appraisal; a temporal and adoption-maturity analysis of developments between 2018 and 2026; and a technology-use-case synthesis that distinguishes operationally documented applications from aspirational or early-stage innovations. The review also connects technical implementation to Nigeria's data-protection, open-banking, cybersecurity, and national AI-policy environment, thereby positioning AI adoption as a socio-technical and governance problem rather than a purely technological one.

Accordingly, the study addresses four questions: Research Question (RQ)1, which AI technologies, models, and banking use cases are reported in the literature, and what level of adoption maturity is documented in Nigeria? RQ2, what operational, customer, inclusion, and risk-management opportunities are associated with these applications? RQ3, what technical, ethical, infrastructural, organisational, and regulatory risks constrain responsible deployment? RQ4, how has the evidence evolved, and what research and policy priorities follow from the identified methodological and implementation gaps?

II. Conceptual And Theoretical Foundations

Artificial intelligence (AI) refers to computational systems that perform learning, classification, prediction, language processing, perception, or decision-support tasks that would otherwise require human cognition. In banking, machine learning and deep learning support fraud detection, credit scoring, behavioural analytics, and cybersecurity; natural language processing supports chatbots, document intelligence, and customer interaction; and robotic process automation combines rules and AI components to automate repetitive workflows [3], [9]. Digital banking, by contrast, concerns the delivery and management of financial services through mobile, internet, platform, and automated channels [10], [11]. AI-driven digital banking, therefore, denotes the integration of algorithmic intelligence into digital financial-service delivery, decision-making, monitoring, and governance.

The technological landscape is heterogeneous. Predictive models estimate default, churn, fraud, or customer propensity; anomaly-detection systems identify transactions that depart from expected behaviour; recommender systems personalise products; computer-vision and biometric systems support identity verification; and generative AI systems increasingly assist customer service, knowledge retrieval, and employee decision support [12]-[14]. These applications differ materially in data intensity, explainability, latency requirements, operational criticality, and regulatory exposure. Treating "AI adoption" as a single binary phenomenon, therefore, conceals important differences between a pilot chatbot, a production fraud-detection model, and enterprise-wide algorithmic decision infrastructure.

The review combines the Technology Acceptance Model, Diffusion of Innovation theory, and the Resource-Based View. TAM explains how perceived usefulness, ease of use, and trust shape customer and employee acceptance [15], [16]. Diffusion theory directs attention to relative advantage, compatibility, complexity, trialability, and observability as determinants of organisational adoption [17], [18]. The Resource-Based View explains why data assets, technical expertise, governance routines, and digital infrastructure can become difficult-to-imitate organisational capabilities [19]. Together, these perspectives imply that AI value depends on the alignment of user acceptance, institutional readiness, and deployable technological resources.

To operationalize this integrated perspective, the review distinguishes four adoption-maturity levels: conceptual or planned use; pilot or experimental use; function-specific operational deployment; and enterprise-wide integration. It further treats governance, data quality, infrastructure, skills, and inter-organisational collaboration as conditions that moderate the relationship between AI capability and banking outcomes. This framework enables the review to assess not only what AI might achieve, but also whether the literature demonstrates implementation, under what conditions, and with what distributional and regulatory consequences.

The resulting analytical lens is deliberately dual: the same capabilities that improve personalisation, inclusion, and fraud detection can intensify profiling, exclusion, cyber exposure, and opacity. The future of AI-enabled banking in Nigeria, therefore, depends on whether innovation is accompanied by institutionally credible safeguards, human accountability, and infrastructure that supports reliable and equitable access.

III. Methodology

A. Review Design and Research Questions

The study used a systematic literature review design and was reported in accordance with PRISMA 2020 [20], [21]. A review protocol specified the research questions, information sources, search terms, eligibility criteria, screening stages, quality appraisal, extraction fields, and synthesis procedures before the final analysis. The protocol was designed to capture both Nigeria-specific evidence and carefully selected emerging-market or global studies with direct conceptual, technological, or regulatory relevance to Nigerian digital banking.

B. Search Strategy and Information Sources

Scopus, Web of Science Core Collection, IEEE Xplore, and Google Scholar were searched for publications issued from 2018 to 2026. Searches were conducted in titles, abstracts, keywords, and equivalent metadata fields. The principal Boolean string was: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "natural language processing" OR "predictive analytics" OR "chatbot" OR "robotic process automation") AND ("digital banking" OR "bank" OR "fintech" OR "financial services") AND ("Nigeria" OR "Nigerian") AND ("adoption" OR "opportunity" OR "benefit" OR "risk" OR "challenge" OR "governance" OR "regulation"). A broader supplementary query replaced the Nigeria term with ("Africa" OR "emerging economy") to identify transferable evidence where Nigerian research was limited. Relevant books and conference proceedings, and authoritative documents from Nigerian regulatory and policy institutions were also examined. Google Scholar served as a supplementary discovery and citation-chaining source rather than the sole basis for inclusion. The search process followed the recommendations of Xiao and Watson [22], ensuring comprehensive coverage and reducing the possibility of publication omission. Studies have emphasized that the use of multiple databases and carefully designed search strings significantly improves the reliability and comprehensiveness of systematic reviews [23], [24].

C. Eligibility Criteria and Study Selection

Records were eligible when they were written in English; addressed AI or an identifiable AI technique in banking, fintech, or digital financial services; examined adoption, implementation, outcomes, risks, governance, or regulation; and provided empirical, conceptual, technical, or policy evidence relevant to Nigeria or a comparable emerging-market setting. Eligible sources comprised peer-reviewed journal articles, full conference papers, scholarly books or chapters, and authoritative organisational or policy reports. Editorials, news items, marketing material, dissertations, book reviews, non-substantive abstracts, inaccessible full texts, duplicate versions, and studies without a clear banking or financial services application were excluded.

Seminal pre-2018 theoretical and methodological works were used only to frame the review and were not counted in the 87-record analytical corpus. The search identified 3,245 database records and 338 additional records, yielding 3,583 records. Removal of 2,325 duplicates left 1,258 records for title, author, and abstract screening. Of these, 1,022 were excluded as outside the review scope, and 236 full texts were assessed. A further 149 full texts were excluded because they lacked a substantive AI-banking focus, did not provide usable evidence, were not sufficiently relevant to Nigeria or comparable emerging markets, or duplicated a more complete publication. The final analytical corpus comprised 87 records, including 62 journal articles, 2 conference proceedings, 10 book chapters,5 books, and 8 scholarly organisational reports. Screening and deduplication were supported by "The Evidence Review Accelerator (TERA)" tool, with final eligibility decisions based on the predefined criteria.

The study's PRISMA flow, which illustrates a rigorous and transparent study selection process following PRISMA 2020 guidelines, is shown in Figure 1.

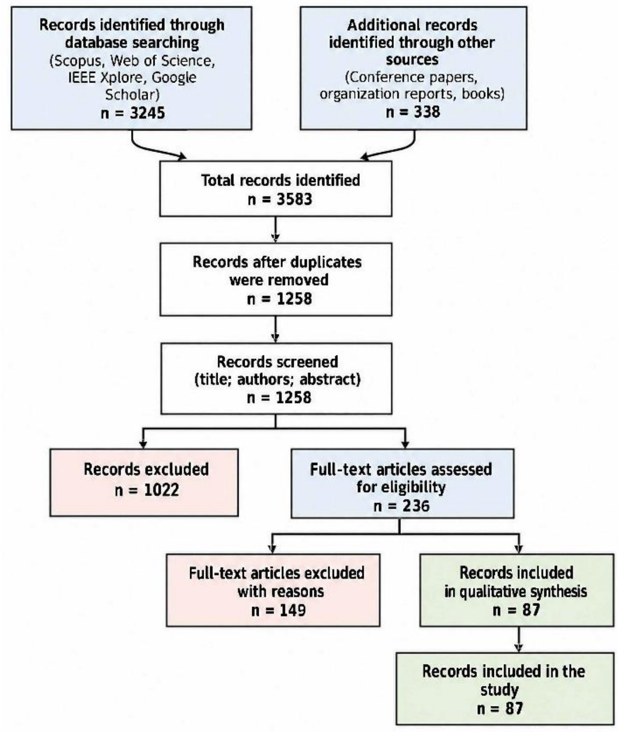

Figure 1: The Study's PRISMA Flow

D. Quality Appraisal and Risk of Bias

Because the corpus contained heterogeneous evidence, quality appraisal was source-sensitive. Empirical qualitative, quantitative, and mixed-methods studies were assessed using design-appropriate criteria from the Mixed Methods Appraisal Tool (MMAT) [25]. Systematic and structured reviews were assessed using relevant AMSTAR 2 domains, including protocol transparency, search adequacy, study selection, appraisal, and synthesis [26]. Organisational and policy documents were assessed with the AACODS criteria of authority, accuracy, coverage, objectivity, date, and significance [27]. Books and conceptual chapters were evaluated for scholarly authority, evidential transparency, analytical coherence, currency, and relevance. Ratings were recorded as met, partially met, or not met and were used to classify evidential confidence rather than to generate a misleading single percentage score. High- and moderate-confidence evidence was prioritised; lower-confidence material was retained only for contextual triangulation and was not used as the sole basis for claims about adoption or impact.

E. Data Extraction and Synthesis

A structured extraction matrix captured publication year, geographical setting, source, and study type, banking-institution category, research design, data source, AI technology or model, banking use case, adoption-maturity level, reported benefits, implementation barriers, risks, governance implications, and quality classification. The analysis combined descriptive profiling with four complementary forms of synthesis: thematic synthesis of opportunities and risks; temporal analysis of research and adoption developments; technology-use-case mapping; and comparative analysis by institution type and adoption maturity. Because designs, outcomes, and units of analysis were highly heterogeneous, statistical meta-analysis was neither appropriate nor attempted [28].

Figure 2 summarises the evolution identified in the corpus. The trajectory is not interpreted as evidence of uniform sector-wide deployment; rather, it shows a shift from foundational digitalisation and adoption discourse toward function-specific AI use and, more recently, explainability, generative AI, data governance, and regulatory oversight.

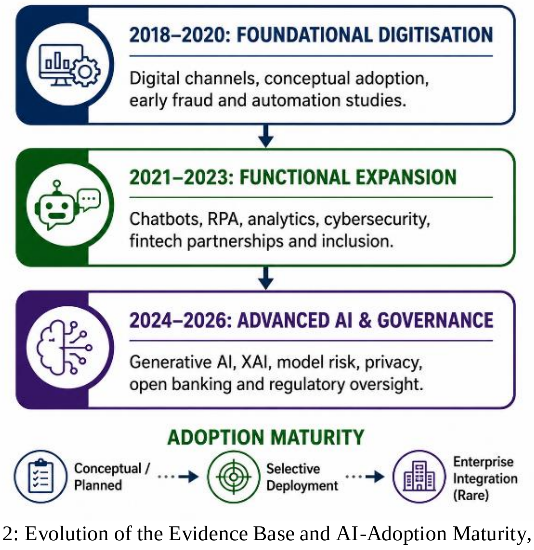

Figure 2: Evolution of the Evidence Base and AI-Adoption Maturity, 2018–2026

Potential publication and review biases were addressed explicitly. Positive or innovation-oriented findings may be more likely to be published than failed implementations, while banks may withhold commercially sensitive deployment and incident data. English-language and database restrictions may underrepresent local professional evidence, and organisational reports may reflect institutional interests. Mitigation measures included multi-database searching, citation chaining, inclusion of authoritative grey literature, source-sensitive appraisal, and triangulation of major claims across independent sources. In the discussion and recommendations, recurrent conclusions in the corpus are distinguished from interpretive proposals developed by the author.

IV. FINDINGS

A. Evidence Profile, Temporal Development, and Adoption Maturity

The 87-record corpus depicts a rapidly expanding but methodologically uneven field. Research published before 2021 largely framed AI as an extension of digital banking, automation, and fintech innovation. Between 2021 and 2023, attention shifted toward chatbots, robotic process automation, predictive analytics, cybersecurity, and financial inclusion. From 2024 onward, the literature expanded sharply and increasingly addressed generative AI, explainability, model risk, privacy, responsible AI, and algorithmic governance [1]-[4], [12], [14]. This evolution indicates growing analytical sophistication, but it also creates a recency bias: many claims concern expected capabilities rather than outcomes observed over sustained deployment.

Geographically, Nigerian studies remain fewer and less technically detailed than global and cross-country studies. Nigeria-specific evidence is concentrated in cross-sectional surveys, conceptual reviews, selected bank or fintech cases, and studies of adoption determinants [29]-[34]. Longitudinal comparisons, independent model benchmarking, deployment audits, and causal evaluations are rare. Consequently, the literature provides stronger evidence that Nigerian institutions are experimenting with or selectively deploying AI than that AI has already produced sector-wide performance transformation.

Adoption maturity varies by function and institutional capacity. Fraud detection, transaction monitoring, cybersecurity, and customer-service automation display the clearest evidence of operational use, particularly among large deposit money banks and digitally native fintech firms [31], [33]-[35]. Credit scoring, customer personalisation, and predictive decision support appear more selective, while explainable AI, generative AI, and enterprise-wide model orchestration remain predominantly emergent. Smaller banks, microfinance institutions, and payment service banks are underrepresented, and their adoption is more likely to depend on cloud services, vendors, or fintech partnerships than on internally developed AI capability.

The quality appraisal reinforces this cautious interpretation. The strongest sources specify samples, data, methods, and limitations, whereas a substantial portion of the Nigeria-focused literature reports perceptions, intentions, or broad technology categories without model architecture, training data, validation procedures, error costs, fairness tests, or post-deployment monitoring. Authoritative policy documents provide high contextual relevance but do not establish operational effectiveness. The evidence base should therefore be characterised as expanding and strategically important, but not yet mature enough to support unqualified claims of widespread transformation.

B. AI Technologies and Implementation Patterns

Fraud detection and anti-money-laundering applications constitute the most technically developed use case. The broader banking literature reports logistic regression, decision trees, random forests, support vector machines, gradient-boosting methods, neural networks, autoencoders, isolation-based anomaly detection, and increasingly graph-based analytics. These models analyse transaction velocity, location, device, merchant, behavioural, and network features to identify suspicious patterns in near real time [33], [36]-[38]. Nigerian evidence confirms institutional interest and selective deployment, but rarely reports class-imbalance handling, calibration, false-positive costs, concept drift, adversarial robustness, or independent production performance.

Credit scoring and customer analytics rely primarily on logistic and tree-based models, random forests, gradient boosting, neural networks, clustering, churn and propensity models, and recommender systems. Alternative data can extend assessment to customers and small firms without conventional credit histories, thereby supporting inclusion [39]-[42]. However, the same data can encode historical disadvantage, proxy sensitive attributes, or produce opaque adverse decisions. Explainability methods such as SHAP and LIME are consequently relevant to feature attribution, audit, and customer recourse, but their use in Nigerian operational studies remains insufficiently documented [43]-[45].

Customer-service applications include intent-classification systems, retrieval-based chatbots, recurrent and transformer-based language models, speech interfaces, and emerging generative-AI assistants. These systems can provide continuous service, route queries, support multilingual interaction, and reduce pressure on call centres [35], [46]. Yet implementation quality depends on local-language coverage, knowledge-based accuracy, privacy controls, hallucination management, and effective escalation to human agents. The literature more often reports availability and perceived convenience than response accuracy, resolution quality, customer harm, or comparative cost-effectiveness.

Back-office automation combines robotic process automation, optical character recognition, rules engines, and machine learning for onboarding, know-your-customer checks, document processing, reconciliation, compliance reporting, and workflow management [47]-[49]. These applications are comparatively feasible because the tasks are structured, but integration with legacy core banking systems, fragmented data ownership, auditability, vendor dependence, and workforce redesign remain major constraints. Across use cases, the central technical gap is therefore not awareness of AI tools but limited reporting of data provenance, model development, validation, deployment architecture, monitoring, and governance.

Table 2 consolidates the principal model families and implementation gaps. It distinguishes techniques commonly reported in the international banking literature from the more limited evidence of operational deployment in Nigeria, thereby avoiding the assumption that technical availability is equivalent to sector-wide adoption.

C. Opportunities and Socio-Economic Value

The clearest opportunity is a more responsive and personalised service. Predictive analytics, recommendation systems, and conversational interfaces can reduce service latency, identify customer needs, and support continuous digital engagement [34], [35], [39]. Their value is greatest when embedded in coherent customer journeys rather than deployed as isolated front-end features. Poor data integration or weak human escalation can instead transfer operational friction to customers and erode trust.

AI can also improve efficiency through process automation, exception prioritisation, real-time monitoring, and decision support [29], [47]-[49]. In principle, these capabilities reduce repetitive work and allow skilled employees to focus on judgement-intensive tasks. However, the evidence does not support a simple technology-to-profit relationship. Benefits depend on data quality, process redesign, interoperability, employee capability, and the capacity to monitor models after deployment.

For financial inclusion, alternative-data credit assessment, lower-cost digital channels, identity technologies, and automated support can extend services to underserved customers, women, rural communities, and small enterprises [40]-[42], [50], [51]. The inclusion effect is conditional rather than automatic. Customers without reliable connectivity, formal digital identities, appropriate devices, or adequate digital literacy may remain excluded, while biased models can reproduce disadvantage at greater speed and scale.

Fraud and cybersecurity analytics also offer a further source of value by identifying anomalous behaviour earlier than manual systems and by directing investigative resources toward high-risk events [36]-[38]. Their effectiveness, however, depends on continually updated data, incident intelligence, adversarial testing, and coordination across banks, payment networks, fintech firms, telecommunications providers, and regulators.

Therefore, the opportunities are mutually reinforcing: better data and analytics can improve service, inclusion, risk detection, and innovation. They are also mutually constraining because the data intensity and automation that produce value simultaneously increase privacy risks, discrimination risks, cybersecurity risks, and operational dependencies.

D. Risks, Implementation Barriers, and Governance Readiness

Algorithmic bias and opacity are particularly consequential in credit scoring, fraud detection, customer segmentation, and identity verification. Unrepresentative training data, proxy variables, label bias, and unequal error rates can disadvantage already underserved groups [43], [44]. Black-box models further complicate adverse-action explanations, internal challenge, regulatory audit, and customer appeal. Responsible deployment, therefore, requires fairness testing across relevant customer groups, interpretable decision pathways, documented human review, and mechanisms for correction.

Data privacy and cybersecurity constitute a second cluster of risks. AI systems aggregate detailed transactional, behavioural, device, identity, and communication data, increasing the consequences of weak access controls, unauthorised secondary use, vendor exposure, and cross-border processing [52]-[56]. AI can strengthen threat detection, but it can also be exploited for deepfake fraud, adaptive phishing, adversarial manipulation, and automated attack scaling. Model security, data security, and conventional cyber resilience must therefore be managed as an integrated control problem.

Implementation barriers are strongly institutional. Unreliable electricity and connectivity, fragmented legacy systems, weak data standards, a shortage of AI and model-risk specialists, high acquisition and maintenance costs, and dependence on third-party platforms constrain scale [8], [57]-[59]. These barriers are more acute for smaller institutions and can concentrate AI capability among large banks and technology vendors, creating competitive and systemic dependencies.

Nigeria's regulatory architecture is developing but remains distributed across multiple instruments and agencies. The Nigeria Data Protection Act 2023 establishes the principal legal basis for lawful processing, data-subject rights, accountability, and the functions of the Nigeria Data Protection Commission [60]. The National Artificial Intelligence Strategy provides a broader national direction for responsible AI capability, innovation, and governance [61]. Within financial services, the Central Bank of Nigeria's Operational Guidelines for Open Banking specify responsibilities for data sharing and ecosystem participation [62], while the 2024 Risk-Based Cybersecurity Framework for deposit money banks and payment service banks strengthens sector-specific cyber governance [63]. Regulatory sandbox arrangements also provide a controlled pathway for testing innovative financial services [64].

These instruments are necessary but do not yet constitute a unified banking-specific AI governance regime. The literature repeatedly supports privacy, cybersecurity, transparency, accountability, human oversight, and model validation [65]-[78]. Building on that recurrent evidence, this review interprets the Nigerian policy gap as the need for an integrated model-risk framework covering AI inventories, risk classification, data lineage, validation independence, explainability, fairness, continuous monitoring, third-party assurance, incident reporting, and customer redress. This integrated framework is an author-derived synthesis of the reviewed evidence and current policy environment, not a claim that all included studies proposed the same institutional design.

V. Discussion

A. *Evidence Maturity and Evolution of the Field*

The central finding is that AI adoption in Nigerian digital banking is real but selective, uneven, and less empirically mature than the rhetoric of transformation suggests. The literature has progressed from broad digital-transformation narratives to more specific applications and governance concerns, yet many studies still measure perceptions of usefulness, readiness, or intention rather than verified deployment outcomes. This distinction matters because adoption intention, pilot activity, and production integration imply different levels of organisational capability and risk.

Methodologically, conceptual reviews, cross-sectional surveys, and case-based studies dominate. These designs are useful for identifying themes and adoption factors but provide limited evidence about causality, durability, error rates, customer welfare, or return on investment. Proprietary restrictions on bank data partly explain the scarcity of model-level studies, but the result is a recurrent evidence gap: broad claims about improved fraud detection, inclusion, or efficiency are rarely connected to reproducible technical metrics or long-term operational performance.

Table 1 summarizes the evidential pattern and its implications. It shows that the field is moving toward governance and explainability, but the empirical base remains concentrated in large banks, fintech firms, and high-visibility applications. Microfinance institutions, payment service banks, rural users, older customers, people with disabilities, and customers using low-resource Nigerian languages remain insufficiently represented.

TABLE 1.
EVIDENCE PROFILE, METHODOLOGICAL MATURITY, AND PRINCIPAL RESEARCH GAPS

Analytical Dimension	Pattern in the 87-Record Corpus	Confidence or Limitation	Interpretation
Temporal development	Sparse early evidence; marked expansion from 2024 to 2026	Recency and publication-lag effects	Rapidly expanding field, but many claims remain prospective
Geographical focus	Nigeria-specific studies supplemented by global and emerging-market evidence	Limited operational data from Nigerian banks	Contextual transfer must be explicit and cautious

Analytical Dimension	Pattern in the 87-Record Corpus	Confidence or Limitation	Interpretation
Research methods	Conceptual reviews, cross-sectional surveys, and case studies dominate	Few longitudinal, causal, or independent benchmarking studies	Impact and adoption claims remain provisional
Institutional coverage	Large deposit money banks and fintech firms receive most attention	Smaller banks, microfinance, and payment service banks are underrepresented	Sector-wide generalisation is limited
Adoption maturity	Functional use in fraud, cybersecurity, and customer service; enterprise integration rarely documented	Potential and intention are often reported as adoption	Adoption is selective rather than uniform
Technical reporting	Model labels are common; data, validation, calibration, and monitoring details are scarce	Weak reproducibility and comparability	Model-level reporting standards are required
Quality and bias	Peer-reviewed empirical evidence is weighted above contextual and grey sources	Positive results, language, and sponsor bias remain possible	Major claims require triangulation across source types

B. Technology–Use Case Relationships

The technology-use-case analysis demonstrates that model choice is inseparable from institutional purpose and risk. Fraud detection favours high-recall, low-latency anomaly and classification systems, but false positives can disrupt legitimate customers. Credit models can widen access through alternative data, but fairness, consent, and adverse-action explanation are central. Chatbots reduce service costs, but language limitations and hallucinations create customer-protection concerns. Robotic Process Automation (RPA) improves throughput, but brittle integration with legacy systems can shift rather than eliminate operational risk.

The review, therefore, rejects a technology-determinist interpretation. AI does not produce value independently of organisational processes, data governance, infrastructure, employee capability, or supervisory expectations. The most credible pathway is incremental and risk-based: institutions should begin with clearly bounded use cases, define measurable service and risk outcomes, validate models independently, monitor performance and distributional effects, and scale only when controls and infrastructure are demonstrably adequate.

Figure 3 presents a socio-technical framework for understanding AI adoption within Nigeria's digital banking ecosystem. It maps the interactions among core AI capabilities, their application across banking functions, the opportunities they create, and the risks they introduce. The framework further shows how institutional quality, regulatory capacity, digital infrastructure, organisational readiness, and public trust moderate these relationships and ultimately shape the extent to which AI adoption produces inclusive, resilient, efficient, and sustainable banking outcomes.

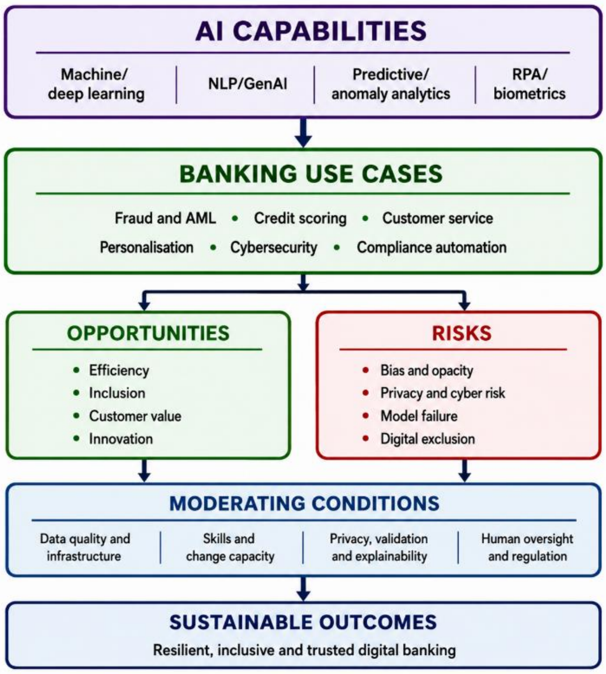

Figure 3: Socio-Technical Synthesis of AI Adoption in Nigeria's Digital Banking Ecosystem

C. Opportunity–Risk Interdependence and Institutional Differentiation

The opportunities and risks identified in the review are structurally interconnected. Personalisation depends on extensive profiling; inclusion through alternative data can create new forms of discriminatory exclusion; real-time fraud detection can increase resilience while creating false-positive and surveillance risks; and automation can reduce cost while intensifying technology dependence and skills displacement. The appropriate analytical question is therefore not whether AI is beneficial or risky in the abstract, but which use case, model, institution, customer group, and governance arrangement produces an acceptable distribution of benefits and harms.

Institutional differences are equally important. Large banks are better positioned to finance cloud infrastructure, data engineering, cybersecurity, validation, and specialist teams. Smaller institutions may obtain rapid capability through vendor platforms but face greater concentration, lock-in, explainability, and third-party-risk concerns. Fintech firms can innovate quickly and reach underserved customers, yet may operate with shorter data histories and less mature governance. Regulation should therefore be proportionate to use-case risk while maintaining consistent minimum requirements for privacy, security, fairness, auditability, and customer redress.

The integrated framework in Figure 3 captures this conditional relationship. AI capabilities influence banking outcomes through specific use cases, but the direction and sustainability of those outcomes are moderated by data and infrastructure readiness, governance safeguards, institutional capability, and policy coordination. This socio-technical explanation extends technology-acceptance and resource-based accounts by placing risk governance and inclusion within the causal pathway from adoption to value.

TABLE 2.
AI MODELS, BANKING USE CASES, ADOPTION MATURITY, AND IMPLEMENTATION GAPS

Banking Use Case	Common Models or Architectures	Reported Nigerian Adoption	Principal Technical and Governance Gaps
Fraud detection and AML	Logistic regression; decision trees/random forests; SVM; gradient boosting; neural networks; autoencoders; anomaly and graph analytics	Strongest evidence of function-specific operational use	Class imbalance; false positives; drift; adversarial attacks; explainability
Credit scoring and risk	Logistic and tree-based models; random forests; XGBoost/GBM; neural networks; alternative-data features; SHAP/LIME	Emerging and selective, particularly in fintech and SME lending	Representativeness; fairness; consent; adverse-action explanation; validation
Chatbots and service	Intent classifiers; retrieval systems; RNN/LSTM; transformers; generative language models	Visible deployment for routine enquiries and 24/7 support	Local-language coverage; hallucination; privacy; human escalation; service-quality metrics
Customer analytics	Clustering; churn and propensity models; recommender systems; sentiment/NLP analytics	Selective, with greater uptake in large banks	Profiling; data silos; consent; feedback loops; limited independent evaluation
Cybersecurity and identity	Anomaly detection; biometric matching; deep learning; behavioural analytics; adversarial ML	Growing strategic priority	Spoofing and deepfakes; model attack surfaces; incident response; vendor risk
Process automation and compliance	RPA; OCR; NLP; rules-plus-ML systems; RegTech analytics	Moderate back-office and onboarding use	Legacy integration; auditability; brittle workflows; workforce redesign
Enterprise decision support	Predictive analytics; optimisation; GenAI copilots; integrated model platforms	Nascent or pilot-stage evidence	Model inventory; accountability; data lineage; continuous monitoring; concentration risk

VI. IMPLICATIONS FOR THEORY, PRACTICE, AND POLICY

A. Theoretical Implications

The findings refine TAM, Diffusion of Innovation, and the Resource-Based View by showing that perceived usefulness and technological advantage do not adequately explain AI adoption in a regulated, infrastructure-constrained financial system. Institutional quality, data governance, model-risk capability, infrastructure reliability, and customer protection determine whether technological resources become sustainable banking capabilities [79]-[81]. Adoption should therefore be modelled as a staged socio-technical process rather than a binary organisational decision.

The review also contributes an opportunity-risk duality: value creation and risk exposure arise from the same mechanisms. Data intensity supports personalisation and detection but increases privacy and bias risks; automation improves efficiency but increases operational dependence; and alternative data can widen inclusion while enabling opaque exclusion. Future theory should explicitly incorporate governance and distributional outcomes into explanations of AI-enabled digital transformation.

B. Managerial and Technical Implications

Bank executives should use AI as a portfolio of risk-classified use cases rather than a broad digital-transformation effort. Each application needs a stated business objective, accountable owner, data lineage, model card, validation standard, performance and fairness metrics, human-oversight protocol, incident procedure, and retirement criteria. For high-impact applications such as credit decisions, fraud blocking, and identity verification, more independent validation and customer-redress methods are required than for low-risk staff productivity solutions [82], [83].

Implementation goals include: interoperable data architecture; robust cloud and connectivity arrangements; cybersecurity-by-design; legacy-system integration; and workforce competency in data engineering; model validation; AI audit; privacy; and operational risk. Vendor contracts should include audit rights, data-location clarity, service-continuity promises, model-change notification, and departure arrangements. Reskilling and job redesign are crucial as sustained automation relies on employees who can oversee, challenge, and enhance algorithmic systems [84].

C. Policy and Regulatory Implications

The recurring evidence across the reviewed studies supports six regulatory priorities: data protection, cybersecurity, transparency, fairness, human oversight, and accountable model governance [65]-[78]. These priorities should be implemented through coordinated supervision rather than a proliferation of disconnected compliance requirements. CBN, NDPC, NITDA/NCAIR, the Securities and Exchange Commission, and other relevant authorities require clear role allocation and information-sharing protocols for AI-enabled financial services.

The authors' policy synthesis is that Nigeria should develop sector-specific guidance that aligns the Data Protection Act, National AI Strategy, Open Banking Guidelines, cybersecurity framework, and sandbox regime [60]-[64]. The guidance should establish risk tiers for AI use cases; minimum requirements for model inventories, impact assessments, validation, explainability, fairness, and monitoring; third-party and cloud assurance; reporting of material model incidents; and enforceable customer rights to information, human review, and complaint resolution. Regulatory sandboxes should evaluate not only product innovation but also data governance, inclusion, and post-pilot control readiness.

D. Infrastructure, Inclusion, and Institutional Implications

Policy support must extend beyond formal regulation to digital infrastructure readiness. Reliable electricity and broadband, secure identity systems, interoperable payment and Application Programming Interface (API) standards, accessible cloud services, and sector-wide fraud-intelligence sharing are enabling conditions for safe AI adoption. Without these foundations, advanced models may increase service concentration in urban and higher-income markets and widen the digital divide [85]-[87].

Financial inclusion should be assessed through disaggregated outcomes rather than aggregate customer growth. Banks and fintech firms should test error rates, approval patterns, service accessibility, and complaint outcomes across gender, geography, income, disability, language, and device constraints. Human-assisted channels must remain available where fully automated services would exclude or disadvantage customers.

VII. LIMITATIONS AND FUTURE RESEARCH AGENDA

This review has several limitations that shape the interpretation of its findings and define priorities for future scholarship. Restricting the search to English-language publications and predominantly indexed databases may have excluded relevant locally produced, practitioner-oriented, and non-indexed evidence. Although Google Scholar broadened coverage, it also reduced search precision and reproducibility. The evidence base may further reflect publication bias, as successful or innovation-positive applications are more likely to be reported than failed deployments, cybersecurity incidents, discriminatory model outcomes, or commercially sensitive performance weaknesses. The inclusion of books, chapters, policy documents, and organisational reports strengthened contextual and regulatory coverage but introduced substantial heterogeneity and possible sponsor bias. These risks were reduced through source-sensitive appraisal and evidential weighting, but they could not be fully eliminated.

The included studies also varied considerably in research design, institutional setting, outcome specification, deployment stage, and level of technical disclosure. This heterogeneity precluded statistical meta-analysis and limited the possibility of estimating pooled causal effects of AI on bank performance, financial inclusion, operational resilience, or customer welfare. Much of the Nigerian evidence remains cross-sectional, conceptual, perception-based, or focused on proposed applications rather than independently evaluated production systems. Accordingly, the review can identify recurring patterns, adoption trajectories, governance concerns, and evidential gaps, but it cannot establish definitive causal relationships. The rapid evolution of generative AI, cybersecurity threats, model-governance practices, and financial regulation also means that the synthesis will require periodic updating.

Future reviews should strengthen transparency and reproducibility by publishing auditable search strategies, extraction matrices, quality-appraisal records, and source-classification procedures. Searches should extend to African and national databases, institutional repositories, regulatory archives, and relevant professional sources. Evidence should also be disaggregated by institution type, including deposit money banks, microfinance banks, payment service banks, fintech firms, and other digital financial-service providers, as well as by deployment stage, from experimentation and pilot testing to enterprise integration and post-deployment monitoring.

Primary research should move beyond cross-sectional adoption studies towards bank-level longitudinal, quasiexperimental, and comparative designs. Priority areas include model calibration and drift, fairness in alternative-data credit scoring, multilingual and low-resource-language conversational systems, adversarial robustness, human-AI decision quality, customer recourse, distributional outcomes, and the cost-effectiveness of governance controls [88]-[90]. Researchers should report data provenance, sample construction, model architecture, baseline comparators, validation procedures, uncertainty estimates, calibration, subgroup performance, explainability methods, operational context, and post-deployment monitoring. Secure research partnerships among banks, regulators, universities, and technology providers will be essential for enabling credible independent evaluation while protecting personal data, proprietary systems, and commercially sensitive information. Such collaboration would materially strengthen the evidence base for responsible, inclusive, and resilient AI adoption in Nigeria's digital banking ecosystem.

VIII. CONCLUSION

This systematic review demonstrates that artificial intelligence is beginning to reconfigure Nigeria's digital banking landscape, although the pace, depth, and evidential strength of adoption remain uneven. The most established applications are concentrated in fraud detection, cybersecurity, customer-service automation, and predictive analytics, where banks have clearer operational incentives and relatively mature implementation pathways. By contrast, AI-enabled credit scoring, personalised financial services, explainable AI, generative AI, and enterprise-wide integration remain selective, experimental, or weakly documented. The available evidence, therefore, supports a pattern of accelerating, function-specific adoption rather than a completed sector-wide transformation.

The review further shows that the benefits of AI are contingent rather than automatic. Improvements in operational efficiency, financial inclusion, customer experience, and risk detection depend on the quality and representativeness of data, the resilience of digital infrastructure, the availability of specialised skills, effective human oversight, and robust institutional governance. Nigeria's emerging regulatory architecture, including data protection, open banking, cybersecurity, regulatory sandbox, and national AI instruments, provides an important foundation for responsible adoption. However, significant gaps remain in banking-specific model-risk governance, algorithmic accountability, consumer redress, post-deployment monitoring, and coordination among financial, data-protection, cybersecurity, and competition authorities.

The principal contribution of this study is the development of a Nigeria-specific, evidence-weighted framework that connects AI capabilities and banking applications with adoption maturity, institutional conditions, operational risks, and regulatory safeguards. This framework moves the debate beyond technologically deterministic claims by showing that the developmental value of AI depends on how systems are designed, governed, validated, and embedded within existing banking institutions. It therefore provides a more rigorous basis for future research, regulatory intervention, organisational investment, and strategic decision-making aimed at building a digital banking ecosystem that is efficient, inclusive, resilient, transparent, and worthy of public trust.

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