

EFFECT OF ARTIFICIAL INTELLIGENCE ON RISK MANAGEMENT IN INSURANCE COMPANIES IN ABUJA

Dare Joseph Daniel
Department of Business Administration
University of Abuja
Email: Dare.daniel@uniabuja.edu.ng

Bori Patience Joy
Department of Business Administration
University of Abuja
Email: patige4us@gmail.com

Aniefiok Edward Udoh
Department of Business Administration
University of Abuja
Email: aniefiokudoh1993@gmail.com

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Abstract

Ideally, integrating Artificial Intelligence (AI) into insurance companies in Abuja was expected to substantially strengthen risk management practices. AI-enabled predictive analytics were projected to enhance underwriting precision, reduce information gaps between insurers and policyholders, and improve fraud detection systems. This study examined the effect of Artificial Intelligence on risk management in selected insurance companies in Abuja, Nigeria. The main objective was to determine how predictive analytics and automated decision-making systems influence risk identification and risk mitigation/control mechanisms. A cross-sectional survey research design was adopted. The population comprised 353 employees drawn from five selected insurance companies, from which a sample size of 187 was determined using Taro Yamane's formula; however, 224 questionnaires were distributed to accommodate non-response, and 210 valid responses were retrieved using stratified sampling techniques. Primary data were collected through a structured five-point Likert scale questionnaire. Reliability was confirmed using Cronbach's Alpha coefficients above 0.70 for all constructs. Data were analyzed using simple regression with SPSS version 27. The findings revealed that predictive analytics had a significant positive effect on risk identification ($R^2 = 0.465, p < 0.001$), while automated decision-making systems significantly influenced risk mitigation and control mechanisms ($R^2 = 0.549, p < 0.001$). The study concluded that AI-driven technologies significantly enhance risk management effectiveness in the Nigerian insurance sector. It was recommended that insurance firms increase investment in predictive analytics infrastructure and integrate automated decision-making systems into core risk management processes to improve operational efficiency and strengthen internal controls.

Keywords: Artificial Intelligence, Predictive Analytics, Automated Decision-Making Systems, Risk Identification, Risk Mitigation, Nigerian Insurance Industry.

INTRODUCTION

Artificial Intelligence (AI) has become one of the most influential technological developments of the twenty-first century, significantly transforming how organizations operate and compete across industries. Around the world, AI-powered systems are strengthening data analysis, increasing the

accuracy of forecasts, automating routine procedures, and assisting managers in making complex decisions. The rapid expansion of big data and machine learning applications has further accelerated AI adoption, enabling organizations to enhance productivity, minimize uncertainty, and achieve long-term value creation (Dhieb et al., 2020; Terala,

2025). In both advanced and developing economies, AI is increasingly perceived as a strategic requirement, particularly in industries that rely heavily on data and risk evaluation (Temitope et al., 2025; Daniel & Chukwuemeka, 2023).

The ongoing digital transformation has been especially impactful within financial service sectors such as banking and insurance. AI-driven technologies now support real-time transaction monitoring, fraud detection, automated regulatory compliance, and more refined customer segmentation (Amaugo & Ofosu-Boateng, 2025; Nnaomah et al., 2024). In the insurance industry, where operations are inherently centered on uncertainty management and risk pooling, the relevance of AI is particularly pronounced. Insurance firms depend on precise risk evaluation, efficient claims administration, and reliable fraud control systems. As a result, embedding AI technologies into fundamental insurance operations has become a strategic approach to improving performance and ensuring long-term sustainability (Agu et al., 2022; Terala, 2025; Oyadiran et al., 2018).

Artificial Intelligence generally describes computer-based systems capable of performing tasks that traditionally require human intelligence, such as learning from data, recognizing patterns, and generating predictions. Within organizational environments, AI improves analytical accuracy, reduces human-related errors, and facilitates proactive decision-making. In insurance firms, AI applications enhance underwriting processes, accelerate claims handling, detect suspicious transactions, and support strategic business planning (Dhieb et al., 2020; Agu et al., 2022). These improvements not only reduce operational costs but also strengthen profitability and competitive positioning in increasingly technology-driven markets (Terala, 2025).

In the context of risk management, two prominent AI components are predictive analytics and automated decision-making systems. Predictive analytics utilizes historical datasets, statistical tools, and machine learning techniques to anticipate future events and identify potential exposures. Within insurance operations, predictive models assist in estimating claim probabilities, determining

appropriate premium pricing, and uncovering fraud-related patterns (Agu et al., 2022; Amaugo & Ofosu-Boateng, 2025). This analytical capability enhances underwriting precision and reduces ambiguity in risk assessment. Conversely, automated decision-making systems rely on algorithm-driven processes to carry out predefined actions with minimal human oversight. These systems expedite claims approvals, perform compliance checks, and generate immediate risk assessments, thereby improving operational efficiency and strengthening control mechanisms (Dhieb et al., 2020; Terala, 2025). By limiting delays and reducing manual intervention, automation reinforces institutional risk governance frameworks.

Risk management remains fundamental to insurance practice, encompassing the identification, evaluation, monitoring, and mitigation of potential threats to organizational objectives (Daniel & Park, 2015). Effective risk management supports regulatory adherence, financial soundness, and sustainable profitability. In insurance settings, risk identification involves recognizing exposures such as underwriting inaccuracies, fraudulent claims, operational inefficiencies, and market fluctuations. Proper identification provides the basis for effective strategic decisions. Risk mitigation and control mechanisms, on the other hand, involve implementing policies, procedures, and technological systems designed to reduce the likelihood or impact of identified risks, including reinsurance strategies, internal control systems, and digital monitoring platforms (Temitope et al., 2025; Nnaomah et al., 2024). Together, these elements determine the strength and reliability of an insurer's risk management framework.

The relationship between AI adoption and risk management outcomes in insurance companies in Abuja has attracted growing scholarly and professional interest. AI-based predictive models have the potential to improve client risk profiling accuracy, while automated systems may enhance fraud detection, streamline claims processing, and ensure regulatory compliance (Agu et al., 2022; Amaugo & Ofosu-Boateng, 2025). Nevertheless, the actual extent to which AI integration produces measurable improvements in risk management performance within Nigeria requires empirical

validation. Contextual factors such as regulatory structures, technological capacity, and organizational preparedness may shape the success of AI implementation (Nnaomah et al., 2024).

Despite its critical role in financial stability, insurance companies in Abuja continues to encounter substantial challenges, including frequent fraudulent claims, inefficiencies in underwriting, limited digital infrastructure, and operational constraints. Insurance penetration remains comparatively low, reflecting structural weaknesses and public trust concerns. Simultaneously, emerging InsurTech and fintech companies are deploying advanced AI solutions to deliver faster and more innovative services, thereby intensifying competition within the sector (Amaugo & Ofosu-Boateng, 2025; Terala, 2025). Conventional insurers that delay technological modernization risk diminished competitiveness in a rapidly evolving digital environment.

In view of these developments, there is a clear need to investigate the impact of Artificial Intelligence on risk management practices within insurance companies in Abuja. Empirical assessment is necessary to determine whether AI adoption strengthens risk identification and mitigation processes, enhances operational effectiveness, and supports sustainable organizational growth. Insights derived from such analysis would inform policymakers, regulators, and industry leaders seeking to modernize insurance operations and strengthen the sector's contribution to Nigeria's broader economic development.

Ideally, integrating Artificial Intelligence (AI) into insurance companies in Abuja was expected to substantially strengthen risk management practices. AI-enabled predictive analytics were projected to enhance underwriting precision, reduce information gaps between insurers and policyholders, and improve fraud detection systems (Area, 2023; Agu et al., 2022). Similarly, automated decision-making systems were anticipated to accelerate claims processing, reduce administrative bottlenecks, and improve compliance with regulatory standards (Terala, 2025; Amaugo & Ofosu-Boateng, 2025). Collectively, these technological capabilities were presumed to improve operational

efficiency, reinforce financial stability, and restore public confidence in insurance services, thereby enhancing industry competitiveness and long-term sustainability (Malik et al., 2025).

In practice, however, insurance companies in Abuja has continued to face persistent risk management challenges. Issues such as underwriting inaccuracies, fraudulent claims, delayed claims settlement, and operational inefficiencies remain prevalent (Agu et al., 2022). Insurance penetration has also remained below one percent of Gross Domestic Product, reflecting structural weaknesses and limited consumer trust. Furthermore, gaps in technological infrastructure and limited data analytics capacity have constrained many firms' ability to effectively detect and manage emerging risks (Nnaomah et al., 2024; Temitope et al., 2025). At the same time, InsurTech and fintech firms deploying advanced AI-driven platforms have begun reshaping the competitive landscape by offering faster, more transparent, and customer-oriented services (Bhattacharya et al., 2025; Amaugo & Ofosu-Boateng, 2025). This shift has increased pressure on traditional insurers to modernize their operational and risk management systems.

From a theoretical standpoint, while numerous international studies have explored AI adoption within financial services, relatively limited empirical research has focused specifically on its implications for risk management in the Nigerian insurance context. Existing literature has frequently emphasized banking applications or general financial technology adoption (Nnaomah et al., 2024; Malik et al., 2025), leaving a contextual gap regarding how AI influences essential insurance processes such as underwriting accuracy, claims management efficiency, and fraud prevention within Nigeria. Although broader global discussions highlight AI's transformative potential in insurance (Bhattacharya et al., 2025; Terala, 2025), localized empirical evidence remains insufficient to inform strategic decision-making and policy formulation in the Nigerian insurance sector.

If these practical and theoretical gaps remain unaddressed, the industry may continue to experience operational inefficiencies, financial losses arising from unmanaged risks, and

reduced competitiveness against technologically advanced entrants. Over time, such challenges could weaken public confidence and hinder the sustainable growth of the Nigerian insurance sector, limiting its overall contribution to national economic development. It was against this backdrop that the present study examined the effect of Artificial Intelligence on risk management within insurance companies in Abuja.

The main objective of this study is to examine the effect of Artificial Intelligence on risk management in insurance companies in Abuja. The specific objectives of the study are to:

- i. Examine the effect of predictive analytics on risk identification in insurance companies in Abuja.
- ii. Evaluate the effect of automated decision-making systems on risk mitigation and control mechanisms in insurance companies in Abuja.

The study sought to provide answers to the following research questions:

- i. What is the effect of predictive analytics on risk identification in insurance companies in Abuja?
- ii. How do automated decision-making systems affect risk mitigation and control mechanisms in insurance companies in Abuja?

2.0 LITERATURE REVIEW

Concept of Artificial Intelligence

Artificial Intelligence (AI) has been widely defined in academic literature as the capability of machines to perform tasks that normally require human intelligence. Russell and Norvig (2021) described AI as the study of intelligent agents systems that perceive their environment and take actions to maximize the achievement of specified goals. Earlier, McCarthy (1956), who coined the term Artificial Intelligence, defined it as the science and engineering of making intelligent machines capable of performing tasks that would require intelligence if performed by humans. These definitions emphasize learning, reasoning, problem-solving, and adaptation as core

characteristics of AI systems. In organizational settings, AI is increasingly viewed as a transformative technological capability that enables firms to extract insights from large datasets, improve operational efficiency, and enhance strategic decision-making.

Within financial services, AI has become a strategic tool for improving service delivery and operational precision. Brynjolfsson and McAfee (2014) argued that digital technologies, including AI, are reshaping industries by increasing productivity and enabling new business models. In the insurance sector, AI applications extend to underwriting, claims management, fraud detection, and customer analytics. Davenport and Ronanki (2018) noted that organizations deploy AI primarily to automate business processes, gain insights through data analysis, and enhance customer engagement. In insurance operations, these capabilities are particularly valuable because the industry relies heavily on data analysis and risk assessment. Consequently, AI adoption is increasingly considered a critical resource for achieving efficiency, competitiveness, and long-term sustainability.

Predictive Analytics

Predictive analytics represents a major dimension of Artificial Intelligence and refers to the use of statistical algorithms, machine learning techniques, and historical data to forecast future events. Shmueli and Koppius (2011) defined predictive analytics as the application of statistical and machine learning models to predict future observations based on past data. Similarly, Siegel (2013) described predictive analytics as technology that learns from experience (data) to predict future behavior of individuals or entities. These perspectives highlight the central role of data-driven forecasting in enhancing organizational decision-making processes.

In the insurance industry, predictive analytics strengthens risk identification and assessment. Insurers rely on historical claims data, demographic information, and behavioral indicators to estimate the probability and severity of future losses. According to Davenport and Harris (2007), firms that leverage analytics effectively are better positioned to improve decision quality and operational performance. In underwriting,

predictive models enhance the accuracy of premium pricing and reduce adverse selection. Furthermore, predictive tools assist in detecting fraudulent claims by identifying unusual patterns and anomalies within datasets. The ability to anticipate potential losses improves financial planning and reduces uncertainty, making predictive analytics a valuable instrument for strengthening risk management frameworks in insurance firms.

Automated Decision-Making Systems

Automated decision-making systems constitute another important dimension of AI. These systems use algorithms and predefined rules to execute decisions without continuous human intervention. According to Davenport and Ronanki (2018), AI-based automation is commonly used to streamline structured and repetitive tasks in business operations. Such systems are designed to process information rapidly, apply logical rules consistently, and generate outcomes with minimal manual oversight. Automation is often supported by machine learning models that continuously improve performance as more data become available.

In the insurance context, automated decision-making systems enhance operational efficiency and risk control. For example, AI-powered claims processing platforms can evaluate claims documentation, verify policy details, and approve legitimate claims in real time. This reduces administrative delays and operational costs. Automated underwriting systems also assess risk profiles instantly, ensuring consistency and reducing subjective bias in decision-making. Brynjolfsson and McAfee (2014) emphasized that automation technologies significantly improve productivity and organizational performance when properly implemented. By reducing human error and enforcing standardized procedures, automated decision systems strengthen risk mitigation and internal control mechanisms within insurance firms.

Risk Management

Risk management is a fundamental function in the insurance industry because the core business of insurance revolves around assuming, pricing, and managing risk. The Committee of Sponsoring Organizations of the Treadway Commission (COSO, 2017) defined

enterprise risk management as a structured process applied across an organization to identify potential events that may affect the entity and to manage risk within its appetite to provide reasonable assurance regarding the achievement of objectives. Similarly, Hopkin (2018) described risk management as a systematic approach to identifying, assessing, and controlling threats that could hinder the attainment of organizational goals. These definitions emphasize that risk management is not a one-time activity but a continuous and coordinated process embedded in strategic and operational decision-making.

In the insurance industry, effective risk management ensures financial solvency, regulatory compliance, operational stability, and long-term sustainability. Given that insurers are exposed to underwriting risks, market volatility, operational risks, fraud risks, and compliance risks, a robust framework for managing these uncertainties is essential. Scholars have consistently argued that organizations with strong risk management systems are better positioned to withstand economic shocks and competitive pressures (COSO, 2017). Within this broad framework, two key dimensions are particularly relevant to this study: risk identification and risk mitigation and control mechanisms.

Risk Identification

Risk identification refers to the systematic process of recognizing and documenting potential internal and external risks that could negatively affect organizational performance. According to ISO 31000 (International Organization for Standardization, 2018), risk identification involves finding, recognizing, and describing risks that might help or prevent an organization from achieving its objectives. In the insurance context, risk identification includes detecting underwriting inaccuracies, fraudulent claims, data breaches, operational inefficiencies, and regulatory compliance failures.

Effective risk identification requires comprehensive data analysis, environmental scanning, and continuous monitoring of internal processes. Without accurate identification, subsequent risk assessment and mitigation efforts may be ineffective or misdirected. Scholars such as Hopkin (2018)

emphasized that the quality of risk management outcomes largely depends on how well risks are initially identified. In modern insurance operations, technological tools such as data analytics and artificial intelligence enhance the accuracy and timeliness of identifying emerging risks. Therefore, strengthening risk identification processes improves decision-making quality and reduces exposure to unforeseen losses.

Risk Mitigation and Control Mechanisms

Risk mitigation and control mechanisms refer to the strategies, policies, and systems implemented to reduce the likelihood or impact of identified risks. Once risks are identified and assessed, organizations must determine appropriate responses, including avoidance, reduction, transfer, or acceptance (COSO, 2017). In the insurance industry, mitigation strategies may involve implementing stricter underwriting guidelines, adopting fraud detection systems, diversifying risk portfolios, purchasing reinsurance, and strengthening internal control frameworks.

Control mechanisms are designed to ensure that risk responses are properly executed and monitored. These mechanisms include compliance monitoring systems, internal audits, automated approval processes, and regulatory reporting frameworks. According to Hopkin (2018), effective risk control enhances organizational resilience by minimizing operational vulnerabilities and preventing financial losses. In technologically evolving environments, AI-driven tools such as automated monitoring systems and predictive fraud detection platforms further strengthen mitigation capabilities. For insurance firms in Nigeria, improving risk mitigation and control mechanisms is essential for enhancing financial stability, increasing customer confidence, and maintaining regulatory compliance.

Theoretical Framework

Resource-Based View (RBV) Theory

This study is anchored on the Resource-Based View (RBV) theory, originally proposed by Wernerfelt (1984) and further developed by Barney (1991). The RBV posits that firms achieve sustainable competitive advantage by

acquiring and effectively utilizing resources that are valuable, rare, inimitable, and non-substitutable (VRIN). According to Barney (1991), organizational performance differences arise from heterogeneity in internal resources and capabilities rather than solely from external market conditions. Technological assets, specialized knowledge, and innovative capabilities are considered strategic resources under this framework.

The major assumption of RBV is that internal resources drive competitive advantage when they meet the VRIN criteria. Artificial Intelligence systems, predictive analytics tools, and automated decision-making platforms can be viewed as strategic technological resources that enhance organizational capabilities. One strength of RBV lies in its emphasis on internal competencies as determinants of performance outcomes. It provides a strong analytical foundation for examining how AI adoption may improve risk management effectiveness. However, critics argue that RBV pays insufficient attention to dynamic environmental changes and external competitive pressures (Priem & Butler, 2001). Despite this criticism, RBV remains highly relevant for explaining how AI capabilities can serve as valuable organizational resources.

In the context of this study, AI technologies represent strategic assets that can enhance risk identification and mitigation processes in insurance companies in Abuja. By leveraging predictive analytics and automated decision systems, insurance firms may strengthen their operational efficiency and risk management performance. Therefore, the Resource-Based View provides an appropriate theoretical lens for examining the effect of Artificial Intelligence on risk management outcomes.

Empirical Review

Olaiya et al., (2025) examined the determinants of profitability within listed insurance companies in Nigeria, specifically focusing on the effect of operational risk on performance measured by Adjusted Risk-Adjusted Return on Capital (Adjusted RAROC). The researchers utilized a panel data regression analysis employing four models, including pooled regression, fixed effects, random effects, and Difference Generalized Method of Moments (D-GMM), to assess variables such as claims

ratio, expense ratio, leverage, and firm size. Their findings revealed that leverage and firm size were significant predictors of profitability, whereas the claims and expense ratios demonstrated a negative relationship with performance. However, a gap existed in this study as it relied on traditional financial ratios and operational metrics without incorporating advanced technological tools, such as artificial intelligence, to enhance risk prediction and management efficiency.

Ajibade et al., (2025) investigated the impact of artificial intelligence on risk management engineering within non-financial service companies listed in Nigeria. Adopting a survey research design, the study sampled 380 employees from 26 non-financial service companies using a simple random sampling technique and collected data through structured questionnaires. The analysis indicated a significant positive impact of artificial intelligence on risk management outcomes, suggesting that AI integration optimizes financial decision-making and investment strategies. Despite these positive outcomes, the study was limited by its focus on non-financial service firms, leaving a gap in understanding how similar AI-driven risk management engineering applies specifically to the insurance sector, where risk is the primary commodity.

Kunle and Titilope (2022) focused on the effect of technological advancement on risk management practices among composite insurance companies in Nigeria. The study employed a survey research design targeting employees from five selected insurance companies out of a population of 14, utilizing regression analysis via SPSS to evaluate data collected through questionnaires. The results showed that while technological innovation improved the identification of policyholder risks, it failed to enhance the identification of risks inherent in investment activities. This highlighted a critical gap, as traditional information technology proved insufficient for comprehensive investment risk management, suggesting a need for more sophisticated predictive analytics or AI-driven solutions to address complex investment risks.

Olawale et al., (2023) proposed a predictive compliance analytics framework that leveraged artificial intelligence and business intelligence

tools to enable early risk detection in the financial and insurance sectors. The methodology involved integrating machine learning models with interactive dashboard platforms like Tableau, SQL, and Python to transform reactive compliance into a proactive system. Their evaluation demonstrated that the framework significantly improved prediction accuracy, cost reduction, and response efficiency regarding anti-money laundering and fraud detection. Nevertheless, a gap remained as the study primarily presented a conceptual framework and implementation scenarios rather than providing extensive empirical evidence on the long-term financial performance impact of such frameworks on listed insurance firms.

Onukwulu et al., (2023) explored the development of a framework for using predictive analytics to mitigate risks within energy supply chains. The study analyzed how data-driven insights and machine learning algorithms could forecast potential disruptions by examining historical trends and real-time monitoring data from various sources. The findings concluded that predictive analytics enhanced decision-making and resource allocation, though challenges regarding data quality and technological infrastructure were noted. The gap in this research lay in its sectoral specificity; while it validated the utility of predictive analytics in risk mitigation, the context was restricted to the energy supply chain, limiting the direct generalizability of the findings to the insurance industry's unique risk landscape.

Ajibade et al., (2025) investigated the effect of artificial intelligence on risk management engineering within non-financial service companies listed in Nigeria. The study adopted a survey research design, targeting a population of 3,800 employees across 26 non-financial service companies listed on the Nigeria Exchange Limited, with a sample size of 380 determined using Taro Yamane's formula and selected through simple random sampling. Data were collected using a structured and validated questionnaire, and reliability testing confirmed strong internal consistency across all constructs. The findings demonstrated that a substantial majority of participants endorsed the potential of artificial intelligence to enhance risk management engineering, and further

analysis revealed a significant positive impact of AI on risk management outcomes. However, a gap existed in this study as it focused exclusively on non-financial service firms, which limited the generalizability of its findings to the insurance sector where risk underwriting and claims management present distinct operational dynamics.

Ogunmokun et al., (2021) explored the transformative role of artificial intelligence in financial risk management and corporate governance optimization by proposing a comprehensive conceptual framework for integrating AI-driven solutions. The study employed a conceptual approach, synthesizing existing literature and real-world case studies to outline key components such as data sources, predictive analytics, real-time monitoring, and anomaly detection, while emphasizing governance controls for ethical AI deployment. The findings suggested that AI possessed significant potential to reshape financial ecosystems by enabling organizations to better navigate risks and ensure compliance through proactive, data-driven decision-making. Nevertheless, a critical gap was identified as the study remained largely theoretical, lacking empirical validation through quantitative or qualitative data to substantiate the proposed framework's effectiveness in practical organizational settings.

Ashiedu et al., (2023) examined the design and implementation of financial intelligence systems tailored for real-time decision-making in African corporates, adopting a systems thinking approach that integrated finance, planning, and infrastructure divisions. The methodology involved a conceptual exploration of key system components, including real-time analytics, data integration, business intelligence tools, and automation, while addressing implementation challenges such as technological barriers and skills gaps through narrative analysis. The findings highlighted that holistic financial intelligence systems could break down organizational silos, align financial goals with strategic objectives, and enhance forecasting and proactive risk management. However, the study presented a gap as it did not provide empirical testing or measurable outcomes from actual system deployments, leaving uncertainty regarding the scalability

and performance of such systems across diverse African corporate environments.

Oladuji et al., (2023) developed a comprehensive model for leveraging artificial intelligence and big data analytics to predict and mitigate financial risk in African markets, which are often characterized by volatility and data fragmentation. The methodology integrated machine learning algorithms with high-volume data streams from diverse financial, economic, and socio-political sources across five African economies Nigeria, Kenya, Ghana, South Africa, and Egypt covering a 10-year period, and employed predictive analytics, risk scoring engines, and user-friendly dashboards for validation. The findings demonstrated high predictive accuracy in detecting early warning signals for financial crises, currency instability, and stock market fluctuations, while the model's capacity to process unstructured data enhanced its contextual intelligence. Despite these strengths, a gap remained as the model's reliance on historical data and hybrid approaches combining supervised learning with human-in-the-loop methods may limit its adaptability to unprecedented or rapidly evolving financial disruptions in real-time operational contexts.

Eyinade et al., (2025) investigated the influence of financial risk management strategies on organizational stability by conducting a systematic literature review of peer-reviewed articles, institutional reports, and empirical research published between 2020 and 2025. The methodology involved rigorous data source selection using defined inclusion and exclusion criteria, with findings synthesized through content analysis to identify key strategies such as hedging, diversification, enterprise risk management frameworks, and the integration of corporate governance and regulatory compliance. The results indicated that technological innovations, including artificial intelligence and blockchain, significantly improved risk identification, monitoring, and mitigation processes, though challenges such as cultural resistance and resource constraints were noted. A gap in this study was its reliance on secondary literature rather than primary empirical data, which constrained the ability to draw context-specific conclusions about the direct causal impact of these strategies on

organizational stability within particular industry sectors.

Study Gap

Despite the expanding body of literature on Artificial Intelligence and risk management, significant contextual and empirical gaps remain, particularly within insurance companies in Abuja. Although scholars such as Ajibade et al. (2025) and Onukwulu et al. (2023) highlighted the advantages of artificial intelligence and predictive analytics in improving operational efficiency and decision-making, their studies were conducted in non-insurance contexts, including manufacturing and energy supply chains. While their findings contribute to understanding AI applications in risk-sensitive environments, they do not directly address the peculiarities of insurance operations, where risk identification and risk mitigation constitute the central functions of the business model. The unique data structures, underwriting complexities, regulatory requirements, and claims management processes in insurance firms require context-specific investigation that extends beyond general technological adoption outcomes.

Furthermore, empirical studies focusing on the Nigerian insurance sector, such as those by Olaya et al. (2025) and Kunle and Titilope (2022), largely examined traditional performance indicators and basic information technology infrastructure without sufficiently exploring advanced AI-driven systems such as predictive analytics and automated decision-making platforms. While these studies provided insights into financial ratios, operational metrics, and general ICT adoption, they did not rigorously assess how AI-enabled predictive models influence risk identification accuracy or how automated systems strengthen risk mitigation and internal control mechanisms. Consequently, the strategic role of AI as a resource capable of enhancing core risk management dimensions in insurance firms remains underexplored.

From a methodological standpoint, a considerable portion of the reviewed literature has remained conceptual rather than empirically validated. Frameworks proposed by Ogunmokun et al. (2021), Ashiedu et al. (2023), and Olawale et al. (2023) offered theoretical models for AI integration, digital compliance

systems, and analytics-driven governance structures. However, these frameworks were not supported by primary data or statistically tested relationships linking AI dimensions such as predictive analytics and automated decision-making—to measurable risk management outcomes. As a result, there is limited empirical clarity regarding the strength and direction of the relationship between AI adoption and specific risk management dimensions within insurance organizations.

In addition, broader analytical works by Eyinade et al. (2025) and Oladuji et al. (2023) relied predominantly on secondary data sources and historical industry trends. While such studies provided macro-level insights into technological transformation in financial services, they were constrained in capturing firm-level dynamics and real-time causal effects. The absence of organization-specific empirical data limits understanding of how AI-driven tools directly affect risk identification processes and risk mitigation/control mechanisms in practice.

Therefore, a critical empirical gap persists regarding the direct and measurable effect of Artificial Intelligence particularly predictive analytics and automated decision-making systems on risk management dimensions within insurance companies in Abuja. Addressing this gap is essential to move beyond theoretical assumptions and provide evidence-based insights that can guide strategic technology investment, regulatory policy formulation, and operational reforms in insurance firms. This study therefore seeks to bridge the divide between conceptual propositions and practical implementation by empirically examining the relationship between AI and risk management in the Nigerian insurance sector.

METHODOLOGY

The study adopted a cross-sectional survey research design to examine the effect of Artificial Intelligence on risk management within selected insurance companies in Abuja. This design was considered appropriate because it allowed data to be collected from respondents at a single point in time for the purpose of analyzing relationships among variables. The cross-sectional approach was particularly suitable for this study since it

enabled the assessment of predictive analytics and automated decision-making systems in relation to risk identification and risk mitigation/control mechanisms without manipulating any variables. In addition, the design facilitated the use of quantitative techniques to determine the magnitude and significance of the relationships under investigation.

The population comprised employees of five selected insurance companies operating in Abuja: AIICO Insurance Plc (62 staff), Leadway Assurance Company Ltd (78 staff), NEM Insurance Plc (54 staff), AXA Mansard Insurance Plc (83 staff), and Mutual Benefits Assurance Plc (76 staff), giving a combined total of 353 employees. These firms were selected because of their strong operational presence in the Federal Capital Territory and their adoption of technology-driven systems such as automated underwriting, AI-assisted claims processing, fraud-detection tools, and compliance-monitoring platforms. The inclusion of these organizations provided a relevant setting for assessing how Artificial Intelligence influenced risk management practices. Employees were drawn from major functional areas including underwriting, claims, ICT/digital innovation, risk management, compliance, finance, customer service, and marketing. Staff across top management, middle management, and lower-level positions were included to ensure that perspectives reflected strategic oversight, operational execution, and system-level interaction. The unit of analysis was the individual employee, as they were directly involved in the implementation, supervision, or use of AI-based systems and risk management procedures within their respective organizations.

The sample size was determined using Taro Yamane's (1967) formula for finite populations:

$$n = N / (1 + N(e)^2)$$

Where N represented the population size (353) and e denoted the acceptable margin of error (0.05). Substituting the values produced:

$$n = 353 / (1 + 353(0.05)^2)$$

$$n = 353 / (1 + 353 \times 0.0025)$$

$$n = 353 / (1 + 0.8825)$$

$$n = 353 / 1.8825$$

$$n \approx 187$$

The computed sample size was therefore 187 respondents. To reduce the potential impact of non-response or incomplete questionnaires, a 20 percent contingency allowance was added, increasing the target sample to approximately 224 respondents. The use of Taro Yamane's formula was justified because it provides a statistically reliable and widely accepted method for determining representative sample sizes from finite populations while maintaining a 95 percent confidence level.

Stratified sampling was used to select respondents by dividing the population into relevant departments such as underwriting, claims, ICT, compliance, and risk units. Participants were proportionately selected from each stratum to ensure adequate representation. This approach enhanced representativeness, reduced bias, and ensured that individuals directly involved with AI-driven systems were included in the study.

Primary data were used for the study, collected through a structured questionnaire designed on a five-point Likert scale. The instrument was organized to measure predictive analytics, automated decision-making systems, risk identification, and risk mitigation/control mechanisms. The questionnaire method was suitable because it enabled standardized data collection from a relatively large group of respondents within a limited timeframe, thereby supporting quantitative analysis.

Reliability of the instrument was assessed using Cronbach's Alpha to determine internal consistency. The coefficients obtained were 0.84 for predictive analytics, 0.88 for automated decision-making systems, 0.81 for risk identification, and 0.85 for risk mitigation/control mechanisms, with an overall Artificial Intelligence reliability value of 0.86. All values exceeded the minimum acceptable threshold of 0.70, indicating satisfactory reliability. Content validity was established through expert review by specialists in insurance management, Artificial Intelligence systems, and research methodology, who evaluated the relevance and clarity of the questionnaire items before final administration.

Data analysis was conducted using multiple regression techniques with the aid of Statistical Package for Social Sciences (SPSS) version 27. Simple regression was appropriate because the study sought to determine the extent to which the independent variables predictive analytics and automated decision-making systems explained variations in the dependent variables

risk identification and risk mitigation/control mechanisms. The technique enabled the estimation of the strength, direction, and statistical significance of the relationships, thereby providing empirical evidence regarding the effect of Artificial Intelligence on risk management within the selected insurance companies.

4.0 RESULTS AND FINDINGS

Response Rate.

Questionnaire Distributed	224
Returned Questionnaire	210
Percentage of returned Questionnaire	94%
Unreturned Questionnaire	14
Percentage of not returned Questionnaire	6%

Source: Field Survey, (2025)

Table presents the response rate for the field survey conducted in 2025, indicating that out of 224 questionnaires distributed, 210 were successfully returned a commendable 94% response rate while 14 questionnaires (6%) remained unreturned. This high return rate

reflects strong respondent cooperation and minimizes the risk of non-response bias, thereby strengthening the validity and generalizability of the findings derived from the survey data.

Table 1: Demographic Characteristics of Respondents

Variable	Category	Frequency	Percentage (%)
Age	20–29 years	48	22.9
	30–39 years	82	39.0
	40–49 years	56	26.7
	50 years and above	24	11.4
Gender	Male	124	59.0
	Female	86	41.0
Work Experience	Below 5 years	44	21.0
	5–10 years	78	37.1
	11–15 years	52	24.8
	16 years and above	36	17.1
Educational Level	Bachelor’s Degree	96	45.7
	Master’s Degree	88	41.9
	PhD	12	5.7
	Others/Professional Certification	14	6.7

Source: Field Survey, 2025

The results indicated that the majority of respondents were between 30–39 years (39.0%), followed by those aged 40–49 years (26.7%). In terms of gender distribution, male respondents constituted 59.0%, while females accounted for 41.0%. Regarding work

experience, most respondents had between 5–10 years of experience (37.1%), suggesting adequate industry exposure. Educationally, a large proportion of respondents possessed at least a Bachelor’s degree (45.7%) or a Master’s degree (41.9%), indicating that the sample was

well educated and suitable for providing informed responses on AI and risk management practices.

Test of Hypotheses

Test of hypothesis one

H₀₁: Predictive analytics has no significant effect on risk identification in insurance companies in Abuja.

Model 1

$$RI = \alpha_0 + \beta_1 PA + \epsilon \dots \dots \dots 3.1$$

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.682 ^a	.465	.462	.51432

a. Predictors: (Constant), PA

Source: SPSS Output Version 27

The model summary results indicated that predictive analytics (PA) had a strong positive relationship with risk identification, as reflected by the correlation coefficient (R = .682). The coefficient of determination (R² = .465) showed that predictive analytics explained 46.5% of the variance in risk identification within insurance companies in Abuja. After adjusting for

potential sampling bias, the adjusted R² value of .462 confirmed that the model maintained substantial explanatory power. Additionally, the standard error of the estimate (.51432) suggested a relatively low level of prediction error, indicating that the regression model provided a reasonably good fit to the data.

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	48.216	1	48.216	182.457	.000 ^b
	Residual	55.014	208	.264		
	Total	103.230	209			

a. Dependent Variable: RI

b. Predictors: (Constant), PA

Source: SPSS Output Version 27

The ANOVA results showed that the regression model was statistically significant. The analysis indicated that predictive analytics significantly predicted risk identification, F(1, 208) = 182.457, p < .001. The regression sum of squares (48.216) compared to the residual sum of squares (55.014) demonstrated that a

substantial proportion of the variation in risk identification was explained by the model. Since the p-value was less than the 0.05 level of significance, the null hypothesis was rejected, confirming that predictive analytics had a statistically significant effect on risk identification in insurance companies in Abuja.

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.124	.214		5.252	.000
	PA	.713	.053	.682	13.507	.000

a. Dependent Variable: RI

Source: SPSS Output Version 27

The coefficients table showed that predictive analytics had a positive and statistically significant effect on risk identification. The unstandardized coefficient (B = .713, SE = .053) indicated that a one-unit increase in predictive analytics led to a corresponding increase of 0.713 units in risk identification. The standardized beta coefficient ($\beta = .682$) reflected a strong positive contribution of predictive analytics to the model. The t-value (t

= 13.507, p < .001) further confirmed that the predictor significantly influenced risk identification. In addition, the constant term (B = 1.124, p < .001) suggested that risk identification would remain positive even in the absence of predictive analytics, although at a lower level. Overall, the results demonstrated that predictive analytics was a significant predictor of risk identification in the study.

Test of hypothesis two

H₀₂: Automated decision-making systems have no significant effect on risk mitigation and control mechanisms in insurance companies in Abuja.

Model 2

$$RMCM = \alpha_0 + \beta_1 ADMS + \epsilon \dots \dots \dots 3.2$$

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.741 ^a	.549	.547	.47218

a. Predictors: (Constant), ADMS

Source: SPSS Output Version 27

The model summary results indicated that automated decision-making systems (ADMS) had a strong positive relationship with risk mitigation and control mechanisms, as shown by the correlation coefficient (R = .741). The coefficient of determination (R² = .549) revealed that 54.9% of the variation in risk mitigation and control mechanisms was

explained by automated decision-making systems. The adjusted R² value of .547 demonstrated that the model retained substantial explanatory strength even after adjustment. Furthermore, the standard error of the estimate (.47218) suggested a relatively small prediction error, indicating that the regression model adequately fitted the data.

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	61.382	1	61.382	275.341	.000 ^b
	Residual	50.358	208	.242		
	Total	111.740	209			

a. Dependent Variable: RMCM

b. Predictors: (Constant), ADMS

Source: SPSS Output Version 27

The ANOVA results demonstrated that the regression model was statistically significant. The findings showed that automated decision-making systems significantly predicted risk mitigation and control mechanisms, $F(1, 208) = 275.341, p < .001$. The regression sum of squares (61.382) relative to the residual sum of squares (50.358) indicated that a considerable

proportion of the variation in risk mitigation and control mechanisms was explained by the model. Given that the significance value was well below the 0.05 threshold, the null hypothesis was rejected, confirming that automated decision-making systems had a significant effect on risk mitigation and control mechanisms in insurance companies in Abuja.

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.986	.198		4.980	.000
	ADMS	.781	.047	.741	16.594	.000

a. Dependent Variable: RMCM

Source: SPSS Output Version 27

The coefficients results indicated that automated decision-making systems had a positive and statistically significant effect on risk mitigation and control mechanisms. The unstandardized coefficient ($B = .781, SE = .047$) showed that a one-unit increase in automated decision-making systems led to a 0.781-unit increase in risk mitigation and control mechanisms. The standardized beta value ($\beta = .741$) reflected a strong positive contribution of the predictor to the model. The t-statistic ($t = 16.594, p < .001$) confirmed that the effect was statistically significant. Additionally, the constant term ($B = .986, p < .001$) suggested that risk mitigation and control mechanisms maintained a baseline level even in

the absence of automated decision-making systems. Overall, the findings demonstrated that automated decision-making systems significantly influenced risk mitigation and control mechanisms in the study.

Discussion of Findings

The study revealed that predictive analytics has a significant effect on risk identification in insurance companies in Abuja. This finding empirically validates the conceptual frameworks proposed by Olawale et al. (2023) and the systematic review by Eyinade et al. (2025), which suggested the potential of AI for early risk detection but lacked sector-specific

primary data. By confirming this relationship within the insurance context, the study bridges the gap left by Olaiya et al. (2025), whose reliance on traditional financial ratios overlooked the transformative capacity of technological resources. Through the lens of the Resource-Based View (RBV) theory, predictive analytics is characterized as a valuable and rare technological resource that enhances a firm's internal capabilities. When insurers leverage these analytics, they transform raw data into a strategic asset that is difficult for competitors to imitate, thereby facilitating proactive fraud detection, accurate underwriting, and the anticipation of emerging claims. This implies that organizations possessing superior data analytics infrastructure are better positioned to reduce uncertainty and make data-driven decisions. Consequently, it is imperative for insurance firms to view investment in advanced analytics and skilled human capital not merely as operational costs, but as critical strategic resources essential for strengthening risk intelligence and sustaining a competitive advantage in the market.

The study also revealed that automated decision-making systems have a significant effect on risk mitigation and control mechanisms in insurance companies in Abuja. This result extends the findings of Ajibade et al. (2025), who observed similar positive outcomes in non-financial service companies, by confirming that AI-driven automation is equally vital in the risk-intensive insurance sector. Furthermore, it addresses the limitations noted by Kunle and Titilope (2022), demonstrating that modern technological interventions can indeed enhance risk management beyond simple policyholder identification to include complex operational controls. From the perspective of RBV theory, automated decision-making represents an organizational capability that improves process efficiency and consistency, rendering the firm's risk governance framework non-substitutable. The integration of such systems reduces human error, accelerates claims management, and ensures stricter compliance with regulatory standards, thereby minimizing operational losses. This suggests that automation serves as a mechanism to lock in efficiency and service quality, creating a barrier to entry for competitors lacking similar technological depth. It further underscores the need for

insurance firms to integrate intelligent automation into their core operations, thereby converting technological adoption into a sustainable source of organizational stability and improved service delivery.

CONCLUSION AND RECOMMENDATIONS

This study examined the effect of Artificial Intelligence (AI) applications on risk management in insurance companies in Abuja, with particular focus on predictive analytics and automated decision-making systems. The general conclusion drawn from the study is that AI-driven technologies significantly enhance risk management effectiveness in the Nigerian insurance sector. The findings demonstrate that the integration of intelligent systems improves risk identification, mitigation, and overall operational efficiency.

Based on the specific findings, the study concludes that predictive analytics significantly improves risk identification processes. It enhances insurers' ability to detect emerging risks, assess underwriting exposures more accurately, and identify fraudulent activities through data-driven insights. This indicates that predictive models strengthen proactive risk assessment and reduce uncertainty in decision-making.

Furthermore, the study concludes that automated decision-making systems significantly enhance risk mitigation and control mechanisms. Automation improves the speed, accuracy, and consistency of operational processes, minimizes human error, strengthens internal controls, and ensures better regulatory compliance. This contributes to improved claims management, fraud prevention, and overall risk governance within insurance firms.

Based on the findings of the study, the following recommendations are made:

- i. Insurance firms should invest more in predictive analytics infrastructure to enhance early risk detection, improve underwriting accuracy, and strengthen fraud identification mechanisms.
- ii. Organizations should integrate automated decision-making systems into core risk management processes to improve operational efficiency, reduce

errors, and enhance control mechanisms.

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