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Artificial Intelligence on Risk Management Engineering in Non-financial Service Companies Listed in Nigeria

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Abstract
Risk management engineering is critical for ensuring stability and resilience in non-financial service firms in Nigeria, especially in the face of economic volatility and operational uncertainties. However, many firms have struggled to optimize risk identification, assessment, and mitigation processes. Studies have shown that the integration of artificial intelligence tools can significantly enhance the effectiveness of risk management engineering. This study examined the effect of artificial intelligence on risk management engineering in non-financial service firms listed in Nigeria. The study adopted survey research design. The population comprised 3,800 employees of the 26 non-financial service companies listed on the Nigeria Exchange Limited as at 31 December 2023. Taro Yamane's formula was used to determine the sample size of 380. Simple random sampling technique was used to select the respondents. Data were collected using structured and validated questionnaire. Reliability testing confirmed strong internal consistency across all constructs. The study achieved a high response rate, and a substantial majority of participants strongly endorsed the potential of artificial intelligence to enhance risk management engineering. Further analysis demonstrated a significant positive impact of artificial intelligence on risk management outcomes. The study concluded that artificial intelligence enhanced risk management engineering in non-financial service companies listed in Nigeria. It was recommended that management of non-financial companies should integrate artificial intelligence to optimize financial decision-making, risk management and investment strategies towards maximizing profits for all stakeholders, also regulatory authorities should facilitate AI adoption through incentives such as tax reliefs for firms investing in AI-based solutions to enhance financial engineering.

Keywords: Algorithms trading, Artificial intelligence, Data mining services, Employee emotional intelligence, Risk management engineering, Robotics and machine learning

1. Introduction

Risk management engineering plays a crucial role in ensuring operational stability, compliance, and sustainability in firms. In a business environment marked by increasing uncertainty, market volatility, regulatory pressures, and technological disruptions, it becomes imperative for firms to embed robust risk management frameworks that are responsive and forward-looking. According to Obidike et al. (2021), poor risk identification, slow mitigation responses, and inadequate predictive capabilities remain fundamental barriers to enterprise resilience in Nigeria's service sector. Ezeaku et al. (2021) highlights that effective risk management engineering is central to enhancing the resilience, sustainability, and operational continuity of firms, particularly those operating in Nigeria's fragile non-financial service sectors. Their study suggests that inadequate risk control mechanisms, insufficient forecasting tools, and reactive crisis management approaches have left firms vulnerable to significant financial losses and reputational damage.

Literature highlights that traditional risk management approaches in many non-financial service companies in Nigeria remain reactive, paper-based, and fragmented across departments (Ajayi & Oseni, 2022; Chukwuma & Ekpenyong, 2023). Financial products and solutions are inherently exposed to various risks, including market risk, credit risk, liquidity risk, and operational risk. Risk managers often face challenges in consolidating cross-functional data, modeling risk scenarios, and responding to emerging threats in a timely manner. This has raised growing concerns about the need for more intelligent, automated, and data-driven risk management systems (Olayemi & Kazeem, 2020; Salawu & Moloi, 2021). Olusanya and Gbadamosi (2023) argued that one key enabler of such transformation is Artificial Intelligence (AI), which has the potential to redefine risk management engineering across several dimensions—ranging from credit risk modeling and fraud detection to compliance automation and real-time risk monitoring. Other studies have shown that AI offers transformative potential to automate, predict, and improve risk management operations in ways that surpass traditional models (Okonkwo & Uche, 2022; Bello et al., 2023).

Artificial intelligence introduces adaptive and predictive capabilities that surpass conventional risk systems. AI tools such as machine learning algorithms, neural networks, and natural language processing enable firms to detect patterns, anomalies, and early warning signals that would otherwise go unnoticed using traditional risk assessment techniques (Eze & Nwachukwu, 2022). For instance, predictive analytics can be employed to forecast loan defaults or identify operational disruptions before they materialize (Adebayo & Ogunleye, 2021). Furthermore, AI-powered robotic process automation (RPA) can streamline risk-related workflows, such as internal audits, insurance claims, and regulatory reporting, thus reducing the likelihood of human errors and delays (Ibrahim et al., 2023). Despite its growing recognition, AI adoption in risk management remains limited among Nigerian non-financial service firms. Structural barriers such as high costs, insufficient AI knowledge, and lack of skilled personnel, poor data infrastructure, and regulatory uncertainty have hindered mainstream integration (Adeoye et al., 2023). Additionally, many Nigerian firms operate without centralized risk data repositories, making it difficult for AI systems to generate comprehensive and accurate risk profiles (Okonkwo et al., 2023).

Vol. 9, No.05; 2025

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Notwithstanding these challenges, global evidence demonstrates that AI-enabled risk management practices have significantly enhanced business resilience, especially in high-risk sectors. Countries like Singapore and the UK have adopted AI risk engines that monitor credit risk exposures in real-time, while banks and insurance companies in South Africa have employed AI models to enhance fraud detection and regulatory compliance (Makinde et al., 2022). These innovations align with the digital transformation agenda in Nigeria, particularly under the Nigeria Digital Economy Policy and Strategy (2020–2030), which emphasizes the role of emerging technologies in strengthening national and corporate resilience (NITDA, 2020).

However, studies specifically investigating the nexus between artificial intelligence and risk management engineering within the context of Nigeria's non-financial service sector are still sparse. While existing research has explored AI applications in fintech and customer analytics (Afolabi & Ajibade, 2021), little empirical evidence exists on how AI affects the systematic engineering of risk across core functions such as operations, finance, regulatory compliance, and supply chains. This presents a critical empirical gap in literature. Oyetunji and Bello (2023) called for targeted studies to evaluate AI's role in reshaping risk systems and improving organizational resilience among non-financial corporations in Nigeria. Addressing this gap is crucial, especially as AI is fast becoming a competitive differentiator in enterprise risk frameworks. Consequently, in contributing to both theory and practice and in line with global best practices in risk engineering, this study examines the effect of artificial intelligence on risk management engineering in non-financial service companies listed in Nigeria.

2. Literature Review

2.1 Conceptual Review

2.1.1 Risk Management Engineering

Financial engineering, according to Okonkwo and Adeyemi (2023), is the application of mathematical modeling, computational techniques, and innovative financial instruments to optimize financial decision-making and risk management. Similarly, Balogun et al. (2024) describe it as the strategic design and implementation of complex financial products and services to enhance market efficiency, meet investor needs, and mitigate financial risks. Olatunji and Musa (2022) emphasize the role of financial engineering in developing algorithm-driven solutions for portfolio optimization, derivative pricing, and corporate financial restructuring. According to Okonkwo and Adeyemi (2022), risk management engineering involves the systematic application of quantitative and qualitative techniques to identify, assess, and mitigate financial risks in complex market environments. Similarly, Balogun et al. (2023) describe it as the integration of mathematical modeling, artificial intelligence, and predictive analytics to enhance decision-making in financial risk assessment and mitigation. In a more technology-focused perspective, Yusuf and Olatunji (2024) define risk management engineering as the utilization of advanced computational models, including machine learning and algorithmic simulations, to anticipate and respond to uncertainties in financial systems. Furthermore, Eze and Uchenna (2025) emphasize its role in optimizing risk-return trade-offs through structured frameworks that incorporate regulatory compliance and market dynamics.

Risk management engineering is a discipline that combines engineering principles with financial risk management frameworks to identify, assess, and mitigate risks in business operations and investments (Kaplan & Mikes, 2012). The field aims to create systems and processes that safeguard organizations from financial, operational, and reputational hazards through systematic and structured techniques (Koller, 2005). In risk management engineering, this involves using advanced technologies such as AI algorithms and machine learning (ML) to predict potential threats to the organization's operations or finances (Hopkin, 2018). The second phase is risk assessment which quantitatively evaluates the potential impact of identified risks, often using statistical models to estimate probabilities and severities of different scenarios (Jorion, 2007). The next is risk control and mitigation. Through proactive interventions, organizations design strategies to control or eliminate risks. Techniques include implementing controls to minimize exposure or using engineering solutions to prevent recurrence (Leitch, 2010). In non-financial service companies, risk management engineering takes multiple forms, with methods ranging from data analytics to contingency planning. (a) Data-driven risk assessment which employs statistical analysis and data mining to evaluate historical data and forecast risk occurrences. AI enhances this by applying ML to analyze complex datasets, enabling companies to make data-backed decisions (Schlegel & Trent, 2014). (b) Simulation and modeling use engineering risk models, such as Monte Carlo simulations, widely used to predict various risk scenarios.

The review above show that risk management engineering is a multidisciplinary field that integrates engineering principles with financial risk management to systematically identify, assess, control, and mitigate risks. It leverages both quantitative and qualitative techniques, employing mathematical models, simulations, and advanced computational methods including artificial intelligence, machine learning, and algorithmic trading—to predict uncertainties and optimize risk-return trade-offs. Scholars emphasize its evolution from traditional qualitative practices to data-driven, precision-oriented frameworks that incorporate regulatory compliance and market dynamics. However, these opinions predominantly focus on financial markets, potentially overlooking the broader spectrum of risks encountered in non-financial service companies. In such contexts, risk management engineering should be understood as an integrated discipline that applies engineering principles alongside both quantitative and qualitative methods to systematically identify, assess, and mitigate a diverse array of risks—including operational disruptions, technological failures, regulatory non-compliance, and environmental hazards.

2.1.2 Artificial Intelligence

According to Adebayo and Chukwu (2022), Artificial Intelligence (AI) refers to the simulation of human cognitive functions—such as learning, reasoning, and problem-solving—through computational models and algorithms designed to enhance decision-making in complex environments. Similarly, Ibrahim et al. (2023) define AI as a multidisciplinary field that integrates data-driven analytics, automation, and machine learning techniques to optimize business processes, improve operational efficiency, and facilitate predictive modeling. In the financial sector, Okonkwo and Adeyemi (2024) describe AI as the application of intelligent algorithms in risk assessment, credit scoring, and portfolio management, enabling firms to develop adaptive financial solutions. Furthermore, Yusuf and Salami (2025) emphasize that AI encompasses robotics, natural language processing, and deep learning frameworks that enhance automation and innovation in industries, including financial engineering. In the business and finance sectors, AI applications range from algorithmic trading to risk management and customer relationship management. AI-driven algorithms in trading systems allow financial markets to operate at unprecedented speeds, making quick, data-informed decisions that maximize profits and minimize losses (Chaboud et al., 2014). Similarly, in risk management, AI identifies patterns in historical data to predict and mitigate future risks, benefiting insurance companies, banks, and investment firms (Huang et al., 2020).

2.1.3 Data Mining Services

According to Zhang and Lee (2023), data mining services involve the process of extracting valuable patterns, trends, and knowledge from large datasets to inform decision-making. In contrast, Singh and Sharma (2025) define it as the computational techniques used to extract knowledge from vast amounts of raw data, aiding in automation and enhancement of business operations. Also, according to Ahmed and Hussain (2022), data mining services are integral to identifying hidden relationships in data, thereby enabling businesses to improve operational efficiency and optimize resource allocation. Lastly, data mining is defined by Fayyad, et al (1996) as the process of discovering patterns in large datasets through methods at the intersection of machine learning, statistics, and database systems. It encompasses several techniques such as clustering, classification, regression, and association rule mining which can identify trends, predict outcomes, and support strategic planning (Han, Kamber, & Pei, 2012). Data mining services include tools and methodologies that enable businesses to analyze data, make predictions, and support decision-making, particularly in areas like customer relationship management, risk management, and market analysis.

2.1.4 Credit Evaluation/Scoring Applications

Credit evaluation or scoring applications refer to automated systems that assess the creditworthiness of individuals or businesses using data-driven algorithms and predictive modeling. According to Zhang et al. (2023), credit scoring applications leverage artificial intelligence and machine learning techniques to analyze borrower profiles, financial histories, and transaction patterns, thereby improving lending decisions. Similarly, Ahmed and Chen (2022) define credit evaluation systems as computational frameworks that integrate big data analytics to assess loan default risks and optimize financial inclusion. Moreover, Patel et al. (2024) highlights that modern credit scoring tools employ deep learning and natural language processing to enhance risk prediction accuracy, reducing bias in traditional credit assessments. These applications have become critical in financial decision-making, enabling lenders to mitigate risks while expanding access to credit (Kumar & Li, 2022). AI-driven credit scoring applications improve the predictive accuracy of credit assessments. Machine learning models can dynamically adapt to new data inputs, refining their algorithms over time. This adaptability enables financial institutions to better assess credit risk and make more informed lending decisions (Marr, 2018). Additionally, the integration of natural language processing (NLP) allows

Vol. 9, No.05; 2025

ISSN: 2456-7760

for the analysis of unstructured data, such as customer feedback and sentiment analysis, adding another layer of insight to credit evaluations (Akay et al., 2020).

2.1.5 Algorithms Trading

Algorithmic trading, according to Adegbite et al. (2023), involves the application of artificial intelligence and quantitative models to optimize trade execution, minimize human error, and enhance market efficiency. Similarly, Johnson and Smith (2022) define algorithmic trading as the automated process of placing and managing financial transactions using complex mathematical models and real-time market data. In the context of Artificial Intelligence (AI), algorithmic trading represents a critical intersection of financial engineering, data science, and computer programming, with far-reaching implications for markets and the broader economy (Chaboud et al., 2009). While algorithmic trading is traditionally associated with financial services firms, recent developments suggest it may hold value for non-financial corporations as they increasingly manage financial risks. Algorithmic trading models range from simple rule-based systems to complex AI-powered systems, including machine learning (ML) and deep learning models. For instance, machine learning algorithms in trading can autonomously detect patterns and adapt trading strategies based on historical and real-time data (Van Vliet, 2018). AI-based algorithmic trading algorithms can predict stock prices, forecast market trends, and assess risk using vast amounts of data, making them invaluable for achieving optimal returns and managing risk.

2.1.6 Robotics and Machine Learning

Johnson et al. (2023) described robotics as the integration of artificial intelligence and mechanical systems to execute complex operations, particularly in financial decision-making and risk assessment. These machines are often programmed to perform tasks that may be repetitive, dangerous, or beyond human capability. Robotics combines elements of mechanical engineering, electrical engineering, computer science, and AI to create systems that can perform autonomously or semi-autonomously. On the other hand, machine learning, a subset of artificial intelligence, is defined by Zhang and Li (2023) as an algorithmic approach that enables systems to learn from data, recognize patterns, and improve decision-making accuracy without explicit programming. Eze and Chukwu (2024) emphasize that machine learning techniques enhance financial engineering by optimizing predictive analytics, fraud detection, and risk management. Furthermore, Patel et al. (2025) assert that both robotics and machine learning are integral to automating financial processes, increasing efficiency, and minimizing human errors in non-financial service companies. In financial engineering, ML contributes significantly through predictive modeling which is valuable for risk assessment and portfolio management, as well as through applications in credit scoring and fraud detection (Goodfellow, Bengio, & Courville,2016). Robotics and machine learning is the convergence of robotic systems with machine learning algorithms, creating autonomous, intelligent machines capable of self-learning, real-time decision-making, and task adaptation.

2.1.7 Employees Emotional Intelligence/Knowledge

Okonkwo and Uchenna (2024) define employees' emotional intelligence/knowledge as the integration of emotional awareness and cognitive adaptability that fosters teamwork, leadership effectiveness, and resilience in a dynamic business environment. Moreover, Chang et al. (2025) emphasized that EEIK encompasses self-regulation, motivation, and interpersonal skills which are essential for navigating workplace complexities and improving employee performance. The foundational theory of EEIK was developed by Mayer and Salovey (1997), who identified it as a form of intelligence that involves the ability to recognize, understand, and manage emotions. They posited four branches of EEIK: perceiving emotions, using emotions to facilitate thinking, understanding emotions, and managing emotions. This model emphasizes cognitive and emotional integration, suggesting that EEIK can enhance decision-making abilities (Mayer, Salovey, & Caruso, 2008; Odunayo et al., 2023). In the context of non-financial service companies integrating Artificial Intelligence, and assuming that AI systems, such as sentiment analysis tools and emotion-aware algorithms, can supplement employees' ability to perceive and manage emotions, improving operational efficiency and financial engineering outcomes, employees' emotional intelligence/knowledge is redefined as the integrated capacity to leverage emotional and cognitive competencies, enabling employees to navigate complex technological innovations and data-driven processes while contributing to risk management, strategic planning, and overall organizational productivity in an evolving economic and financial landscape.

2.2 Theoretical Review

2.2.1 Theory of Financial Innovation

The concept of financial innovation has been discussed extensively in economic theory but was formalized in modern financial literature by economists like Joseph Schumpeter (1942) and developed further by scholars such as Merton and Miller who examined the role of financial innovation in economic growth and risk management. The theory traces its roots to early 20th-century discussions but was significantly shaped in the late 20th century, particularly between 1986 and 1992. Financial innovation is assumed to drive efficiency in financial markets and instruments by creating new financial products, processes, and services that better allocate resources and risks. It assumes that financial innovation responds to the evolving needs of the economy, allowing for more adaptive, robust financial solutions (Lerner & Tufano, 2011; Frame & White, 2004; Tufano, 2003; Merton, 1992).

Studies like Merton (1992) and Tufano (2003) suggest that financial innovation helps diversify risk by creating financial products that suit different risk profiles and investment preferences. Financial innovation reduces transaction costs and increases the accessibility and affordability of financial services (Lerner, 2006). Furthermore, innovations such as algorithmic trading or risk management tools are seen as supporting regulatory requirements, reducing financial misconduct (Allen & Gale, 1994). Critics of the theory argue that financial innovation can lead to systemic risk, as seen during the 2008 financial crisis, where products like mortgage-backed securities contributed to market instability (Stiglitz, 2010). They also argue that financial innovations often create complex financial instruments that can obscure risk levels and reduce transparency And that, new financial products can outpace regulatory frameworks, leading to potential exploitation or unregulated risk exposure, and as well, may disproportionately benefit larger institutions or investors, potentially increasing economic inequality (Philippon, 2015; Gennaioli et al., 2012; Lerner & Tufano, 2011).

2.3 Empirical Review

Haosen et al. (2024) studied leveraging AI for risk management engineering in financial services. A systematic structured analysis was conducted from the data sourced from the field. The application of AI and in risk management engineering were proved effective and significantly interrelated. The study concluded that AI had a significant effect on risk management engineering of financial services. Similarly, Zhang and Lee (2023) explored the effect of AI applications in optimizing risk management for investment portfolios applying quantitative model simulation on investment portfolios on investment firms and asset managers. The proxies were deep learning models and sentiment analysis while the theoretical framework was Portfolio theory. After testing whether AI models offer better portfolio risk-adjusted returns using Value-at-Risk (VaR) and Sharpe ratio statistical tools, the result revealed that AI models achieved higher returns and reduced volatility which could curb the inefficiencies that abound with the use of traditional portfolio risk assessment.

Furthermore, Ihenyen et al. (2023) looked into how digital transformation affected Nigerian firms' growth, especially small and medium-sized businesses (SMEs). 200 SMEs in Nigeria from a range of industries were surveyed for the study using a descriptive research design. To ascertain the connection between SMEs' financial success and their adoption of digital transformation, the gathered data was subjected to regression analysis. The results show a strong positive correlation between SMEs' financial performance and their adoption of digital transformation. In particular, competitive advantage, current implementation, increased operational efficiency, and enhanced customer experience are the factors that have the most effects on financial success. According to the study's findings, SMEs in Nigeria should give adopting digital transformation top priority if they want to boost their financial performance.

Maha (2020) used data from thirteen Saudi Arabian institutions to investigate how AI and big data affect lending decisions. Regression analysis was employed to investigate the influence of independent variables, and the Cronbach Alpha coefficient was utilized to assess stability. The findings show that over 50% of loan decisions are heavily impacted by AI and big data. Furthermore, the quality of loan decision-making is statistically improved by AI. Additionally, experience, educational background, and the use of AI and big data were positively correlated. In Saudi Arabian banks, using AI to approve loan decisions is currently unpopular. Banks may use artificial technology to improve loan analytical capabilities, but loan decisions are primarily the responsibility of the loan director. Also, Murwaningsari (2018) used regulations as a moderating variable to examine how AI and operational risk management affected banking performance. A survey of 170 bank employees who have adopted banking digitization was used to collect data for this study. Using several linear analysis techniques, the researchers discovered that whereas

Vol. 9, No.05; 2025

ISSN: 2456-7760

operational risk management engineering significantly improved bank performance, AI deployment had no effect on banking performance in the study region.

More still, Faccia et al. (2019) investigated integrated cloud accounting, AI applications and blockchian on auditing practice and risk management engineering. A combination of Ex-post facto research design and data collected from personal interview were used for the study. The result of the study pointed to the fact of the uniqueness of AI and that AI had a significant relationship with change of accounting and auditing and enhanced risk management engineering processes quality. Through the use of Taro Yamane's formula, a sample size of 170 oil and gas companies was obtained for Ikegwuru's (2022) causal study on a population consisting of 295 oil and gas companies in Rivers State, which examined the implementation of digital supply chain technologies and the sustainable competitiveness of these companies. Evaluating the CEOs or branch managers of the companies under investigation in relation to the key respondents. 334 of the 510 copies of the structured questionnaire that were sent out were returned, resulting in a 75.1% response rate. The data analysis method used was multiple regression analysis. The study regression analysis revealed that digital supply chain exerted a significant effect on risk management engineering among the oil operations sampled.

In the same manner, Haenlein and Kaplan (2021) empirically examined the implications and effect of AI. The study sought to establish the impact of AI on the product quality and process engineering in interpreting statements in selected hotels in the AQABA. The study explored an *ex-post facto* research method as data were extracted from the documented database of the hotels performance seeking for quality product and services reengineering. The data were subjected diagnostics tests, and the estimation results showed that application of AI analytics tools had a significant effect on product and services reengineering of the hotels sampled in the study. Aniceto et al. (2020) examined the suitability of borrower classification models using machine learning techniques by contrasting the predictive accuracy of SVM, DT, Bagging, Ada Boost, and RF with a benchmark based on a Logistic Regression model. Primary data was used using structured interviews and descriptive statistics was adopted. The result showed significant effect. In addition, Elegunde & Shotunde (2020) concentrated on the crucial role that artificial intelligence had played in loan recovery. The study employed a database of 124,624 consumer loans with a 24-month term and monthly repayment obligations from a major Brazilian financial institution. Two-month loan repayment delays indicate default because the financial institution uses this criterion to categorize clients. The results demonstrate that ML is superior to the conventional methods.

Wang (2019) investigated how digitization affected business performance in China's manufacturing sector. The researchers carefully examined panel data collected over a number of years using a longitudinal research approach in order to identify the dynamic relationship between company performance measures and the degree of digitalization. Their research showed a strong positive correlation between the level of digitization and a number of performance metrics, such as export performance, profitability, and innovation. These results demonstrated how digitalization has the power to revolutionize conventional manufacturing methods and promote sustainable growth in China. The researchers developed a set of strategic suggestions to help industrial companies embrace digitization as a strategic imperative, building on these findings. Similarly, The research objective of Luong et al.'s (2019) study on the use of sophisticated algorithms in assessing loan applications was how organizational practices and technology impact businesses' performance when they use AI/ML for complicated decision-making. 152 students from Baruch College participated in this controlled laboratory experiment, which was designed in accordance with the main principles of experimental economics research. Hypotheses about the connection between AI/ML, incentive structures, and loan decision-making were then tested using linear regression analysis.

Schneider et al. (2019) examined the effect of artificial intelligence, digitalization opportunities and the relationship among the small and medium enterprises. In addressing the problem and opportunities of artificial intelligence, the study employed structured interviews in collected data from the software experts on the significance of AI. The analyzed data showed that AI has a significance association between AI and digitalized opportunities. Al-Araji et al. (2020) studies the effect of financial engineering on the ability of the company's strategic plans in hedging risks and avert financial risks and their implication on the financial performance of the companies sampled in the study. Islamic financial institutions were sampled in the study. The data were extracted from the Islamic banks' responses based on the research questionnaires administered to a selection of the banks. Consequent to the regression analysis, the study found that financial engineering using information technology had a significant effect on the risk management and financial performance of the Islamic banks tested in the study.

Caroli et al. (2019) investigate how digital transformation affects corporate efficiency. Secondary data were obtained from the financial records of the manufacturing companies listed in Italy. Digital transformation has a favorable impact on both financial and non-financial performance metrics, according to the authors' analysis of data from a survey of Italian manufacturing companies. Using panel regression analysis, the study found a positive but insignificant effect. Additionally, the study discovered that businesses operating in more dynamic contexts and those implementing complementary organizational changes are more affected by digital transformation. The study emphasizes how crucial it is to comprehend how digital technologies generate value and how businesses must design a thorough digital strategy that considers organizational and technological factors. Similarly, the study carried out by Gupta and Verma (2019) empirically examined the influence of AI and digitalization on small and medium-sized companies. The study explored primarily sourced data in analyzing the implication of AI on service delivery engineering. A total 130 respondents' responses were retrieved from the online platform used for the study. Consequent to the descriptive analysis and demographic analysis of the respondents, the study concluded that majority of the respondents agreed that AI and digitalization positively enhanced product performance of respondents who were exposed to the use of digitalization of their businesses.

The absence of research addressing these contextual factors results in a knowledge gap that limits the applicability of global AI-financial engineering frameworks to Nigerian service firms.

Vol. 9, No.05; 2025

ISSN: 2456-7760

There is a need for empirical studies that assess AI's role in financial engineering within the constraints of Nigeria's technological infrastructure and financial ecosystem.

Research Hypothesis: *Artificial Intelligence does not significantly affect risk management engineering of non-financial service companies listed in Nigeria*

3. Methodology

The study adopted survey research design. The population comprised 3,800 employees of the 26 non-financial service companies listed on the Nigeria Exchange Limited as at 31 December 2023. Taro Yamane's formula was used to determine the sample size of 380. Simple random sampling technique was used to select the respondents. Data were collected using structured and validated questionnaire. Cronbach's alpha coefficient for the constructs ranged from 0.73 to 0.95. Response rate of 95.26% was achieved. Data were analyzed using descriptive and inferential (multiple regression) statistics at 5% level of significance.

3.1 Model Specifications

This study was premised on two variable types, namely the independent variable (artificial intelligence) and dependent variable (risk management engineering).
The functional model is expressed as:
RKME = *f*(DESA, CESA, ALTD, ROML, EEIK)…………………………………......*(1)*
The econometric model is derived as:
$RKME_i = \alpha_0 + \beta_1 DESA_i + \beta_2 CESA_i + \beta_3 ALTD_i + \beta_4 ROML_i + \beta_5 EEIK_{\boldsymbol{i}} + \varepsilon_i$----------*(2)*
Where: RKME = Risk Management Engineering; DESA = Data Mining Services (DESA); CESA = Credit Evaluation/Scoring Applications (CESA); ALTD = Algorithms Trading (ALTD); ROML = Robotics and Machine Learning (ROML); EEIK = Employees' Emotional Intelligence/Knowledge (EEIK); $B_{1\text{-}5}$ = coefficients of the independent variable, α = regression intercept which is constant; i = Cross sectional unit; ε = error term of the model.

3.2 Reliability of the Research Instrument

This study carried out Cronbach Alpha and KMO and Bartlett Tests and the results are as shown:

Table 1: Reliability Coefficient of the Research Instrument

Variables	No of Items	Cronbach's Alphas
Risk Management Engineering	5	0.905
Artificial Intelligence	5	0.945
Data Mining	5	0.926
Credit Evaluation and Scoring Applications	5	0.896
Algorithms Trading	5	0.932
Robotics and Machine Learning	5	0.872
Employees' Emotional Intelligence and Knowledge	5	0.891

Source: Pilot Study Results (2024)

Table 1 shows the Cronbach's alpha results for the variables using the Statistical Product for Service Solution (SPSS) for analysis which reveal a range of 0.871-0.945 showing that all items were above the 0.70 scale as recommended by Al-Jabri and Al-Jabri (2012). Therefore, all instrument proved reliable.

Table 2: KMO and Bartlett tests

Variables	No of Items	KMO	Bartlett Test Chi^2 (Sig.)
Risk Management Engineering	5	0.786	167.835 (0.000)
Artificial Intelligence	5	0.733	210.020 (0.000)
Data Mining	5	0.734	242.107 (0.000)
Credit Evaluation and Scoring Applications	5	0.850	164.422 (0.000)
Algorithms Trading	5	0.756	150.610 (0.000)
Robotics and Machine Learning	5	0.745	114.977 (0.000)
Employees' Emotional Intelligence and Knowledge	5	0.748	185.392 (0.000)

Source: Researcher's Study, 2024

In Table 2, the computed KMO values range from 0.733 to 0.850 which showed 0.7 {> 0.7} The results of the KMO and Bartlett tests results revealed that value are all significant at 5% significance level {Sig. < 0.05} affirming the adequacy of the data.

4. Data Analysis, Results and Discussions

4.1 Descriptive Statistics

4.1.1 Response Rate

The response rate is a critical determinant of data quality, influencing the generalizability and statistical validity of empirical findings. The sample size was 362. However, to account for errors in returned questionnaires, 5% of the sample size (18) was added, which is in line with the opinion of Saunders et al (2024). Out of the 380 questionnaires distributed, 362 were fully completed and deemed usable, representing an exceptionally high response rate of 95.26%. Eighteen questionnaires (4.74%) were returned incomplete and excluded from the final analysis.

Table 3: Response Rate

Category	Frequency N	Percentage%
Completed usable copies of questionnaire	362	95.26
Incomplete copies of questionnaire	18	4.74
Total	**380**	**100**

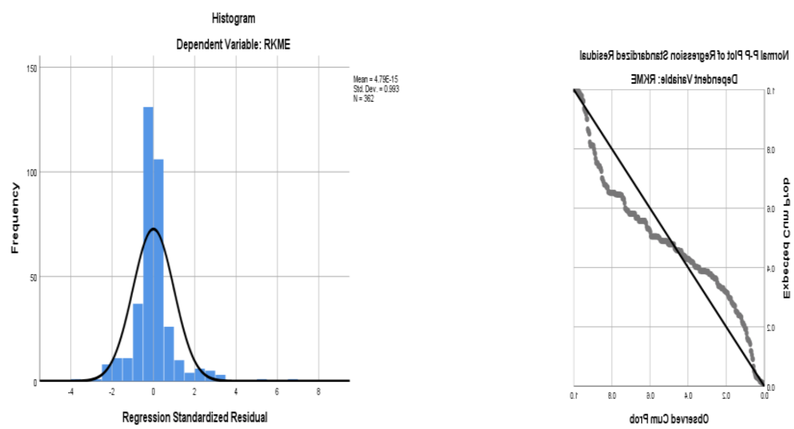
Source: Author's field report, 2025

4.2. Preliminary Tests

4.2.1 Results of Normality Test

To test for normality, the histogram was used to assess the normality of the model as shown in the figures 1 and 2.

Figure 1 & 2: Histogram for Normality test and Normal P-P plot for Normality test



The normality of the regression residuals were assessed using both histograms and normal probability–probability (P-P) plots

4.2.2 Linearity Test (Pearson Correlation Coefficient)

Linearity is a fundamental assumption in multiple regression analysis, ensuring that the relationship between independent variables and the dependent variable is approximately linear. To confirm this assumption, Pearson's correlation coefficient was used to assess the degree of association between each explanatory variable and financial engineering, as presented in Table 4.

Table 4: Linearity Test (Pearson Correlation Coefficient)

Variables	Correlation	Financial Engineering	Conclusion
Data mining Services	**Pearson correlation**	**0.572**	Linear
	Sig. (2 tailed)	0.000	
	N	362	
Credit Evaluation /Scoring Application	**Pearson correlation**	**0.665**	Linear
	Sig. (2 tailed)	0.000	
	N	362	
Algorithm Trading	**Pearson correlation**	**0.546**	Linear
	Sig. (2 tailed)	0.000	
	N	362	
Robotics & Machine Learning	**Pearson correlation**	**0.640**	Linear
	Sig. (2 tailed)	0.000	
	N	362	
Employees' Emotional Intelligence / Knowledge	**Pearson correlation**	**0.546**	Linear
	Sig. (2 tailed)	0.000	
	N	362	

Source: Author's Field Report, 2025

The results indicate that all predictor variables exhibit statistically significant and positive correlations with financial engineering at the 1% level (p<0.01p < 0.01p<0.01), confirming linearity. Specifically, focusing on the strength and direction of correlation, the Pearson correlation coefficients range between 0.546 and 0.665, signifying moderate to strong positive relationships. Specifically, credit evaluation/scoring applications exhibit the strongest correlation (r=0.665r = 0.665r=0.665), followed by robotics and machine learning (r=0.640r = 0.640r=0.640), data mining services (r=0.572r = 0.572r=0.572), algorithm trading (r=0.546r = 0.546r=0.546), and employees' emotional intelligence/knowledge (r=0.546r = 0.546r=0.546). These positive coefficients indicate that as the utilization of artificial intelligence (AI)-driven financial solutions increases, financial engineering outcomes improve. The relatively high correlation values suggest that these AI applications play a significant role in shaping financial engineering in non-financial service firms listed in Nigeria.

4.2.3 Result of Multicollinearity Test

Multicollinearity occurs when independent variables in a regression model are highly correlated, potentially distorting coefficient estimates and inflating standard errors. To assess multicollinearity, the study employed the Variance Inflation Factor (VIF) and Tolerance Statistics.

Table 5: Result of Multicollinearity Test

Variables	Collinearity Statistics	
	Tolerance	**VIF**
Data mining Services	0.767	1.304
Credit Evaluation / Scoring Application	0.758	1.320
Algorithm Trading	0.848	1.179
Robotic & Machine Learning	0.709	1.410
Employees' Emotional Intelligence / Knowledge	0.717	1.394
Average	**0.7598**	**1.3214**
Dependent Variable: Financial Engineering		

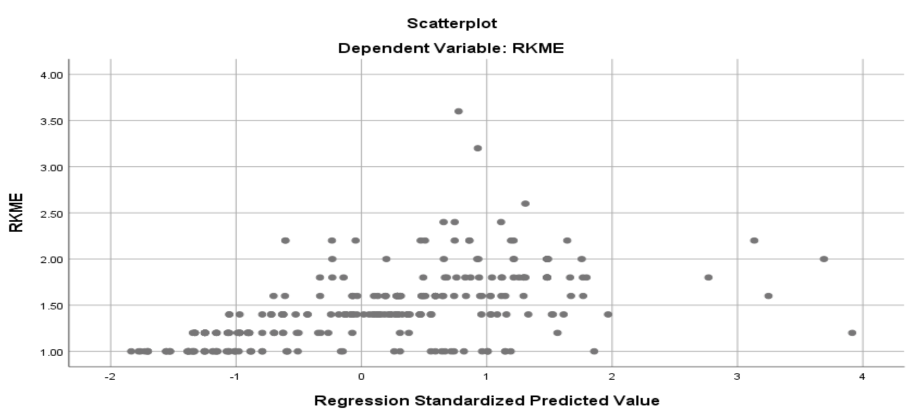
Source: Author's Field Report, 2025

As shown in Table 5, all predictor variables—data mining services, credit evaluation/scoring applications, algorithm trading, robotic and machine learning, and employees' emotional intelligence—have VIF values ranging between 1.179 and 1.410, with an average of 1.3214. These values remain well below the critical threshold, indicating minimal risk of multicollinearity. Similarly, the tolerance values range from 0.709 to 0.848, reinforcing the conclusion that no independent variable is excessively correlated with the others. The absence of multicollinearity implies that the regression model can reliably estimate the unique contribution of each explanatory variable to financial engineering without bias. This finding strengthens the validity of subsequent regression analysis, ensuring that parameter estimates remain stable and interpretable.

4.2.4 Result of Homoscedasticity Tests

The scatterplots presented in this subsection assess heteroscedasticity by plotting regression standardized residuals against predicted values for different dependent variables.

Figure 3: Scatter plot for Homoscedasticity tests



Vol. 9, No.05; 2025

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Residuals in the scatterplot appear randomly dispersed across the regression standardized predicted values without a discernible pattern.

4.3 Regression Analysis

The descriptive analysis of the respondents' opinions was done in this section. This was achieved by firstly dealing with each independent variable, followed by the dependent variable that proffered answers to the research questions. The responses were based on a Five-point Likert scale coded with numerical values for ease of analysis. The values assigned were 5 for strongly agree, 4 for Agree, 3 for undecided, 2 for disagree and 1 for strongly disagree. Interpretation of results was done using descriptive statistics such as percentages, mean, and standard deviation. The mean of the responses using a width of class interval and a grand standard deviation of more than one indicated that the responses were widely distributed or no convergence, and less than one indicated convergence in responses of respondents

4.3.1 Respondents responses on Risk Management Engineering

The results presented in Table 6 indicate a strong consensus on the role of technological innovations and human capital in enhancing risk management engineering within non-financial service firms in Nigeria. Across all measured items, the mean values range from 4.49 to 4.63, reflecting a high level of agreement among respondents.

Table 6: Respondents responses on Risk Management Engineering

Items	**SD**	**D**	**U**	**A**	**SA**	**Total**	
	N %	**N %**	**N %**	**N %**	**N %**	**Mean**	**SD**
Data mining services assist in effective risk management engineering of your organization.	0.0%	0.28%	0.8%	45.3%	53.6%	4.52	0.53
Credit evaluation and scoring applications impact on risk management engineering of your organization.	0.0%	0.28%	4.7%	40.6%	54.4%	4.49	0.60
Application of algorithms and machine learning capabilities enhance risk management engineering of your organization.	0.0%	0.28%	0.8%	34.3%	64.6%	4.63	0.52
Robotics and machine learning are capable of increasing the quality risk management engineering of your organization.	0.3%	0.00%	1.1%	35.6%	63.0%	4.61	0.54

Employees' emotional intelligence and knowledge is capable of improving the risk management engineering of your organization.	0.0%	0.28%	1.1%	34.5%	64.1%	4.62	0.52

Source: Author's Field Report, 2025

Application of algorithms and machine learning (Mean = 4.63, SD = 0.52) received the highest level of agreement, with 64.6% of respondents strongly agreeing that these technologies enhance risk management. Similarly, robotics and machine learning (Mean = 4.61, SD = 0.54) were perceived as crucial tools, with 63.0% of respondents strongly agreeing with their potential to improve risk management engineering. Employees' emotional intelligence and knowledge (Mean = 4.62, SD = 0.52) was also widely endorsed, with 64.1% of respondents strongly agreeing, highlighting the critical role of human expertise in managing portfolio risks. Data mining services (Mean = 4.52, SD = 0.53) and credit evaluation and scoring applications (Mean = 4.49, SD = 0.60) were also viewed positively, with strong agreement at 53.6% and 54.4%, respectively. The low standard deviations (ranging from 0.52 to 0.60) suggest that respondents' perceptions were relatively homogeneous, reinforcing the statistical reliability of the findings. Overall, the results indicate that both technological innovations and human cognitive skills are pivotal in optimizing portfolio management engineering, with strong policy implications for financial risk management practices in Nigerian firms.

4.3.2 Research Hypothesis, Analysis and Discussion

Table 7: Summary of multiple regression between Artificial Intelligence and Risk Management Engineering

Observations	**Model - 5**	**B**	**SE**	**t-stat**	**Sig.**
362	(Constant)	0.381	0.083	4.586	0.000
	DESA	-0.008	0.027	-0.287	0.775
	CESA	0.198	0.049	4.058	0.000
	ALTD	0.094	0.039	2.398	0.017
	ROML	0.294	0.041	7.108	0.000
	EEIK	0.101	0.040	2.522	0.012
	Model Fitness				
	ANOVA (Sig.)	**R**	**Adjusted R^2**	**F (5,356)**	
	0.000	0.590	0.339	37.983	
	Predictors: (Constant), EEIK, ALTD, CESA, DESA, ROML				
	Dependent Variable: RKME				

Source: Author's Field Report, 2025.

Note: Financial Solution Engineering (FISE), Employees' Emotional Intelligence/Knowledge (EEIK), Algorithms Trading (ALTD), Credit Evaluation/Scoring Applications (CESA), Data Mining Services (DESA), Robotics and Machine Learning (ROML). A significance level of 5% (α = 0.05) has been adopted.

Interpretation

Data Mining Services (DESA) (β = -0.008, p = 0.775) showed an insignificant and negative relationship with risk management engineering. This suggests that while data mining services may provide valuable insights for decision-making, their direct impact on risk management remains minimal. Organizations may rely on more specialized AI applications, such as credit scoring and algorithmic trading, to enhance risk management processes rather than solely depending on data mining techniques. Credit Evaluation Scoring Application (CESA) (β = 0.198, p = 0.000) had a strong positive and statistically significant effect on risk management engineering. This indicates that AI-powered credit evaluation tools are essential for managing financial risks, particularly in assessing creditworthiness and reducing exposure to high-risk transactions. The use of AI in credit evaluation enhances risk mitigation strategies by providing more accurate and efficient assessments of financial risks. Algorithm Trading (ALTD) (β = 0.094, p = 0.017) demonstrated a positive and statistically significant effect on risk management engineering. This implies that AI-driven trading algorithms contribute to effective risk management by optimizing investment decisions, predicting market trends, and mitigating financial risks. Automated trading systems help organizations minimize losses by identifying and responding to market fluctuations in real time.

Robotic and Machine Learning (ROML) (β = 0.294, p = 0.000) had the highest positive and statistically significant effect on risk management engineering. This suggests that AI-driven automation and machine learning models are crucial in enhancing risk identification, fraud detection, and predictive analytics. AI-enabled fraud detection systems help organizations proactively identify anomalies and mitigate financial risks before they escalate. Employees' Emotional Intelligence/Knowledge (EEIK) (β = 0.101, p = 0.012) also had a positive and statistically significant effect on risk management engineering. This finding highlights the role of employees' ability to interpret and integrate AI-driven insights into risk management frameworks. Organizations that invest in AI literacy and training programs for employees are likely to improve their risk mitigation strategies.

The R-value of 0.590 indicates a moderate correlation between artificial intelligence and risk management engineering, while the Adjusted R^2 value of 0.339 suggests that AI components collectively explain 33.9% of the variation in risk management engineering. This implies that AI plays a significant role in shaping risk management strategies, although other external factors contribute to risk management outcomes.

The predictive multiple regression model can be expressed as:

$RKME = 0.381 - 0.008DESA + 0.198CESA + 0.094ALTD + 0.294ROML + 0.101EEIK$…..(Equation 1: Predictive Model)

Since DESA was found to be statistically insignificant, the prescriptive model can be refined as: RKME = 0.381 + 0.198CESA + 0.094ALTD + 0.294ROML + 0.101EEIK… (Equation 2: Prescriptive Model)

This adjusted model suggests that when all variables are held constant, the baseline level of financial solution engineering is 0.381. The findings indicate that robotic and machine learning, employees' emotional intelligence, credit evaluation applications, and algorithmic trading are the most influential AI components enhancing risk management engineering.

Discussion of Findings

The magnitude and sign of the coefficients reveal that a one-unit increase in credit evaluation/scoring (CESA = 0.198), algorithmic trading (ALTD = 0.094), robotics and machine learning (ROML = 0.294), and employees' emotional intelligence/knowledge (EEIK = 0.101) yields corresponding increments in risk management engineering, with ROML exerting the strongest influence; conversely, the negative-insignificant coefficient for data mining services (DESA = –0.008) indicates that standalone data mining does not meaningfully drive risk management outcomes in these firms. The findings align with existing research that emphasizes AI's role in improving risk management practices. The strong positive effect of robotic and machine learning (ROML) reinforces the argument that AI-driven automation and machine learning models are essential for enhancing risk assessment, fraud detection, and predictive analytics. Organizations that integrate AI-driven automation into risk management frameworks are better positioned to identify, assess, and mitigate potential risks. The significant effect of credit evaluation scoring applications (CESA) and algorithm trading (ALTD) highlights the importance of AI-driven financial decision-making tools in risk management. AI-powered credit evaluation enhances risk assessment by providing objective and data-driven creditworthiness evaluations, reducing the likelihood of financial misjudgements. Similarly, algorithmic trading systems enable organizations to optimize investment decisions and manage market-related risks more efficiently.

The positive impact of employees' emotional intelligence/knowledge (EEIK) suggests that AI's effectiveness in risk management is enhanced when employees are equipped with the necessary knowledge and skills to interpret AI-driven insights. This finding underscores the need for continuous training programs to improve employees' ability to integrate AI technologies into risk management frameworks. However, the insignificant effect of data mining services (DESA) suggests that while data mining may contribute to data-driven decision-making, its direct impact on risk management engineering is limited. This could be due to the need for complementary AI-driven risk assessment tools that translate data insights into actionable risk mitigation strategies. These findings have practical implications for organizations seeking to enhance risk management strategies through AI adoption. Businesses should prioritize AI-driven credit evaluation, algorithmic trading, and machine learning models to improve risk identification and mitigation. Additionally, fostering AI literacy among employees is essential for maximizing AI's effectiveness in risk management.

Conclusion

This study investigated the effect of artificial intelligence on risk management engineering in non-financial service companies listed in Nigeria. The application of algorithms and machine learning (Mean = 4.63, SD = 0.52) received the highest level of agreement, with 64.6% of respondents strongly agreeing that these technologies enhance risk management. Similarly, robotics and machine learning (Mean = 4.61, SD = 0.54) were perceived as crucial tools, with 63.0% of respondents strongly agreeing with their potential to improve risk management engineering. The regression revealed that the variables of CESA, ALTD, ROML, and EEIK had significant effects, however, DESA exhibited insignificant effects. In addition, the joint statistics using the entire explanatory variables revealed significant effect, hence the study concluded that artificial intelligence had a significant effect on risk management engineering in non-financial service companies listed in Nigeria.

5 Recommendations

The findings indicate that data mining services and algorithmic trading significantly influence risk management engineering in service companies listed in Nigeria. This underscores the need for a proactive governmental approach to risk management, particularly in mitigating financial risks, fraud, and operational inefficiencies that hinder business performance. Hence, the study recommends that the government should strengthen financial regulations by integrating AI-driven risk assessment tools for real-time fraud detection, anomaly identification, and predictive analytics in regulatory compliance. Additionally, policymakers should facilitate AI adoption through incentives such as tax reliefs for firms investing in AI-based risk management solutions. Service companies should leverage AI-powered data mining to enhance early warning systems, detect financial irregularities, and optimize decision-making. Regulatory bodies should collaborate with AI experts to develop adaptive frameworks that align with global best practices while addressing Nigeria's unique economic environment. Moreover, AI-driven cybersecurity measures should be prioritized to safeguard financial data, prevent cyber threats, and enhance the overall resilience of the financial ecosystem in Nigeria's service sector.

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