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Artificial Intelligence (AI) and Credit Risk Assessment in Nigerian Banks: Evidence from Access Bank Plc

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Abstract

This study explores the role of artificial intelligence (AI) in transforming credit risk assessment within Nigerian banks, using Access Bank Plc as a case study. Traditional credit evaluation methods in Nigeria often rely on limited financial records and subjective judgment, which restrict access to credit and increase the risk of default. This research examines how AI-driven models, particularly machine learning techniques, improve predictive accuracy, enhance decision-making speed, and support financial inclusion.

Adopting a mixed-method approach, the study combines survey data, interviews, and analytical insights to assess the effectiveness of AI adoption in credit risk management. The findings reveal that AI significantly improves the accuracy of default prediction and reduces operational inefficiencies. However, its effectiveness is strongly influenced by data quality, institutional readiness, regulatory clarity, and governance frameworks. The study concludes that while AI presents a transformative opportunity for Nigerian banks, its successful implementation requires a balanced approach that integrates technological innovation with ethical safeguards, data governance, and regulatory compliance.

Keywords: Artificial Intelligence, Credit Risk Assessment, Machine Learning, Financial Inclusion, Nigerian Banks, Access Bank Plc

Introduction

Credit risk assessment remains a core function of banking, shaping how financial institutions allocate capital and manage risk. In Nigeria, traditional credit evaluation methods rely heavily on collateral, financial statements, and human judgment. While these approaches have been useful, they are increasingly inadequate in a dynamic economy characterized by informality and data gaps (Akerlof, 1970).

Artificial intelligence (AI) has emerged as a powerful alternative, capable of analyzing large datasets and identifying complex patterns that traditional models may overlook. Machine learning techniques, in particular, allow banks to generate more accurate predictions of borrower behavior (Bussmann et al., 2021). In advanced economies, AI has significantly improved credit scoring systems by incorporating alternative data sources such as digital transactions and mobile activity (Berg et al., 2020).

This study examines how AI can be applied within the Nigerian banking context, focusing on Access Bank Plc, and evaluates both its benefits and implementation challenges.

Statement of the Problem

Despite global advancements in AI-driven credit risk assessment, Nigerian banks continue to rely on traditional methods that are often inefficient and exclusionary. These systems fail to adequately assess borrowers without formal financial records, leading to credit rationing and limited financial inclusion (Stiglitz & Weiss, 1981). As a result, many potentially creditworthy individuals and SMEs are excluded from formal lending, while banks face increased exposure to non-performing loans due to weak predictive models. Although AI offers a promising solution, its adoption in Nigeria is constrained by poor data quality, lack of technical expertise, high costs, and regulatory uncertainty (Philippon, 2016). This creates a gap between the potential of AI and its practical implementation in the Nigerian banking sector.

Objectives of the Study

The main objective of this study is to examine the impact of AI on credit risk assessment in Nigerian banks.

Specific objectives include:

a To evaluate the effectiveness of AI in improving credit risk prediction

b To identify challenges affecting AI adoption in Nigerian banks

c To assess the role of AI in promoting financial inclusion

d To examine governance and ethical considerations in AI implementation

Conceptual Review

Artificial intelligence refers to systems capable of performing tasks that typically require human intelligence, including learning, reasoning, and decision-making (Russell & Norvig, 2021). In banking, AI is applied through machine learning, predictive analytics, and data-driven decision systems.

Credit risk assessment involves estimating the likelihood that a borrower will default on a loan. Traditional approaches rely on statistical models and historical financial data, while AI-based models incorporate dynamic and diverse datasets, including alternative data sources (Berg et al., 2020). The integration of AI introduces key concepts such as predictive accuracy, automation, and real-time monitoring, while also raising concerns around fairness, transparency, and data privacy (Bussmann et al., 2021).

This study develops a conceptual framework that brings together economic theory, technology adoption theory, and institutional perspectives to explain how AI-driven credit risk assessment can function effectively within Nigerian banks. Rather than treating artificial intelligence as a purely technical upgrade, the framework recognizes that its success depends on the interaction between technology, organizational capacity, regulatory systems, and broader economic realities.

From an economic standpoint, the foundation of this framework lies in the theory of information asymmetry. Akerlof (1970) demonstrated how imperfect information can distort markets, while Stiglitz and Weiss (1981) showed that when lenders cannot accurately assess borrower risk, they often respond by rationing credit rather than adjusting interest rates. This insight is central to understanding Nigeria's credit landscape. AI-driven models, particularly those using alternative data, offer a potential solution by reducing informational gaps and enabling more precise risk differentiation.

However, adopting AI is not simply a matter of purchasing software. Technology adoption theories such as the Technology Acceptance Model (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) emphasize that perceived usefulness, ease of implementation, and organizational readiness strongly influence adoption decisions. Similarly, the Technology Organization Environment

(TOE) framework (Tornatzky & Fleischer, 1990) highlights that external pressures, regulatory structures, and institutional environments shape technological uptake.

Institutional theory further strengthens this perspective. North (1990) argues that economic performance is deeply shaped by formal and informal institutions, while DiMaggio and Powell (1983) explain how organizations conform to regulatory and normative pressures. In the context of AI adoption, this suggests that regulatory clarity, governance norms, and supervisory expectations will significantly influence how Nigerian banks implement and manage AI systems.

Taken together, these theoretical foundations inform a framework in which AI adoption is shaped by contextual conditions, mediated by internal organizational decisions, and moderated by governance mechanisms, ultimately producing operational and socio-economic outcomes.

Theoretical Framework

This study is anchored on three core theories that provide a solid foundation for understanding the role of Artificial Intelligence (AI) in enhancing credit risk assessment within the banking sector. These theories Information Asymmetry Theory, Technology Acceptance Model (TAM), and Financial Intermediation Theory collectively explain the existing challenges in traditional credit systems, the drivers of technological adoption, and the evolving role of financial institutions in a data-driven economy.

The first theoretical underpinning of this study is the Information Asymmetry Theory, originally introduced by George Akerlof in 1970. The theory explains situations where one party in a transaction possesses more or better information than the other. In the context of lending, borrowers typically have more accurate knowledge about their financial situation, repayment capacity, and intentions than lenders. This imbalance often leads to two major problems: adverse selection and moral hazard. Adverse selection occurs when lenders are unable to distinguish between high-risk and low-risk borrowers before granting loans, while moral hazard arises when borrowers engage in risky behavior after receiving loans because the lender cannot fully monitor them.

In traditional banking systems, especially in developing economies like Nigeria, information asymmetry is more pronounced due to weak credit reporting systems, limited access to reliable financial data, and a high level of informal economic activities. As a result, banks may either deny credit to potentially good borrowers or extend loans to high-risk individuals, leading to increased default rates and inefficiencies in credit allocation.

Artificial Intelligence plays a transformative role in addressing these challenges by leveraging large datasets, machine learning algorithms, and predictive analytics to generate more accurate borrower profiles. Unlike traditional credit scoring methods that rely heavily on historical financial records, AI can analyze alternative data sources such as transaction patterns, mobile usage, and behavioral indicators. This significantly reduces information gaps and enhances the lender’s ability to make informed decisions. Consequently, AI helps mitigate both adverse selection and moral hazard by improving transparency and enabling continuous monitoring of borrower behavior. Therefore, the Information Asymmetry Theory provides a strong justification for the adoption of AI in credit risk management.

The second theoretical foundation of this study is the Technology Acceptance Model (TAM), developed by Fred Davis in 1989. TAM is widely used to explain how users come to accept and use new technologies. The model posits that two key factors perceived usefulness and perceived ease of use determine an individual's intention to adopt a technological system. Perceived usefulness refers to the degree to which a person believes that using a particular system will enhance their job performance, while perceived ease of use relates to how effortless the system is to use.

In the context of Nigerian banks, TAM is particularly relevant in understanding the adoption of AI-driven credit risk assessment tools. Despite the potential benefits of AI, its implementation depends largely on how bank employees, management, and other stakeholders perceive the technology. If AI systems are viewed as complex, unreliable, or difficult to integrate into existing workflows, resistance to adoption is likely to occur. On the other hand, if these systems are perceived as efficient, accurate, and capable of improving decision-making processes, adoption rates will increase.

Furthermore, organizational factors such as training, infrastructure, and management support play a critical role in shaping these perceptions. In many developing economies, technological adoption is often hindered by limited technical expertise, inadequate infrastructure, and high implementation costs. Therefore, TAM helps to explain not only the behavioral intentions of individuals within banks but also the broader institutional challenges that may influence AI adoption. By applying this model, the study is able to assess the readiness of Nigerian banks to integrate AI into their credit risk frameworks and identify potential barriers to successful implementation.

The third theoretical perspective underpinning this study is the Financial Intermediation Theory, as elaborated by Xavier Freixas and Jean-Charles Rochet in 2008. This theory emphasizes the role of financial institutions, particularly banks, as intermediaries that facilitate the flow of funds between savers and borrowers. Banks perform critical functions such as mobilizing deposits, evaluating investment opportunities, managing risks, and ensuring efficient allocation of financial resources.

One of the key challenges faced by financial intermediaries is the accurate assessment of credit risk. Inefficient risk assessment can lead to poor lending decisions, increased non-performing loans, and ultimately financial instability. Traditional methods of credit evaluation often rely on limited financial data and manual processes, which may not adequately capture the complexity of modern financial behavior.

The integration of AI into banking operations significantly enhances the intermediation function by improving the accuracy, speed, and efficiency of credit risk assessment. AI systems can process vast amounts of data in real time, identify patterns that are not easily detectable by humans, and generate predictive insights that support better decision-making. This leads to more efficient allocation of credit, reduced default rates, and improved financial performance for banks.

Moreover, AI enables financial institutions to extend credit to previously underserved populations by utilizing alternative data sources. This aligns with the broader objective of financial intermediation, which is to promote financial inclusion and ensure that resources are allocated to their most productive uses. In this sense, AI not only strengthens the traditional role of banks but also expands their capacity to serve a wider segment of the economy.

In summary, the integration of these three theories provides a comprehensive framework for understanding the impact of AI on credit risk assessment. The Information Asymmetry Theory highlights the fundamental problem that AI seeks to address, the Technology Acceptance Model explains the factors influencing its adoption, and the Financial Intermediation Theory underscores its implications for the broader banking system. Together, these theories offer valuable insights into how AI can transform credit risk management and enhance the efficiency and effectiveness of financial institutions, particularly in developing economies like Nigeria.

Empirical Review

Empirical studies show that AI significantly improves credit risk prediction. Research by Bussmann et al. (2021) finds that machine learning models outperform traditional statistical methods in predicting loan defaults. Similarly, Berg et al. (2020) demonstrate that alternative data improves credit scoring accuracy and expands access to credit.

In emerging markets, AI has been shown to enhance financial inclusion by reducing information asymmetry and enabling lenders to assess previously excluded borrowers (Fuster et al., 2022).

In Nigeria, studies indicate that digital transformation has improved banking efficiency, although research specifically focused on AI remains limited.

Existing findings suggest that while AI adoption improves performance, its effectiveness depends heavily on institutional readiness, data quality, and governance structures.

The empirical literature on AI-powered credit risk assessment has grown significantly over the past decade. Much of this article seeks to determine whether machine-learning techniques outperform traditional statistical models in predicting loan default.

Comparative studies generally conclude that machine-learning algorithms deliver superior predictive accuracy. For example, Khandani et al. (2010) demonstrate that non-linear machine-learning methods improve default prediction compared to conventional models. Similarly, Lessmann et al. (2015), in a large benchmarking study, find that advanced classification techniques outperform logistic regression across multiple credit datasets.

Beyond predictive accuracy, fintech research shows that AI models using alternative data can meaningfully expand access to credit. Berg et al. (2020) find that digital footprint variables enhance risk prediction even in the absence of formal credit bureau data. Jagtiani and Lemieux (2019) report that fintech lenders leverage machine learning and alternative data to serve borrowers who would otherwise be excluded from traditional banking channels.

However, emerging evidence also highlights important concerns. Fuster et al. (2022) show that while machine learning improves efficiency, it can alter credit allocation patterns in ways that raise distributional and fairness questions. This reinforces the importance of governance mechanisms in AI implementation.

In emerging markets, AI adoption presents both opportunities and constraints. The Bank for International Settlements (2021) and the World Bank (2021) emphasize that institutional capacity, supervisory oversight, and data governance structures are critical determinants of successful implementation.

Within Nigeria, empirical research remains relatively limited. Reports from the Central Bank of Nigeria (2021–2024) indicate that digital transformation initiatives have improved operational efficiency and monitoring capacity. However, most Nigerian studies aggregate digitalization broadly and rarely isolate advanced machine-learning applications from rule-based automation systems. Furthermore, many studies rely on small samples or single-bank case analyses, limiting generalizability.

Findings

The study reveals several important insights regarding the adoption of AI in credit risk assessment within Nigerian banks, particularly Access Bank Plc.

First, AI significantly improves predictive accuracy compared to traditional credit scoring methods. Machine learning models demonstrate a stronger ability to detect patterns in borrower behavior, leading to better identification of high-risk and low-risk clients. This results in more informed lending decisions and reduced default rates.

Second, AI enhances operational efficiency by reducing the time required for credit assessment. Automated systems enable faster processing of loan applications, minimizing delays associated with manual evaluation and improving overall customer experience.

Third, the study finds that AI contributes to financial inclusion by enabling banks to assess borrowers who lack formal financial records. By leveraging alternative data such as transaction histories and behavioral indicators, AI allows previously underserved individuals and SMEs to access credit.

However, the findings also highlight critical challenges. Data quality remains a major constraint, as incomplete or inconsistent datasets reduce the effectiveness of AI models. Additionally, limited technical expertise within banks hinders proper implementation and management of AI systems.

Regulatory uncertainty and concerns around data privacy and algorithmic bias also affect adoption. Without clear governance frameworks, there is a risk that AI systems may produce unfair or non-transparent outcomes.

Overall, the findings suggest that while AI offers substantial benefits, its success depends on the alignment of technology with institutional capacity, governance structures, and regulatory support.

Conclusion

Artificial intelligence presents a significant opportunity to transform credit risk assessment in Nigerian banks. It improves predictive accuracy, enhances operational efficiency, and promotes financial inclusion. However, its effectiveness is not guaranteed and depends on the broader institutional and regulatory environment.

Successful AI adoption requires a holistic approach that integrates technology with governance, human expertise, and regulatory oversight.

Recommendations

Building on the findings of this study, the following recommendations are presented to guide banks, regulators, and other key stakeholders toward the effective and responsible adoption of Artificial Intelligence (AI) in credit risk assessment. These recommendations are not merely technical suggestions but practical, human-centered strategies that reflect the operational realities of the banking sector, particularly in developing economies like Nigeria.

a Banks Should Invest in High-Quality Data Infrastructure

At the heart of every successful AI system lies data accurate, consistent, and reliable data. Many of the challenges observed in AI-driven credit risk assessment can be traced back to poor data quality, fragmented databases, and outdated data management systems. Therefore, banks must make deliberate investments in building robust data infrastructure that can support advanced analytics.

This involves more than just acquiring new software; it requires a complete transformation of how data is collected, stored, processed, and governed. Banks should prioritize the integration of data from multiple sources, including internal transaction records, customer interactions, and alternative data such as mobile usage and behavioral patterns. A centralized data architecture, such as a data warehouse or data lake, can help eliminate silos and improve accessibility across departments.

Equally important is data quality management. Inaccurate or incomplete data can lead to flawed AI predictions, which may ultimately increase credit risk rather than reduce it. Banks should implement strict data validation processes, regular audits, and automated cleansing mechanisms to ensure data integrity.

Moreover, cybersecurity must be treated as a critical component of data infrastructure. As banks handle increasingly sensitive customer information, the risk of data breaches also rises. Investing in secure systems, encryption technologies, and compliance with data protection regulations will not only safeguard customer trust but also ensure the long-term sustainability of AI initiatives.

b Regulators Should Establish Clear AI Governance Frameworks

While AI offers significant opportunities for improving credit risk assessment, it also introduces new risks related to transparency, accountability, and ethical use. This makes the role of regulators more important than ever. Regulatory bodies must move beyond general guidelines and develop clear, structured frameworks specifically tailored to AI in financial services.

These frameworks should define standards for model validation, data usage, algorithm transparency, and risk management. For instance, banks should be required to explain how their AI models make decisions, particularly in cases where loan applications are rejected. This concept, often referred to as “explainable AI,” is essential for maintaining fairness and accountability.

Regulators should also introduce monitoring mechanisms to ensure that AI systems do not unintentionally discriminate against certain groups of customers. Bias in AI models can arise from historical data that reflects past inequalities, and without proper oversight, such biases can be amplified.

In addition, the creation of regulatory sandboxes can provide a safe environment for banks and fintech firms to test AI solutions under controlled conditions. This encourages innovation while allowing regulators to better understand emerging technologies and their implications.

Ultimately, a well-defined governance framework will create a balance between innovation and risk control, ensuring that AI adoption contributes positively to the stability of the financial system.

c Hybrid Human AI Decision Should Be Adopted

Despite the growing capabilities of AI, it is neither practical nor advisable to rely entirely on automated systems for credit decisions. Human judgment remains a critical component, especially in complex or ambiguous cases where contextual understanding is required.

Banks should adopt a hybrid decision-making approach that combines the strengths of AI with human expertise. In this model, AI systems can be used to analyze large volumes of data, identify patterns, and generate risk scores, while human credit officers review these outputs and make final decisions.

This approach offers several **Systems** advantages. First, it reduces the risk of over-reliance on algorithms, which may sometimes produce inaccurate or biased results. Second, it allows for the consideration of qualitative factors such as character, business potential, or market conditions that may not be fully captured by data.

Third, it enhances accountability, as human decision-makers can be held responsible for outcomes.

In practice, banks can implement tiered decision systems where low-risk applications are automatically approved, high-risk applications are rejected, and borderline cases are escalated to human reviewers. This not only improves efficiency but also ensures a balanced and responsible use of AI.

d Continuous Staff Training in AI and Data Analytics Should Be Prioritized

The successful adoption of AI in banking is not solely dependent on technology; it also requires a workforce that understands and can effectively utilize these tools. One of the key barriers identified in this study is the lack of technical expertise among bank staff.

To address this, banks should invest in continuous training and capacity-building programs focused on AI, data analytics, and digital literacy. These programs should be tailored to different roles within the organization. For example, data scientists may require advanced technical training, while credit officers need practical knowledge on how to interpret AI-generated insights.

Training should not be a one-time event but an ongoing process that evolves with technological advancements. Partnerships with academic institutions, training organizations, and fintech companies can help banks stay up to date with the latest developments.

Additionally, fostering a culture of learning and innovation is essential. Employees should be encouraged to embrace new technologies rather than fear them. Clear communication from management about the benefits of AI and its role in enhancing not replacing human capabilities can help reduce resistance to change.

e Ethical Standards Should Be Enforced to Ensure Fairness and Transparency

As AI becomes more integrated into credit decision-making, ethical considerations must take center stage. Without proper safeguards, AI systems can perpetuate existing inequalities, invade customer privacy, and erode trust in financial institutions.

Banks should establish clear ethical guidelines governing the use of AI. These guidelines should address issues such as data privacy, consent, fairness, and accountability. Customers should be informed about how their data is being used and should have the right to challenge decisions made by AI systems.

Transparency is particularly important in building trust. Banks should strive to make their AI models as explainable as possible, providing clear reasons for credit decisions. This not only improves customer satisfaction but also aligns with regulatory expectations.

Regular audits of AI systems should be conducted to detect and correct biases. Independent oversight, either through internal ethics committees or external reviewers, can further strengthen accountability.

By prioritizing ethical standards, banks can ensure that AI is used as a tool for inclusion and empowerment rather than exclusion and discrimination.

f Collaboration Between Banks, Fintech Firms, and Regulators Should Be Strengthened

The complexity of AI adoption in the financial sector makes collaboration not just beneficial but necessary. Banks, fintech firms, and regulators each bring unique strengths to the table, and their combined efforts can accelerate innovation while minimizing risks.

Banks often have access to large datasets and established customer bases, while fintech companies bring agility, technical expertise, and innovative solutions. By partnering with fintech firms, banks can overcome internal limitations and adopt cutting-edge technologies more efficiently.

Regulators, on the other hand, play a crucial role in providing oversight and ensuring that innovations align with broader economic and social objectives. Open communication between regulators and industry players can help create policies that are both practical and forward-looking.

Collaborative initiatives such as industry forums, joint research projects, and shared innovation hubs can facilitate knowledge exchange and foster a more cohesive ecosystem. In addition, cross-border collaboration can enable the sharing of global best practices, helping developing economies leapfrog traditional challenges.

In essence, the successful integration of AI into credit risk assessment requires a holistic approach that goes beyond technology. It demands strong data foundations, supportive regulatory environments, skilled human resources, ethical responsibility, and collaborative efforts across the financial ecosystem.

When these elements are effectively aligned, AI has the potential to significantly improve the accuracy of credit decisions, reduce non-performing loans, and expand access to financial services. However, without careful implementation and oversight, the same technology could introduce new risks and challenges. Therefore, these recommendations serve as a roadmap for ensuring that AI adoption in banking is both effective and sustainable.

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