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ARTIFICIAL INTELLIGENCE AND RISK MANAGEMENT OF DEPOSIT MONEY BANKS IN NIGERIA: EMPIRICAL EVIDENCE FROM GUARANTY TRUST BANK

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Abstract

Risk management remains a persistent challenge for deposit money banks in Nigeria due to systemic vulnerabilities such as fraud, credit default, and operational inefficiencies. Traditional risk management methods often fall short in effectively identifying and mitigating these risks, resulting in financial losses and instability. Artificial intelligence (AI) presents a transformative opportunity to address these issues by enhancing precision, efficiency, and responsiveness in risk assessment and mitigation processes. However, the adoption of AI in Nigerian banks remains limited, with efforts focused more on infrastructure upgrades than on leveraging AI for advanced decision-making and risk management. The study employed a survey research design, utilizing estimation techniques such as simple percentages and regression analysis to analyze the effect of artificial intelligence on risk management of Guaranty Trust bank in Nigeria. The findings underscore a significant positive impact of AI adoption, AI-driven credit scoring, and AI-based fraud detection on risk management in these banks, emphasizing the importance of integrating AI into operational processes to achieve transformative effects in the Nigerian banking sector. The study recommends that regulators should ensure effective compliance with AI regulations that align with global standards. Additionally, ethical considerations, including data privacy and transaction security concerning AI adoption, should be carefully addressed by banks.

Keywords: *Artificial intelligence, Risk management, Financial system, Credit default, Systemic vulnerabilities*

INTRODUCTION

The banking sector, especially deposit money banks (DMBs), plays an integral role in the economic development of Nigeria by facilitating the mobilization of savings, providing credit, and fostering economic growth. However, risk management remains one of the most significant challenges faced by these institutions. Banks are exposed to various risks, such as credit, market, liquidity, operational, and systemic risks, which can threaten their stability and performance. Risk management strategies are essential for mitigating these challenges, yet traditional approaches have often proven insufficient in addressing the dynamic and evolving nature of risks in the modern banking environment (Akinlo, 2020). This inadequacy is particularly evident in Nigerian banks, where outdated systems, inadequate risk prediction models, and

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inefficiencies in the management of large volumes of data have contributed to financial instability (Akinola et al., 2019).

Traditional risk management in Nigerian banks primarily relies on manual processes, which are time-consuming and prone to errors. This results in slow decision-making, higher operational costs, and inadequate identification of emerging risks. For instance, credit risk assessment often relies on historical data and subjective judgment, which may not fully account for current market conditions or new patterns of borrower behavior (Ogunleye, 2020). Similarly, market risks, particularly those related to fluctuations in foreign exchange rates and commodity prices, can lead to significant losses due to the lack of timely and accurate data analysis. Furthermore, liquidity management remains a concern, as banks struggle to predict and manage cash flow requirements effectively, especially in a volatile economic environment (Olokoyo et al., 2019).

Given the limitations of traditional risk management techniques, there is a growing recognition of the potential for technological innovations to improve risk mitigation strategies in Nigerian banks. Artificial Intelligence (AI) has emerged as a powerful tool in transforming the way banks identify, assess, and manage risks. AI encompasses machine learning, data analytics, and automation techniques that allow for more accurate predictions, faster decision-making, and the ability to analyze vast amounts of data in real time (Akinola & Odhiambo, 2020). AI systems can process large datasets, identify patterns and trends that may not be immediately apparent to human analysts, and generate predictive insights that support proactive risk management.

For instance, AI-powered credit scoring models can analyze a wide range of borrower data, including transactional histories, social media behavior, and macroeconomic factors, to make more accurate assessments of creditworthiness. This reduces the likelihood of defaults and enhances the overall stability of the bank’s loan portfolio (Audu & Abiola, 2022). Similarly, AI-driven market risk management tools can analyze real-time data on economic indicators, market trends, and geopolitical events, allowing banks to make timely adjustments to their portfolios and hedge against potential losses (Armbrust et al., 2010). AI can also enhance liquidity management by predicting cash flow needs and optimizing asset-liability management in a more efficient and dynamic manner (Gartner, 2022).

In the context of Nigeria’s banking sector, AI holds the potential to revolutionize risk management practices. Given the country's economic volatility, AI’s ability to process large datasets and provide real-time insights is invaluable for DMBs that must navigate the complexities of both local and global financial landscapes. AI systems, such as machine learning models for fraud detection, can help identify suspicious activities and potential security breaches, reducing the risk of financial losses. Additionally, AI-based analytics can assist in monitoring regulatory compliance, ensuring that banks meet the ever-evolving requirements set by Nigerian authorities (Ogunleye, 2020).

Despite its promising benefits, the adoption of AI in Nigerian banks faces several challenges, including high implementation costs, lack of skilled workforce, and concerns about data privacy and security (Olokoyo et al., 2019). Moreover, there is a need for a more robust regulatory framework to govern the use of AI in financial services, ensuring that its deployment is aligned with both global best practices and local regulatory requirements.

While previous studies, such as Olokoyo et al. (2019), Abioye et al. (2020), and Eze & Chukwuemeka (2021), have explored the challenges of AI adoption in Nigerian banks, including high costs, workforce limitations, and regulatory concerns, they largely overlook the specific impact of AI on risk management practices within deposit money banks. Additionally, studies like Adebayo & Olayinka (2022) emphasize the potential benefits of AI but fail to provide empirical evidence on its application in managing risks at the institutional level, such as in Guaranty Trust Bank. This gap in the literature underscores the need for focused research on how AI tools are employed to identify, assess, and mitigate risks, and how banks navigate the associated regulatory and operational challenges.

This study aims to examine the role of AI in enhancing risk management strategies within Nigerian deposit money banks. It will explore how AI technologies can improve the identification, assessment, and mitigation of risks, thereby enhancing the overall financial stability of banks. The study also seeks to provide insights into the challenges and opportunities that AI presents for Nigerian banks, with a view to fostering a more secure and resilient banking sector. The broad objective of this study is to investigate the effect of artificial intelligence on risk management in listed deposit money banks in Nigeria. Specifically, it examines how AI adoption influences risk management practices, evaluates the impact of AI-driven credit scoring on mitigating credit-related risks, and investigates the role of AI-powered fraud detection systems in enhancing the overall risk management framework of these banks.

LITERATURE REVIEW

2.1 Conceptual Review

2.1.1 Concept of Artificial Intelligence

Artificial Intelligence (AI) has emerged as a transformative technology with the potential to revolutionize various sectors, including finance. As AI continues to advance, its applications in areas such as credit scoring, fraud detection, and customer service are becoming increasingly prevalent. The ability of AI to process vast amounts of data, recognize patterns, and make decisions with minimal human intervention offers significant benefits to financial institutions, improving accuracy, efficiency, and risk management (Brynjolfsson & McAfee, 2017; Davenport, 2018). This review explores the adoption of AI in the financial sector, focusing on its impact on credit scoring and fraud detection, and highlights the advancements, challenges, and opportunities associated with these innovations.

AI adoption has become a significant transformative force across various industries, including finance. According to Davenport (2018), AI adoption refers to the integration of intelligent systems capable of performing tasks that typically require human cognition, such as learning, reasoning, and problem-solving. This adoption is driven by the increasing availability of data, advancements in machine learning algorithms, and the growing need for businesses to enhance efficiency, accuracy, and customer experience. AI allows for the automation of repetitive processes, improved decision-making, and the development of personalized services, making it a vital tool in modern business practices (Brynjolfsson & McAfee, 2017).

In the context of credit scoring, AI has significantly impacted traditional credit risk assessment methods. According to He, Li, and Lin (2020), AI-based credit scoring systems use machine learning algorithms to analyze vast amounts of data, including alternative data sources such as social media activity and transaction history, to assess an individual's creditworthiness. These AI systems can provide more accurate and personalized credit scores, especially for individuals who may lack a traditional credit history, thereby improving financial inclusion (Cheng et al., 2020). The use of AI in credit scoring also reduces human bias and enhances the objectivity of credit assessments, as machine learning algorithms can process data without the limitations of traditional credit scoring models.

AI's role in fraud detection within financial institutions is another area where its capabilities have been extensively utilized. According to Ngai et al. (2011), AI algorithms, particularly machine learning and neural networks, are highly effective in detecting fraudulent activities by analyzing transaction patterns in real-time. These AI systems can identify anomalies that deviate from normal behaviors, enabling banks and financial institutions to prevent fraudulent activities before they occur. AI-based fraud detection systems can continuously learn from new data and adapt to evolving fraud tactics, improving their accuracy and effectiveness over time (Liu & Miao, 2021). The implementation of AI in fraud detection not only enhances security but also reduces operational costs and minimizes false positives, leading to better customer experiences and improved trust in financial institutions.

On the other hand, the banking sector is inherently exposed to various risks that can threaten its financial stability and operational effectiveness. These risks include credit risk, market risk, operational risk, liquidity risk, and compliance risk, all of which stem from the dynamic and complex nature of financial markets (Basel Committee on Banking Supervision, 2011). Effective risk management is essential to mitigate these exposures, safeguard depositors' funds, and maintain trust in the financial system. Banks must adopt proactive strategies to identify, assess, monitor, and control risks while complying with regulatory requirements and maintaining profitability (Hull, 2018). This review explores the conceptual framework of risk management in the banking sector, focusing on the techniques and strategies banks use to mitigate risks, enhance resilience, and ensure long-term sustainability.

In conclusion, the adoption of AI in credit scoring and fraud detection demonstrates the technology's potential to revolutionize the financial sector by enhancing decision-making processes, improving operational efficiency and reducing risks. As AI continues to evolve, its impact on financial services is likely to expand, offering new opportunities for innovation and growth (Brynjolfsson & McAfee, 2017).

2.1.2. Risk Management

Risk management in banking involves a structured process of identifying, measuring, and controlling risks that can impact a bank's performance and solvency. According to Crouhy, Galai, and Mark (2014), risk management frameworks encompass policies, procedures, and practices designed to align risk appetite with strategic objectives. Key components include credit risk management, which addresses the risk of borrower default, and market risk management, which focuses on mitigating losses from changes in market variables such as interest rates, exchange rates, and equity prices. Operational risk, as defined by the Basel Committee, includes risks arising from inadequate internal processes, human error, or external events, underscoring the importance of robust internal controls (Basel Committee on Banking Supervision, 2011).

Credit risk remains one of the most significant exposures for banks. Kolapo, Ayeni, and Oke (2012) argue that effective credit risk management requires comprehensive borrower assessments, strict lending policies, and regular monitoring of loan portfolios to minimize defaults. Tools such as credit scoring models and portfolio diversification help banks balance risk and return. Similarly, market risk management involves the use of hedging strategies, such as derivatives, to protect against adverse market movements. Hull (2018) notes that value-at-risk (VaR) models are widely used to estimate potential losses and ensure adequate capital reserves to absorb market shocks. Liquidity risk is another critical area of focus, as it directly impacts a bank's ability to meet its financial obligations. According to Bessis (2015), maintaining a healthy liquidity buffer and adhering to liquidity coverage ratios (LCR) are vital for managing short-term liquidity pressures. Stress testing and scenario analysis are also integral tools for evaluating a bank's capacity to withstand liquidity shocks during periods of market turbulence.

Operational risk management emphasizes the implementation of strong governance frameworks, advanced technology, and regular audits to mitigate risks associated with fraud, cyber threats, and compliance failures. According to Cruz, Peters, and Shevchenko (2015), the integration of enterprise risk management (ERM) systems enables banks to take a holistic approach to risk, ensuring that all risk categories are interlinked and managed cohesively.

In conclusion, risk management is a cornerstone of banking sector's stability and resilience. By employing sophisticated tools and strategies, banks can effectively navigate the complex risk environment and protect stakeholders' interests. As financial markets continue to evolve, the importance of dynamic and adaptive risk management cannot be overstated (Crouhy, Galai & Mark, 2014).

2.2 Theoretical Framework

Theoretically, there are three theories that underpin this study. These include the Technology Acceptance Model Decision Theory and Financial Intermediation Theory. However, The Technology Acceptance Model (TAM), developed by Fred Davis in 1986, provides a foundational framework for understanding the adoption of new technologies, including Artificial Intelligence (AI) in risk management. Building on the Theory of Reasoned Action (TRA) by Fishbein and Ajzen (1975), TAM emphasizes the roles of perceived usefulness (PU) and perceived ease of use (PEOU) in influencing user decisions to adopt technology. The model suggests that users are more likely to adopt a technology if it enhances their performance and is easy to use. In the banking sector, TAM has been instrumental in explaining how AI technologies are adopted to improve operational efficiency and bolster risk mitigation strategies, such as fraud detection and credit risk assessment (Marangunić & Granić, 2015; Okoye et al., 2019).

While TAM has proven robust in predicting technology adoption and has been expanded through frameworks like the Unified Theory of Acceptance and Use of Technology (UTAUT), it has faced criticism for its limitations. Critics, such as Bagozzi (2007) and O'Neil (2016), argue that TAM oversimplifies the adoption process by neglecting factors like organizational culture, regulatory frameworks, and ethical concerns, including data privacy and algorithmic biases. Despite these critiques, TAM remains relevant for analyzing AI adoption in banking risk management, particularly when its focus on PU and PEOU is combined with considerations of broader contextual factors. This ensures its applicability to evolving challenges in integrating AI systems within financial institutions (Brynjolfsson & McAfee, 2017; Marangunić & Granić, 2015).

Another theory that underpin this study is the Decision theory which provides a robust framework for analyzing decision-making processes, particularly in uncertain or risky environments. Originating from the works of theorists like Blaise Pascal and formalized by von Neumann and Morgenstern in their 1944 publication Theory of Games and Economic Behavior,

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it focuses on optimizing outcomes by evaluating options against associated risks and benefits. The theory's assumptions—rational decision-making, access to relevant information, and consistent preferences—align with the capabilities of AI systems to provide data-driven insights. This alignment makes Decision Theory particularly relevant to AI in risk management, where it supports applications like credit risk assessment and fraud detection by enhancing decision-making processes through predictive analytics and risk minimization (Kahneman & Tversky, 1979).

Despite its strengths, Decision Theory faces criticism for oversimplifying human behavior and ignoring cognitive biases, emotional influences, and incomplete information, as noted by behavioral economists like Kahneman and Tversky. Critics also highlight concerns about algorithmic biases and ethical implications when relying solely on AI for critical decisions. Nonetheless, Decision Theory remains crucial for integrating AI into risk management, providing a structured approach for evaluating risks and making informed strategic choices. Incorporating behavioral insights and ethical considerations into AI systems guided by Decision Theory ensures more resilient and responsible risk management practices for financial institutions (Raiffa, 1968; Brynjolfsson & McAfee, 2017)

Another important theory is the Financial Intermediation Theory, introduced by Leland and Pyle in 1977, which explains the critical role financial intermediaries, such as banks, play in bridging the gap between savers and borrowers. The theory highlights how intermediaries reduce information asymmetry, lower transaction costs, and provide liquidity, thus enabling efficient capital allocation in the economy. By mitigating risks through monitoring services and reducing moral hazards, financial intermediaries ensure that funds are directed toward the most productive uses. This theory's relevance to Artificial Intelligence (AI) in risk management lies in how AI enhances these intermediation functions, particularly in credit risk assessment, fraud detection, and decision-making (Leland & Pyle, 1977).

Supporters of Financial Intermediation Theory, like Levine (2005), emphasize the indispensable role of intermediaries in fostering economic growth by directing funds to productive investments. AI technologies further reinforce this view by improving the efficiency of lending processes and risk management through advanced data analytics and predictive modeling (Carson & Peterson, 2019). However, critics argue that financial intermediaries can sometimes lead to inefficiencies, such as higher costs or restricted market access, and the reliance on AI raises concerns about algorithmic biases, data privacy, and ethical implications (Mayer-Schönberger & Cukier, 2013). These challenges highlight the need for cautious integration of AI into financial systems to enhance intermediation functions without exacerbating existing inefficiencies.

The Technology Acceptance Model (TAM), developed by Fred Davis in 1986, serves as the theoretical framework for understanding AI adoption in banking risk management. By emphasizing perceived usefulness (PU) and perceived ease of use (PEOU), TAM explains how these factors influence the adoption of AI tools for tasks like fraud detection and credit risk assessment. Unlike other theories, TAM focuses on individual-level decision-making, making it particularly relevant for studying AI integration in the banking sector. Its structured approach highlights the key drivers of AI adoption, offering valuable insights into improving risk management practices in financial institutions.

2.3 Empirical Review

Empirical studies have highlighted the significant role of Artificial Intelligence (AI) in enhancing the banking sector, particularly in risk management, decision-making, and operational efficiencies. However, there remains a gap in understanding the full extent of AI's impact, especially in developing economies where the adoption and integration of AI are still in their early stages.

Several studies have demonstrated a significant positive relationship between AI adoption and banking performance. Issa et al. (2023) emphasize AI-based solutions' contribution to improving risk management, reducing costs, and boosting customer trust in the banking industry. Similarly, Tang and Tien (2020) find that AI positively influences financial decision-making by improving bank performance, cost management, customer experience, and regulatory compliance. In line with this, Kruse, Wunderlich, and Beck (2019) identify ease of use and accessibility as crucial factors driving AI adoption in finance, while Abusalma (2021) shows positive effects on employee efficiency in Jordan's banking industry. Bagana et al. (2021) further confirm that ease of use, accessibility, and information security are key factors influencing AI chatbot adoption in Indonesian banks.

In the Nigerian context, Aziz, Jibril, and Bello (2023) observe that AI enhances organizational systems, boosting operational, managerial, and process efficiencies, while Elegunde and Osagie (2020) report improvements in employee performance due to automation in Nigerian banks. Additionally, Ahmad (2020) highlights AI's positive impact on wealth creation and risk-sharing through digital currencies in sub-Saharan Africa, and Singh and Thakur (2021) find that AI improves fraud detection in Indian banks, enhancing customer trust. Chen et al. (2022) also underscore AI's role in improving credit risk assessments in Chinese banks through machine learning and big data.

Furthermore, the study by Brynjolfsson and McAfee (2017) illustrates that AI adoption is not only linked to operational improvements but also significantly boosts innovation in banking services. Similarly, Vocke and Gangur (2022) identify that the strategic integration of AI into financial decision-making enhances risk mitigation, including credit, operational, and market risks, thus proving the wider applicability of AI technologies in the financial sector. Buchanan et al. (2021) add that AI-driven wealth management tools provide accurate predictions for portfolio performance, while Nwosu and Odum (2022) highlight AI's role in enhancing financial inclusion through mobile banking applications in sub-Saharan Africa.

AI's impact on employee efficiency and perceptions has also been explored. Kumar et al. (2020) reveal that AI adoption fosters mixed perceptions among banking employees, with concerns about job security despite improved efficiency. Research by Choi et al. (2022) emphasizes the use of AI for predictive analytics to anticipate market trends and customer behavior in South Korean banks.

However, despite AI's transformative potential, some studies indicate a significant negative relationship or challenges to full AI integration. Fadi et al. (2023) find that despite AI's potential, Jordanian banks show low disclosure of AI activities in financial reports, which could limit transparency and stakeholder trust. Additionally, Mayer-Schönberger and Cukier (2013) caution that the increasing reliance on AI in banking could result in data privacy and security challenges, limiting its widespread adoption despite its benefits. Similarly, studies by Kumar and Garg (2021) highlight that the application of AI in banking can sometimes exacerbate

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inequality due to algorithmic biases, undermining the effectiveness of risk management processes.

Finally, several studies reveal no significant relationship between AI implementation and certain outcomes. Vocke and Gangur (2022) underscore cost reduction and efficiency as key drivers of AI implementation in finance but note that these benefits are not significantly tied to immediate profitability in all cases. Njoku and Abiodun (2022) reveal no significant relationship between AI implementation and customer retention in Nigerian banks, suggesting that other factors, such as service quality, play a larger role. Similarly, O'Neil (2016) points out that AI adoption, though beneficial for some aspects of risk management, may not substantially improve decision-making in all organizational contexts, particularly in environments where data quality is poor or where the workforce lacks adequate training to maximize AI tools' potential.

Chen and Li (2023) found no significant relationship between AI investments and short-term return on assets in Chinese banks, suggesting that the benefits of AI may be more long-term. Smith and Jørgensen (2021) observed no notable impact of AI on loan approval times in some European SMEs, as traditional credit scoring models remained dominant. Finally, Johnson and Patel (2022) reported no significant improvement in customer loyalty metrics in Indian banks despite extensive AI-based CRM implementations, pointing to the enduring importance of human interaction and service quality in banking.

DATA AND METHODOLOGY

The study utilized a survey methodology. Due to the specific nature of the study, a convenience sampling technique was employed, as the respondents possess sufficient knowledge about AI in Nigeria. Additionally, regression techniques were used to determine the effect of financial decision-making processes in Nigeria.

According to Taherdoost (2016), the research population encompasses the entire group of cases from which the sample is drawn. Using data from the Guarantee Trust Banks (GTB) database, it was determined that the population consists of 400 staff members at or above the position of Assistant Manager within Ikeja branches. GTB is known for its team of experienced professionals with extensive expertise in Nigerian deposit money bank operations. GT Bank was selected for this study due to its large customer base among Nigerian banks

. To ensure fair and sufficient representation of respondents' opinions, the Guillford and Flruchter formula will be used to calculate the sample size. The formula is as follows:

Where;

N= Population Size
Q = alpha

$$\frac{400}{1 + 0.05^2(400)}$$

$$= \quad 200$$

Two hundred employees will make up the overall sample size, drawn from the entire population.

The primary instrument for data collection in this study will be a structured questionnaire

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divided into eight sections, each tailored to specific research objectives. The initial section will gather demographic information, providing a detailed overview of the respondents' profiles. The subsequent sections will focus extensively on questions related to Artificial Intelligence and financial decision-making processes in the Nigerian banking sector, using a five-point Likert scale. The questionnaire will be distributed via Google Forms. Once completed, responses will undergo a coding process to assess the impact of AI on banking decision-making processes. The model assessing the impact of artificial intelligence on risk assessment and management in Nigerian deposit money banks is specified as follows.

$RAM=\beta o+ \beta_1 AIA+ \beta_2 AIDC+ \beta_3 AIFD+\mu$……………………………………………….1

Where:

Risk Management is RAM
Artificial Intelligence Adoption is AIA
Artificial Intelligence Driven Credit scoring is AIDC
Artificial Intelligence fraud detection is AIFD
βo is the intercept of the model
β_1 is the slope of the independent variables
μ is the error term

The dependent variable is risk management, which evaluates the procedures used by banks to identify potential risks. Independent variables include AI adoption, AI-driven credit scoring, and AI fraud detection, each representing different facets of AI integration in the banking sector. Data collected through the questionnaires were analyzed using the Statistical Package for the Social Sciences (SPSS). Quantitative findings were summarized using descriptive statistics, including frequencies, percentages, and mean scores, to provide a comprehensive overview of data distribution and central tendencies. Inferential statistics from regression analysis was employed to identify relationships and patterns within the data, enhancing the understanding of the interplay between variables and facilitating the interpretation of broader implications of the study.

RESULTS AND DISCUSSIONS

This section presents the data and methodology used in the study, including the demographic profile of respondents, their job roles, and educational background. It also details the results of the analysis of the impact of Artificial Intelligence (AI) on risk management in the Nigerian banking sector

Demographic Description

Table 4.1: Description of Respondents Gender Distribution

Gender	Frequency	Percent
Male	94	47.0
Female	106	53.0
Total	200	100.0

Sources: Authors' Computation from SPSS Output, 2024

Table 4.1 details the gender distribution of the study's respondents. Among the 200 participants, 47% (94 respondents) were male, while 53% (106 respondents) were female. This distribution

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suggests a fairly balanced gender representation, with a slightly higher number of female respondents than male respondents.

Table 4.2: Description of Respondents Age Distribution

Years	Frequency	Percent
21-30	29	14.5
31-40	94	47.0
41-50	63	31.5
51-60	12	6.0
61 and Above	2	1.0
Total	200	100.0

Sources: Authors' Computation from SPSS Output, 2024

Table 4.2 presents the breakdown of respondents' age distribution. The largest proportion, 47%, falls within the age bracket of 31 to 40 years, followed by 31.5% aged between 41 and 50 years. Respondents aged 21 to 30 years constitute 14.5% of the sample. Smaller percentages include respondents aged 51-60 years (6%) and those aged 61 years and above (1%). This distribution reflects a diverse age range among the respondents, with the majority falling within the middle-aged group of 31-50 years.

Table 4.3: Description of Respondents Designation Distribution

	Frequency	Percent
Senior Management	16	8.0
Branch Manager	21	10.5
Financial Advisor	24	12.0
Fraud Analyst	37	18.5
Other	102	51.0
Total	200	100.0

Sources: Authors' Computation from SPSS Output, 2024

In Table 4.3 above, the job roles of respondents who answered the questions are depicted. The largest segment, comprising 51% of the sample, is categorized as "Other," encompassing a diverse array of roles not explicitly listed. Following this, Fraud Analysts make up 18.5% of the sample, while Financial Advisors account for 12%. Branch Managers and Senior Management constitute smaller portions of the sample, at 10.5% and 8% respectively. This distribution shows a diverse representation of job roles among the respondents, with a notable presence in roles related to fraud analysis and financial advising.

Table 4.4: Description of Respondents Educational Attainment Distribution

Education Attainment	Frequency	Percent
University Degree	91	45.5
Post University Degree	97	48.5
Other	12	6.0
Total	200	100.0

Sources: Authors' Computation from SPSS Output, 2024

Table 4.4 illustrates the distribution of qualifications among the respondents. The majority, comprising 48.5%, possessed a Post-University Degree, while 45.5% held a University Degree. A smaller segment, 6%, categorized under "Other," likely includes respondents with qualifications outside of university or post-university degrees. This distribution highlights a notably high level of educational achievement among the respondents, with a majority holding post-university qualifications. Having known the demographic nature of the respondents, this study goes further and assess the impact of AI on risk management of the banking sector in Nigeria and the results are reported in Table 4.5.

Table 4.5: the impact of AI on risk assessment and management in Nigerian banks

Model.	UnstandardizedCoeff.		Standardized Coeff.	T	Sig.
	B	Std. Error	Beta		
(Constant)	1.363	.676		2.015	.045
Artificial intelligence adoption	.158	.046	.201	3.437	.001
Artificial intelligence driven credit scoring	.223	.061	.231	3.641	.000
Artificial intelligence Fraud detection	.423	.064	.440	6.562	.000

SOV	SOS	Df	MS	F-Ratio.	Sig
REGRE	433.576	3	144.525	86.251	$.000^b$
RESID.	328.424	196	1.676		
Total	762.000	199			

R = .754; Multiple R^2 = .569; R^2 (Adjusted) = .562 SEE = 1.2945

a. Dependent Variable: Risk assessment management

b. Predictors: (Constant), Artificial intelligence Fraud detection, Artificial intelligence adoption, Artificial intelligence driven credit scoring

Sources: Authors' Computation from SPSS Output, 2024

The results reported in Table 4.5 show that Artificial Intelligence (AI) adoption has a significant positive impact on risk management in the banking sector in Nigeria at the 1% significance level (p = 0.001). This indicates that an increase in AI adoption will lead to an improvement in risk management practices within the sector. Specifically, a 1-unit increase in AI adoption will result in a 0.158 unit increase in risk management practices. Furthermore, AI-driven credit scoring also demonstrates a significant positive effect on risk management at the 1% significance level (p = 0.000). This suggests that as AI-driven credit scoring is implemented, the risk management processes will improve. A 1-unit increase in AI-driven credit scoring will enhance risk management practices by 0.223 units. AI fraud detection has the most substantial effect, with a significant positive relationship with risk management at the 1% significance level (p = 0.000). This implies that a 1-unit increase in AI fraud detection leads to a 0.423 unit improvement in risk management practices. This highlights the critical role of AI in detecting and mitigating fraud, enhancing the overall risk management framework in Nigerian banks.The regression model as a whole is significant, with an F-statistic of 86.251 ($p < 0.001$), and explains 56.2% of the variance in risk management ($R^2 = 0.562$). This demonstrates that AI adoption, AI-driven credit scoring, and AI fraud detection are crucial factors in shaping risk management practices within Nigerian banks.

4.1 Discussion of Findings

The findings from this study on the effect of artificial intelligence on risk management in Nigerian banks align with previous research while also providing new insights. The significant positive impact of AI adoption on risk management is consistent with studies such as Issa et al. (2023), which highlight AI's role in improving risk management, reducing operational costs, and increasing customer trust in the banking sector. Similarly, Tang and Tien (2020) emphasize AI's ability to enhance decision-making processes and operational efficiency, aligning with the results of this study, where AI adoption positively influences risk management practices. Furthermore, the significant effect of AI-driven credit scoring supports previous research by Chen et al. (2022), which demonstrates that AI can improve credit risk assessments by providing more accurate evaluations of borrowers' creditworthiness. The study's finding that AI fraud detection significantly impacts risk management is also in line with Singh and Thakur (2021), who observed that AI is crucial in enhancing fraud detection and minimizing fraudulent activities in banks.

Contrasting with the findings of this study, some authors report challenges in the integration of AI into risk management. Fadi et al. (2023) highlight that the adoption of AI in banks, particularly in the Middle Eastern region, is constrained by limited disclosure of AI activities in financial reports, which could reduce transparency and erode stakeholder trust. This lack of transparency contradicts the positive impact observed in this study, where AI adoption was linked to enhanced risk management, including fraud detection and credit scoring. Furthermore, Mayer-Schönberger and Cukier (2013) raise concerns about the data privacy and security risks associated with AI implementation. Their research suggests that these concerns may deter banks from fully adopting AI, despite its potential benefits, especially in developing economies where infrastructure and regulatory frameworks may not be sufficiently robust to address such risks. Similarly, Kumar and Garg (2021) emphasize that AI adoption may exacerbate inequality due to algorithmic biases, suggesting that the use of AI in banking could inadvertently affect the fairness and effectiveness of risk management processes. This view contrasts with the findings of this study, which suggest that AI's integration into risk management in Nigerian banks has been relatively beneficial, with no significant indications of such biases. Moreover, the research by O'Neil (2016) points out that AI's effectiveness in improving decision-making and risk management may be limited in environments where data quality is poor or employees lack the necessary training to leverage AI tools. This view aligns with the broader critique that while AI has transformative potential, its success is contingent on factors such as data quality, regulatory support, and human capital development—factors that may limit its applicability in certain contexts. These findings indicate that while AI adoption is generally viewed as beneficial, its integration and impact are not universally positive and may be subject to significant regional and contextual variations.

CONCLUSION

In conclusion, the findings from this study underscore the significant role of artificial intelligence (AI) in enhancing risk assessment and management within Nigerian banks. AI adoption, AI-driven credit scoring, and AI-based fraud detection all demonstrate positive impacts on improving risk management practices. Among these, AI-driven fraud detection shows the strongest effect, contributing the most to enhanced risk management. The regression analysis indicates that these AI-driven strategies together explain a substantial portion (56.2%) of the variation in risk management practices. These results highlight the growing importance of AI in the banking sector, not only in improving operational efficiencies but also in mitigating risks effectively.

RECOMMENDATIONS

In regards to the findings, the following recommendations were made

I. The significant positive impact of AI adoption on risk management suggests that Nigerian banks should continue to integrate AI technologies across various departments, including credit assessment, fraud detection, and operational risk management. Banks should prioritize the adoption of AI systems that can automate routine tasks, improve decision-making processes, and reduce human error, ultimately enhancing risk management capabilities.

II. Given the significant influence of AI-driven credit scoring on risk management, banks should invest in more advanced machine learning algorithms to improve the accuracy and reliability of credit assessments. This would help banks reduce the risk of bad loans and improve the overall quality of their loan portfolios. Banks should also collaborate with fintech firms to enhance their credit scoring models and ensure they are leveraging the most up-to-date data and technologies.

III. The strong relationship between AI fraud detection and risk management highlights the need for continuous investment in AI-powered fraud detection systems. Banks should focus on expanding their fraud detection systems to cover a wider range of fraudulent activities, including digital fraud and cybersecurity risks. By using AI to monitor transactions in real-time, banks can identify suspicious activities more quickly and reduce the overall risk of financial fraud.

IV. While AI adoption has proven beneficial, it is important for banks to ensure that their employees are adequately trained to work with AI systems. Providing regular training on how to use AI tools effectively will enhance employee performance and help banks fully capitalize on AI's potential. This could include specialized programs for risk management teams, fraud analysts, and credit officers to improve their understanding and ability to interpret AI-generated data.

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