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Artificial Intelligence and Risk Mitigation in Nigeria's Banking Sector: Challenges and Policy Implication (A Study of Zenith Bank)

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Abstract: Artificial Intelligence (AI) is ushering in a new era in banking, characterized by improved efficiency and a stronger emphasis on customer satisfaction. Persistent challenges continue to confront Nigeria's banking system, spanning credit risk exposures, operational shortcomings, cybercrime, regulatory lapses and reputational vulnerabilities. The main objective of this study is to assess the challenges and policy implication of artificial intelligence and risk mitigation in Nigeria's banking sector. The study employed a survey research design, utilizing estimation techniques such as simple percentages and regression analysis to analyze data collected through primary sources. The primary data were collected with the aid of a structured 5-point likert scale questionnaires. Purposive sampling technique was used to select 7 branches of Zenith Bank in Enugu State. The questionnaires were distributed to a sample size of 383 from a population of 9,271 using Taro Yamane (1967) formula. Data were analyzed using both traditional econometric techniques and AI-driven predictive model (Neural Network).The study concludes that AI applications have strong potential in mitigating credit risk and operational risks in Nigerian banks while applications in cyber fraud management are still emerging. The study also concludes that AI tools when aligned with strong internal control systems play a critical role in strengthening enterprise risk management in Nigerian banks. The study recommends that AI tools should be combined with human expertise (risk managers must interpret AI insights) to ensure context specific decision making. Banks should also strengthen data quality and cyber security infrastructure for AI deployment.

Keywords: Artificial Intelligence, Credit Risk, Operational Risk, Cyber Fraud, Enterprise Risk Management and Internal Control

Introduction

The emergence of artificial intelligence (AI) in the banking sector marks a pivotal shift towards more efficient, secure, and customer-oriented services. AI's integration into banking processes has not only revolutionized the way financial transactions are conducted but also significantly enhanced the sector's competitiveness by fostering innovation, agility, and scalability (Maheswari, Karthika, & Anusrii, 2023). The profound impact of AI on banking is evident in various facets, including improved fraud detection mechanisms, enhanced credit risk assessments, operational cost reductions, and the streamlining of compliance processes (Remesh, 2021). Furthermore, the adoption of AI technologies has been instrumental in adapting to the demands of technologically savvy customers, offering seamless mobile and e-banking experiences that meet the expectations for convenience and efficiency.

One of the most significant benefits of AI in banking is its role in information security. As financial institutions become increasingly digitalized, the threat landscape expands, necessitating sophisticated measures to protect against cyber threats. AI technologies enable banks to build resilient cyber-defense mechanisms, ensuring the safety and integrity of customer data, service quality, customer satisfaction, and consumer buying behavior and enhance customer banking experience (Gorian, 2021; Akinyemi, Omoge, & Horky, 2022).

Statement of the Problem

The integration of AI into banking operations has enabled a more dynamic, predictive approach to risk management. Through the application of machine learning algorithms, banks can now process and analyze vast datasets in real-time, identifying patterns, anomalies, and potential threats that would be impossible for human analysts to detect within the same timeframe (Leo, Sharma, & Maddulety, 2019). However, Nigeria's banking sector continues to grapple with persistent risk challenges ranging from credit defaults, operational lapses, data privacy concerns, ethical use of AI, potential biases in algorithmic decision-making and cyber fraud to regulatory non-compliance and reputational damage. Traditional risk management approaches anchored in static models, manual monitoring and fragmented data often fail to provide timely and accurate insights, leading to recurring financial losses and weak customer trust. Additionally, the successful deployment of AI in risk management requires significant investment in technology infrastructure and skilled personnel capable of developing, managing, and overseeing AI systems (Danielsson, Macrae, and Uthemann 2017 and Maskey, 2018)

Previous studies, such as Adedire-Ampitan et al.(2024), 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, regulatory concerns and impact of AI on risk management practices within deposit money banks, they largely overlook the specific concerns of how AI can be systematically applied in credit risk, operational risk, cyber fraud, and compliance management into Nigerian banks, both to mitigate risks and to align with national financial stability objectives. Additionally, studies like Adebayo & Olayinka (2022) emphasize the potential benefits of AI while Adedire-Ampitan et al.(2024), provided empirical evidence on application of potential benefits of AI in managing risks at the institutional level. These studies failed to assess how AI can be systematically integrated into Nigeria's banking risk management framework and improve financial risk mitigation. This gap in the literature underscores the need for this research.

Objectives of the Study

The main objective of this study is to assess the challenges and policy implication of artificial intelligence and risk mitigation in Nigeria's banking sector. The specific objectives of this study include the following to evaluate the potential applications of AI in credit risk management, operational risk control and cyber fraud mitigation within Nigerian banks and examine how AI tools improve internal control systems for effective enterprise risk management within Nigerian banks.

Conceptual Framework

Risk Management Policy Objectives

The risk management Policy emphasizes the maintenance of financial stability through sound asset quality, adequate capitalization, and prudent liquidity management. These measures ensure resilience against systemic shocks and support sustainable operations (Adedire-Ampitan et al.2024 & Nnaomah, et. al. 2024). Principal Credit Risk Policies primary objective is to maximize returns on a risk-adjusted basis from the banking book, while ensuring that all credit risk exposures are managed within the framework of the Credit Risk Management Policy. All proposed credit requests must be subjected to thorough review and approval by the designated credit approval authorities before disbursement. Upon approval, loans are disbursed to beneficiaries, while ongoing monitoring and management of such loans are undertaken jointly by the Relationship Management teams and the Credit Risk Management Group (Basel Committee on Banking Supervision, 2011 & Chukwu & Patel, 2023; Adeoye, 2021; Brown, 2022; Ononiwu, Onwuzulike, Shitu, & Ojo, 2024 ; Central Bank of Nigeria, 2018; Obienusi & Obienusi, 2015; Ajibo, 2015; Ogunbado, Ahmed & Abubakar, 2017 & Hassan, Ewuga & Abdul, 2024).

Artificial Intelligence and Risk Management in Banking Operations

In the banking sector, risk management is not merely a regulatory requirement but a cornerstone of sustainable business practice. It ensures financial stability, protects against potential losses, and upholds the trust of clients and investors alike. The integration of AI technologies has fundamentally transformed risk management in banking, offering unprecedented capabilities for risk identification, assessment, and mitigation. (Nnaomah, et. al. 2024). Artificial Intelligence operates through machine learning and Deep learning. According to Deloitte (2019), machine learning refers to the process of enabling computer systems to analyze large datasets, identify hidden patterns, classify information, and predict future outcomes Gartner's (2023). Deep learning, often referred to as Deep Neural Networks (DNN), has been increasingly applied by organizations to extract complex, high-level features from raw datasets to perform these tasks such as inventory assessments, audit report drafting, and the processing of structured and semi-structured data (Sun, 2019; Gholami et al. 2023; Fombellida et al., 2020 & Gartner 2023).

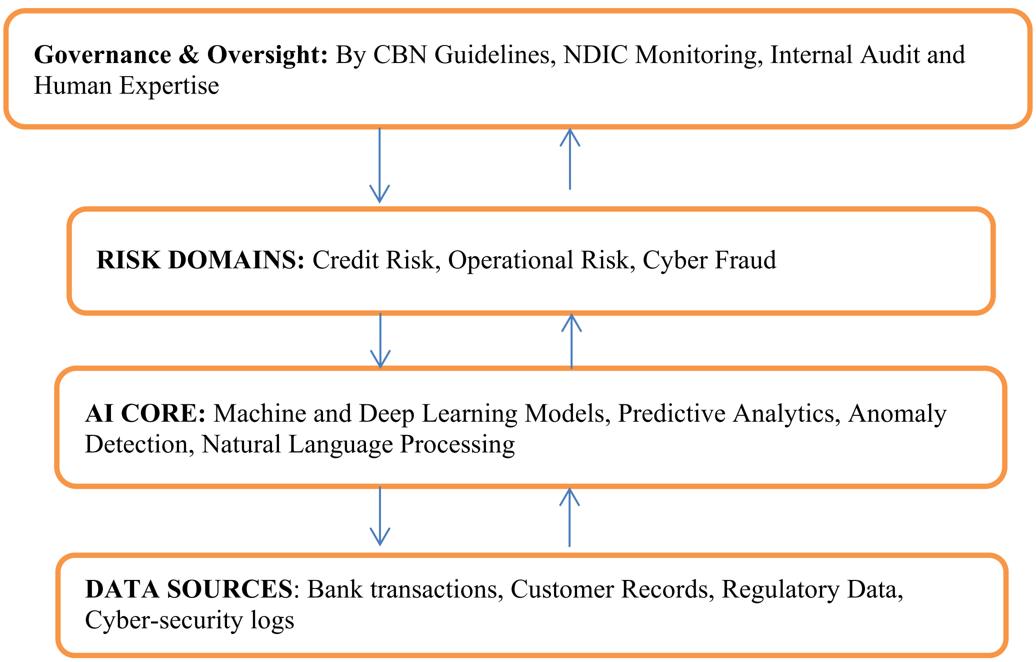

Fig 1. AI-Enabled Risk Management Framework for Nigerian Banks

Source: Author's Design (2025)

The fig. 1 model shows how Data Sources feed into the AI Core, which then addresses different risk domains, all under the watch of governance and oversight bodies (CBN, NDIC, Internal Audit and Human expertise)

Theoretical Framework

The theories adopted for this study are Technology Acceptance Model (TAM) and Financial Intermediation Theory

Technology Acceptance model (TAM)

The Technology Acceptance Model (TAM) was introduced by Davis in 1989. The reason why TAM is underpinned as a one of the theories of this is study is because TAM explains technology adoption based on two factors which include perceived ease of use and perceived usefulness. Perceived ease of use means the extent to which users agree in adopting a technology that will be free from stress, while perceived usefulness is the extent to which users believe the technology will enhance their performance or provide value. In this study, the model underscores how policymakers may be inclined to adopt AI if it is both practical and effective in strengthening debt risk analysis (Davis, 1989).

Financial Intermediation Theory

According to the Financial Intermediation Theory which was first propounded by Schumpeter, (1911) and further developed by Gurley & Shaw (1960). Banks facilitate economic growth by channeling savings into productive investments, reducing transaction costs, and managing financial risks. The theory explains the critical role of banks as financial intermediaries that mobilize savings from surplus units (depositors) and allocate them to deficit units (borrowers). Banks reduce transaction costs, manage risks through diversification, and enhance capital allocation efficiency.

Empirical Framework

Nnaomah, et al. (2024) conducted a study on AI in Risk Management: An Analytical Comparison between the U.S. and Nigerian Banking Sectors. The review synthesizes existing literature, including case studies, industry reports, and academic research, to outline the current state of AI in risk management. The findings suggested that U.S. banks have a more mature implementation of AI in risk management, characterized by the adoption of advanced analytics, machine learning models, and natural language processing for enhanced decision-making, fraud detection, and compliance monitoring.

Kumar et al. (2020); Chen et al. (2022); Choi et al. (2022) and AL Washah, EL Zanati, & Weshah, (2024) conducted a research on the Role of Artificial Intelligence Methods in Reducing Internal Control Risks: Systematic Literature Review. Data was extracted using data abstraction table before being analyzed through narrative approach for qualitative and quantitative findings. They revealed that Artificial intelligence is a critical tool for improving the efficiency of financial audit functions; however, requires more organizational input to overcome the inherence challenges, such as inadequate employees' knowledge and skills. (Issa et al. 2023; Tang & Tien 2020; Kruse, Wunderlich, & Beck, 2019)

Within the Nigerian context, empirical evidence reinforces these global findings. Aziz, Jibril, and Abusalma, (2021) and Bello (2023) show that AI enhances organizational systems by improving operational, managerial, and process efficiencies. Similarly, Elegunde and Osagie (2020) reveal that automation has strengthened employee performance across Nigerian banks. Beyond Nigeria, Ahmad (2020) emphasizes the role of AI in wealth creation and risk-sharing through the adoption of digital currencies in sub-Saharan Africa. Singh and Thakur (2021) report that AI technologies strengthen fraud detection in Indian banks, thereby improving customer trust

Gap in Literature

While prior studies provide valuable insights into the adoption and impact of Artificial Intelligence (AI) in the banking sector across different regions, several gaps remain. Existing research (e.g., Issa et al., 2023; Tang & Tien, 2020; Chen et al., 2022) has largely concentrated on the operational benefits of AI, such as cost reduction, risk management improvements, and fraud detection. However, there is limited empirical evidence on how AI adoption influences holistic risk management frameworks which include potential applications of AI in credit risk, operational risk and cyber fraud within banks. There is also limited empirical evidence on how AI tools improve internal control systems for effective enterprise risk management within Nigerian banks particularly in emerging economies like Nigeria where regulatory environments, infrastructural limitations, and technological readiness differ significantly from developed contexts. Most studies either focus narrowly on operational efficiency or on fraud detection, leaving a gap in understanding how AI can serve as a strategic tool for long-term risk mitigation, compliance, and corporate governance. Therefore, the gap in literature this research seeks to address is: the lack of comprehensive, context-specific evidence on how AI can be used to improve the way banks in Nigeria identify and measure, monitor and manage credit risk, operational risk and cyber fraud and internal control systems.

Methodology

The study employed a survey research design, utilizing estimation techniques such as simple percentages and regression analysis to analyze data collected through primary sources. To test the hypothesis, Analysis of Variance (ANOVA) was used. The primary data were collected with the aid of a structured 5-point likert scale questionnaires. Participants include risk managers, compliance offices, IT/AI specialists and executive and other senior management staff. The population of the study comprises of over 500 branches of Zenith Bank with substantial total workforce that stood at 9,271 employees as of December 31st, 2024 in Nigeria (stockanalysis.com, www.zenithbank.com). Purposive sampling technique was used to select 7 branches of Zenith Bank in Enugu State. The questionnaires were distributed to a sample size of 383 from a population of 9,271 using Taro Yamane (1967) formula at 95% confidence level stated as follows:

$$n = \frac{N}{1 + N(e)^2}$$

Where N= Population size, e = error margin which the researcher chose to be 5%. n= sample size.

$$\text{Thus } n = \frac{9{,}271}{1 + 9{,}271\,(0.05)^2} = 383 \text{ questionnaires}$$

Out of the 383 copies of questionnaires distributed to the 7 branches of Zenith Bank in Enugu state, 103 were not returned while 280 were returned, representing a return rate of 73.1%. The study adopts credit risk management, operational risk control and cyber fraud mitigation and internal control systems as proxies for risk mitigation. Artificial Intelligence is proxied by Machine Learning and Deep learning. Data were analyzed using both traditional econometric techniques and AI-driven predictive model (Neural Network).

Data Presentation

Table 4.1. Distribution of Respondents by Educational Qualifications

Qualification	Number	Percentage (%)
O' LEVEL	-	-
OND	-	-
B.Sc / HND	154	55
M.Sc /MBA	103	36.8
Ph.D and Others	23	8.2
Total	280	100

Source: Field Survey 2025

Table 4.2. Distribution of Respondents by Working Experience.

Working Experience	Number	Percentage (%)
BELOW 5 YEARS	9	3.2
5- 10 YEARS	28	10
11- 15 YEARS	75	26.8
16- 20 YEARS	76	27.1
21 YEARS AND ABOVE	92	32.9
TOTAL	280	100

Source: Field Survey 2025

Table 4.3. Distribution of Respondent by Departments

Department	Number	Percentage (%)
Risk management	59	21.1
Internal Control	48	17.1
IT/Info Tech	25	8.9
Compliance	46	16.4
Audit	52	18.6
Others	50	17.9
TOTAL	280	100

Source: Field Survey 2025

Table 4.4. The potential applications of AI in credit risk within Nigerian banks.

Q1	Credit Risk	SA	A	UN	D	SD
1	Our bank make use of AI model to improve probability-of-default (PD) estimation	130	100	15	25	10
2	AI has improved the accuracy of credit scoring for retail and SME lending	125	95	9	30	21
3	AI-driven early-warning indicators help us detect deteriorating loan accounts sooner	136	107	10	14	13
4	Human credit decisions are rarely improved by AI insights.	54	74	45	50	57

Source: Field Survey 2025

Table 4.5. The potential applications of AI in operational risk within Nigerian banks

S/N	Operational Risk	SA	A	UN	D	SD
5	AI tools help identify process bottlenecks that increase operational risk.	140	105	10	15	10
6	AI-based analytics improve incident/root-cause analysis for loss events.	130	110	8	11	21
7	AI has reduced manual errors in high-volume back-office processes	138	111	5	13	13
8	Our operational risk controls are too context-specific for AI to add value	100	52	31	49	48

Source: Field Survey 2025

Table 4.5. The potential applications of AI in cyber fraud within Nigerian banks

S/N	Cyber Fraud	SA	A	UN	D	SD
9	AI models effectively detect anomalies transactions indicative of fraud	150	110	5	10	5
10	AI has improved real-time monitoring of phishing and account-takeover attempts	140	122	6	3	9
11	AI-enabled fraud alerts are actionable and reduce false positives	148	121	4	4	3
12	Fraudsters adapt faster than our AI systems, limiting AI's usefulness	10	5	3	129	133

Source: Field Survey 2025

Table 4.6. How AI tools improve internal control systems for effective enterprise risk management within Nigerian banks.

Q2	Internal control systems	SA	A	UN	D	SD
13	Staff have sufficient skills to interpret AI outputs for control decisions	25	30	45	85	95
14	AI improves segregation of duties, breach detection across systems	145	120	5	5	5
15	Control deficiencies are remediated faster when AI analytics are used	135	130	1	6	8
16	AI adoption has improved compliance with regulatory guidelines	100	70	30	35	45
17	AI enhances the timeliness of control testing and monitoring	150	100	0	10	20

Source: Field Survey 2025

Data Analysis and Interpretation

Using Traditional Econometric Technique to analyze the potential applications of AI in credit risk, operational risk and cyber fraud within Nigerian banks

Table 4.7 Model Summary the potential applications of AI in credit risk, operational risk and cyber fraud within Nigerian banks

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.890 a	.791	.752	.72237	.791	20.218	3	16	.000	.615
a. Predictors: (Constant), CYBERFRAUD, OPERARISK, CRERISK										
b. Dependent Variable: VAR001										

Source: Researcher's SPSS computation (2025)

Table 4.8 Coefficients of the potential applications of AI in credit risk, operational risk and cyber fraud within Nigerian banks

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations		
		B	Std. Error	Beta			Zero-order	Partial	Part
1	(Constant)	1.547	.276		5.608	.000			
	CRERISK	.013	.015	.413	.904	.380	.769	.220	.103
	OPERARISK	.028	.012	.976	2.309	.035	.809	.500	.264
	CYBERFRAUD	-.016	.005	-.690	-3.215	.005	.458	-.626	-.367
a. Dependent Variable: VAR001									

Source: Researcher's SPSS computation (2025)

Table 4.7 of the model summary of the multiple regression results of R = 0.890 shows a strong positive relationship between the independent variables (AI applications in credit risk, operational risk and cyber fraud) and the dependent variable (overall effectiveness or performance in Nigerian banks). The coefficient of determination (R square = 0.791) shows that 79.1% of the variation in the dependent variable (banking risk management effectiveness) is explained by AI applications in credit risk, operational risk and cyber fraud. The high explanatory power demonstrates the robustness of the model. The remaining 20.9% is explained by other factors not captured in the model. Adjusted R square = 0.722. The adjusted R Square value of 0.7 and above depicts strong relationship between the variables, 0.5 to 0.7 depicts moderate relationship between the variables while below 0.5 shows weak relationship. Hence Adjusted R square of 0.722 is the adjusted number of predictors in the model which depicts strong relationship between the variables. This confirms that the model is statistically reliable and not inflated by irrelevant predictors. The regression model reveals a strong and statistically significant relationship between AI applications in credit risk, operational risk and cyber fraud. This further means that even after adjustment, AI applications significantly explain risk management effectiveness. The test for autocorrelation in a regression model's output is known as Durbin-Watson (DW). In Table 4.7 the DW statistics is .615. Figures below 2.0 reveals that there is positive autocorrelation and above 2.0 reveals negative autocorrelation. This indicates that there is a positive autocorrelation between AI applications in credit risk, operational risk and cyber fraud within Nigerian banks.

Using Neural Network (AI-Driven Model) to analyze the potential applications of AI in credit risk, operational risk and cyber fraud within Nigerian banks

Table 4.9 Case Processing Summary

		N	Percent
Sample	Training	16	80.0%
	Testing	4	20.0%
Valid		20	100.0%
Excluded		0	
Total		20	

Source: Researcher's SPSS computation (2025)

Interpretation: The sample is small (20), but evenly split into training and testing, meaning the model generalizes fairly well with no missing cases.

Table 4.10 Model Summary

Training	Cross Entropy Error	8.745
	Percent Incorrect Predictions	31.2%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.03
Testing	Cross Entropy Error	1.109
	Percent Incorrect Predictions	25.0%
Dependent Variable: VAR001		
a. Error computations are based on the testing sample.		

Source: Researcher's SPSS computation (2025)

Interpretation: The neural network shows reasonable predictive performance. The fact that test error is lower than training error suggests good generalization (not over fitted).

Table 4.11 Independent Variable Importance

	Importance	Normalized Importance
CRERISK	.388	83.7%
OPERARISK	.463	100.0%
CYBERFRAUD	.149	32.2%

Source: Researcher's SPSS computation (2025)

Interpretation: The results suggest that Nigerian banks derive maximum benefits of AI in managing operational risk, followed by credit risk while cyber fraud detection lags behind (possibly due to infrastructure or data challenges).

Using Traditional Econometric Technique to analyze AI tools on internal control systems for effective enterprise risk management within Nigerian banks

Table 4.12 Model Summary of AI tools improve internal control systems for effective enterprise risk management within Nigerian banks

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.599[a]	.359	.331	1.18064	.359	12.870	1	23	.002	.853
a. Predictors: (Constant), INTCONTROL										
b. Dependent Variable: VAR001										

Source: Researcher's SPSS computation (2025)

Table 4.12 of the model summary of the multiple regression results of R = 0.599 shows a moderate positive relationship between the AI tools (independent variable) and internal control (dependent variable). R Square = .359. The model explains about 36% of the variation in internal control systems through AI tools. This means AI has a substantial influence but other factors also explain the remaining 64.1%. Adjusted R Square = .331 (33.1%). After adjusting for the number of predictors and sample size, the explanatory power remains fairly strong. This suggests that AI tools significantly improve internal control systems in Nigerian banks, but the strength of the relationship is moderate rather than strong. The test for autocorrelation in a regression model's output is known as Durbin-Watson (DW). In Table 4.12 the DW statistics is .853. Figures below 2.0 reveals that there is positive autocorrelation and above 2.0 reveals negative autocorrelation. This reveals that there is a positive autocorrelation between internal control systems and effective enterprise risk management within Nigerian banks.

Table 4.13. Coefficients of AI tools on internal control systems for effective enterprise risk management within Nigerian banks						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.064	.352		5.864	.000
	INTCONTROL	.017	.005	.599	3.588	.002
a. Dependent Variable: VAR001						

Source: Researcher's SPSS computation (2025)

Using Neural Network (AI driven Model) to analyze AI tools on internal control systems for effective enterprise risk management within Nigerian banks

Table 4.14 Case Processing Summary			
		N	Percent
Sample	Training	20	80.0%
	Testing	5	20.0%
Valid		25	100.0%
Excluded		0	
Total		25	

Source: Researcher's SPSS computation (2025)

Interpretation: The sample is small (20), but evenly split into training and testing, meaning the model generalizes fairly well with no missing cases.

Table 4.15 Network Information			
Input Layer	Covariates	1	INTCONTROL
	Number of Units[a]		1
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		2

	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	VAR001
	Number of Units		5
	Activation Function		Softmax
	Error Function		Cross-entropy
a. Excluding the bias unit			

Source: Researcher's SPSS computation (2025)

Interpretation: The network is simple and enough to capture a nonlinear mapping

Table 4.16	**Model Summary**	
Training	Cross Entropy Error	31.014
	Percent Incorrect Predictions	85.0%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.05
Testing	Cross Entropy Error	7.505
	Percent Incorrect Predictions	60.0%
Dependent Variable: VAR001		
a. Error computations are based on the testing sample.		

Source: Researcher's SPSS computation (2025)

Table 4.17 Independent Variable Importance		
	Importance	Normalized Importance
INTCONTROL	1.000	100.0%

Source: Researcher's SPSS computation (2025)

Interpretation: The only independent variable, Internal control had an importance weight of 1.000 (100%) normalized importance. This indicates that internal control is the sole driver of the predictive model in explaining how AI tools impact enterprise risk management.

Using Traditional Econometric Technique to analyze AI-enabled risk management framework suitable for adoption by Nigerian banks and regulatory agencies

Table 4.18 Model Summary of AI-enabled risk management framework suitable for adoption by Nigerian banks and regulatory agencies

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.809[a]	.654	.639	.86703	.654	43.512	1	23	.000	.487
a. Predictors: (Constant), RISKMGT										
b. Dependent Variable: VAR001										

Source: Researcher's SPSS computation (2025)

Interpretation: R is 0.809 signifies a strong positive correlation between AI adoption and effective risk management. This means that AI tools have a substantial impact on mitigating risks in Nigerian banks. R square is 0.654 (65.4%) signifies that about 65% of the variation in risk management effectiveness can be explained by AI- enabled frameworks. This is a solid explanatory power. Adjusted R Square is 0.639 (63.9%) confirms that the model is reliable with little inflation from irrelevant variables. The predictors remain valid even after adjustment.

The test for autocorrelation in a regression model's output is known as Durbin-Watson (DW). In Table 4.18 the DW statistics is 0.487. Figures less than 2.0 mean there is positive autocorrelation while Figures more than 2.0 reveals negative autocorrelation. This reveals that there is a positive autocorrelation between AI adoption and effective risk management.

Table 4.19 Coefficients of AI-enabled risk management framework suitable for adoption by Nigerian banks and regulatory agencies

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.776	.254		6.990	.000
	RISKMGT	.022	.003	.809	6.596	.000
a. Dependent Variable: VAR001						

Source: Researcher's SPSS computation (2025)

Test of Hypotheses

Hypothesis One

i. Artificial intelligence does not have significant potential applications in credit risk management, operational risk control and cyber fraud mitigation within Nigerian banks.

ii. Artificial intelligence has significant potential applications in credit risk management, operational risk control and cyber fraud mitigation within Nigerian banks.

Table 4.20 ANOVA of Hypothesis One

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	31.651	3	10.550	20.218	.000[b]
	Residual	8.349	16	.522		
	Total	40.000	19			

a. Dependent Variable: VAR001

b. Predictors: (Constant), CYBERFRAUD, OPERARISK, CRERISK

Source: Researcher's SPSS computation (2025)

From the ANOVA table 4.20 which uses the computed F-value to test the acceptability of the model from a statistical perspective, the decision criterion is stated below as follows:

F calculated > Sig value	Reject the null hypothesis
F calculated < Sig value	Accept the null hypothesis

Decision: Since the F cal. (20.218) is greater than the Sig. value (.000) at a 5% level of significance and 2 degrees of freedom, we reject the null hypothesis and accept the alternate hypothesis that Artificial intelligence has significant potential applications in credit risk management, operational risk control and cyber fraud mitigation within Nigerian banks.

Hypothesis Two

i. AI tools do not have a significant effect on the improvement of internal control systems for effective enterprise risk management within Nigerian Banks.

ii. AI tools have a significant effect on the improvement of internal control systems for effective enterprise risk management within Nigerian Banks.

Table 4.21		ANOVA of hypothesis Two				
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	17.940	1	17.940	12.870	.002
	Residual	32.060	23	1.394		
	Total	50.000	24			
a. Dependent Variable: VAR001						
b. Predictors: (Constant), INTCONTROL						

Source: Researcher's SPSS computation (2025)

From the ANOVA table 4.21 which uses the computed F-value to test the acceptability of the model from a statistical perspective, the decision criterion is stated below as follows:

F calculated > Sig value Reject the null hypothesis
F calculated < Sig value Accept the null hypothesis

Decision: Since the F cal. (12.870) is greater than the Sig. value (.002) at a 5% level of significance and 2 degrees of freedom, we reject the null hypothesis and accept the alternate hypothesis that AI tools have a significant effect on the improvement of internal control systems for effective enterprise risk management within Nigerian Banks.

Results and Discussion of Findings

Using traditional econometric techniques

The outcome of the test of hypothesis one revealed that Artificial intelligence has significant potential applications in credit risk management, operational risk control and cyber fraud mitigation within Nigerian banks. In other words, AI adoption in these three risk areas strongly predicts improved banking risk management. This implies that increased adoption of AI significantly enhances banks' ability to manage risks effectively. The regression results demonstrate that AI adoption has a substantial and positive impact on the management of credit risk assessment, operational risk and cyber fraud prevention in Nigerian banks.

Overall Interpretation using AI-driven Model (Neural Network)

For hypothesis one, the neural network model demonstrates that AI applications are relevant and predictive in banking risk management. Operational risk control (fraud prevention in operations, compliance automation, transaction monitoring) is the most significant area. Credit risk management (default prediction, loan approvals, scoring) also benefits strongly. Cyber fraud, while important globally, seems to have a lesser immediate impact in Nigerian banks, likely reflecting current adoption or data limitations.

Using traditional econometric techniques

The outcome of the test of hypothesis two revealed that AI tools have a significant effect on the improvement of internal control systems for effective enterprise risk management within Nigerian Banks.

Overall Interpretation using AI-driven Model (Neural Network)

For hypothesis two, the neural network analysis reveals that AI tools when aligned with strong internal control systems play a critical role in strengthening enterprise risk management in Nigerian banks. This further means that AI enhances risk management effectiveness by improving fraud detection, compliance monitoring and operational efficiency within internal control systems.

Summary of findings, Conclusion, Recommendation and Policy Implication

Summary of findings

The study summarizes that artificial intelligence has significant potential applications in credit risk management, operational risk control and cyber fraud mitigation within Nigerian banks.

The study also summarize that AI tools have a significant effect on the improvement of internal control systems for effective enterprise risk management within Nigerian Banks.

Conclusions

The study concludes that AI applications have strong potential in mitigating credit risk, and operational risks in Nigerian banks while applications in cyber fraud management are still emerging. This implies that banks and regulators should prioritize strengthening AI tools for cyber fraud to balance risk control across all domains.

The study concludes that AI tools when aligned with strong internal control systems play a critical role in strengthening enterprise risk management in Nigerian banks.

Recommendations

The study recommends that AI tools should be combined with human expertise (risk managers must interpret AI insights) to ensure context specific decision making.

Banks should also strengthen data quality and cyber security infrastructure for AI deployment.

Policy Implication

Banks can reduce operational risks, credit risks and cyber fraud more effectively by embedding AI tools such as predictive analytics, anomaly detection and machine learning- based fraud monitoring.

Regulators such as CBN and NDIC should mandate the adoption of AI-enabled internal control frameworks as part of risk management compliance for banks, given its central role in mitigating operational and financial risks.

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