



2nd FPISMS International Conference <https://sms2interconf.federalpolyilaro.edu.ng>

ARTIFICIAL INTELLIGENCE AND ENTERPRISES RISK MANAGEMENT IN HEALTHCAE SECTOR

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Abstract

This study focused on the relationship between artificial intelligence (AI) and enterprise risk management (ERM) in the healthcare sector of Ogun State, Nigeria. A stratified multistage sampling approach was used to conduct a cross-sectional survey of healthcare personnel from six healthcare zones. Data were gathered from 259 respondents via Google Forms and analyzed using descriptive and inferential statistical methods. The reliability analysis via Cronbach's Alpha of 0.944, indicating great internal consistency. The study observed a strong positive correlation ($r = 0.670$, $p < 0.01$) between AIMC and RI, as well as a moderate but significant correlations ($r = 0.560$, $p < 0.01$) between AIPE and RA. Regression analysis revealed that AIMC and AIPE significantly predict RI and RA, accounting for 44.9% and 31.4% of the variance, respectively. The study concluded that AI improves risk management procedures by increasing risk detection, evaluation, and overall decision-making efficiency. It suggested that state hospitals should engage in AI-driven risk management techniques, predictive analytics, and automated risk detection technologies to effectively mitigate possible hazards. Furthermore, policymakers should create conditions that encourage AI innovation through research incentives, mentorship programs, and the development of strategic initiatives targeted at increasing intellectual mobility and lowering brain drain.

Keywords: Artificial Intelligence, Risk Management

Introduction

Artificial intelligence (AI) is the ability of a computer or computer-enabled robotic system to process information and generate outcomes that are similar to human cognitive processes in learning, decision-making, and problem-solving (Soori, Arezoo, and Dastres, 2023). AI systems seek to tackle complicated issues by applying reasoning and logic at the human level. Thus, based on the groundwork established by computer science, robotics, and machine learning, artificial

intelligence (AI) has arisen as a result of technical innovations and advancements (Dexter and Lewis, 2024).

In order to identify, assess, and mitigate risks that could jeopardize the organization's capacity to accomplish its goals, risk management is a crucial component of any strategy framework. Modern corporate hazards are complicated and unpredictable, making traditional risk management techniques like manual analysis and reviewing past data inadequate (Taherdoost, 2024). With its capacity to analyze enormous datasets, spot trends, and generate forecasts in real time, artificial intelligence (AI) offers a promising answer to these problems.

Managing risk associated with organizational processes has become a crucial part of business. However, one significant aspect of contemporary corporate processes is risk management based on artificial intelligence. Furthermore, the danger associated with data management and privacy has increased as machine intelligence is used more and more in all fields. Nevertheless, the risks associated with technology use and the difficulties in managing or utilizing technology in the workplace must be recognized by businesses (Tircovnicu & Hategar, 2023).

There are difficulties in applying AI to risk management which include difficulty of incorporating AI into current organizational structures, the requirement for qualified staff, the high implementation costs, reluctance to change, and problems with data quality. The broad use of AI in risk management procedures is frequently hampered by these obstacles (Tircovnicu & Hategar, 2023).

Furthermore, the use of AI in business models for information management is still in its infancy. As a result, there is a lack of research in the area of cybersecurity that deals with business applications of AI (Marcin, 2024).

Health organizations would gain from the research's conclusions since integrating AI into their current risk management procedures would be advantageous. Improved decision-making, reduced resource waste, and increased efficiency have all been linked to higher forecast applicability. Furthermore, AI analysis can offer insight for risk management, which will strengthen the company's defenses against unstable health conditions.

From a scholarly perspective, this research contributes to the body of knowledge on AI and ERM in the healthcare industry. The study offers significant empirical evidence that would be helpful

for both practitioners practice and future scholarly researchers by outlining the justification for these technologies in risk management. Additionally, this contribution encourages the expansion of scholarly research while bringing the competing challenges of a digital economy to the attention of policymakers and planning strategists in the health sector.

The research objectives of this study are thus:

- i. To investigate how risk identification is impacted by AI management capabilities.
- ii. To ascertain how AI personnel expertise affects risk assessment.

Conceptual Review

The creation of computer systems that are capable of learning, problem-solving, reasoning, perceiving, and comprehending language—tasks that normally require human intelligence, is known as artificial intelligence (AI). By imitating human brain processes and behaviors, artificial intelligence (AI) systems may assess complex data, make well-informed decisions, improve over time, and adjust to changing environments (Khaleel, Jebrel & Shwehdy, 2024).

The study of human brain functions and the analytical calculations that take place in the mind is the focus of artificial intelligence (AI), a quickly developing and popular technology that makes tasks easier to complete and more intelligent (Patel, 2021). According to Malik, Pathania, and Rathaur (2019), artificial intelligence is the development and comprehension of intelligent computers and software that are able to reason, remember, learn, communicate, adapt, and recognize objects. It uses computations to grasp logic and then uses that understanding to create decisions (Delipetrev, Tsinaraki, & Kostic 2020). Artificial intelligence, according to Bankole (2023), is a branch of computer science that aims to create intelligent machines, mostly by writing clever computer programs. It builds systems that can solve problems by fusing large datasets with computer science.

Over time, artificial intelligence has evolved from the first rule-based systems to the most recent machine learning and deep learning techniques. Numerous applications, such as virtual assistants, expert systems, robotics, image recognition, and natural language processing, have been made possible by this progression. As AI develops, it has the potential to drastically change entire sectors, our way of life and work leading to notable gains in productivity, efficiency, and creativity (Khaleel, Jebrel & Shwehdy, 2024). As stated below, Amanawa and Amanawa (2024) examined the use of AI in medical imaging and diagnosis: efficiency in image interpretation and analysis; accurate detection; disease detection and classification of cancer early; neurological disorders;

organ segmentation; lesion detection; integration with electronic health information; and quality assurance (image quality improvement).

The literature on AI in enterprise risk management emphasizes the growing interest and potential of AI technologies in supplementing traditional risk management frameworks. A number of studies (Majka, 2024; Sarioguz, & Miser, 2024) have looked at how AI can improve various aspects of ERM, including risk identification, assessment, mitigation, and monitoring.

AI in Risk Identification: AI tools, especially machine learning algorithms, are effective in analyzing large datasets to detect emerging risks that may not be apparent through traditional methods. Machine learning models can identify patterns and anomalies that indicate potential risks, such as supply chain disruptions, credit defaults, or cybersecurity breaches.

AI in Risk Assessment: AI can help improve risk assessment models by making more accurate predictions. Machine learning models can examine historical data and current market patterns to predict the possibility of various dangers.

AI for Risk Mitigation: AI-powered decision-making systems can automate responses to detected threats. AI systems, for example, can recommend or automatically conduct financial risk-mitigation steps such as revising investment portfolios or changing business processes.

AI in Monitoring and Reporting: AI systems can enhance risk monitoring by continuously evaluating real-time data and alerting risk managers to developing concerns.

The use of ERM frameworks in Nigeria has been prompted by regulatory requirements, globalization, and the demand for better corporate governance. Adewuyi and Olowookere (2018) found that firms that use ERM frameworks have better decision-making, resource allocation, and risk mitigation outcomes.

Theoretical Review

Dynamic Capabilities Theory

David Teece, Gary Pisano, and Amy Shuen defined dynamic capabilities theory in their 1997 study, *Dynamic Capabilities and Strategic Management*. The theory describes how businesses can adapt to and benefit from fast changing technologies. It focuses on an organization's ability to adapt, integrate, reconfigure internal and external resources, talents, and functional competencies, and meet the needs of a changing environment. The theory contends that organizations must

constantly adjust their capacities to meet changing environments. In terms of risk management, dynamic capabilities theory emphasizes the necessity of incorporating AI as a capability that improves the organization's ability to recognize, grab, and reorganize its resources in response to new hazards.

Decision Making Theory

Herbert A. Simon, the Nobel Prize laureate in Economics, established decision-making theory in 1978. He is most recognized for his research on corporate decision-making, generally known as behaviorism. Decision-making theory explains how reasonable people should behave in the face of risk and uncertainty. According to the theory, decision-making is adopting and applying rational choices to efficiently manage a private, business, or governmental organization. It suggested that making a decision entails choosing between multiple paths of action, which can include both action and inaction. Decision theory is the study of how individuals and organizations make decisions, especially when faced with ambiguity. AI helps risk managers make better decisions by providing probability models, scenario analysis, and simulations.

Empirical Review

In Kalogiannidis, Kalfas, Papaevangelou, Giannarakis, and Chatzitheodoridis (2024) research, the study investigated the efficacy of artificial intelligence (AI) technologies in predicting risk and their contribution to business continuity. This study sought to comprehend how various AI components, such as natural language processing (NLP), AI-powered data analytics, AI-driven predictive maintenance, and AI integration in incident response planning, improve risk assessment and support business continuity in an environment where businesses face a variety of risks, including natural disasters, cyberattacks, and economic fluctuations. The study employed a cross sectional design and a quantitative method to collect data from 360 technology specialists. The findings of this study demonstrate that AI technologies have a significant impact on business continuity and predictive risk assessment. Notably, NLP was found to increase the accuracy and speed of risk assessment procedures. The use of AI into incident response plans proved especially beneficial, significantly reducing business disruptions and increasing recovery from unforeseen incidents.

Methodology

A cross-sectional study was conducted using a questionnaire among healthcare personnel in Ogun State hospitals. Using Google forms, data were collected across the six healthcare zones via a stratified multistage sampling strategy. Taro Yamane sampling procedure was utilized to determine a sample size of 259 from a target population of 792 health personnel. The collected data underwent descriptive and inferential statistical analyses.

Model Specification

$$RM = f(AI)$$

$$RM = f(AIMC, AIPE)$$

$$RM = \beta_0 + \beta_1 x + \beta_2 x + \dots \text{et}$$

$$RI = \beta_0 + \beta_1 AIMC + \dots \text{et}$$

$$RA = \beta_0 + \beta_1 AIPE + \dots \text{et}$$

Where

AIMC = Artificial Intelligence Management Capabilities

AIPE = Artificial Intelligence Personnel Expertise

RA = Risk Assessment

RI = Risk Identification

RM = Risk Management

β_0 = Constant

$\beta_1 - \beta_2$ = Coefficient correlation

Result and Discussion

Table 1: Reliability Test

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.944	.945	20

Source: Researcher' Computation, 2025

Values above 0.9 usually imply great dependability, which means that the items are closely connected and measure the same underlying construct..

Table 2: Descriptive

		Mean	Std. Deviation	N
Hyp 1	RI	7.8571	3.88683	259
	AIMC	9.1699	3.95641	259
Hyp 2	RA	10.9961	4.85647	259
	AIPE	8.9653	4.07235	259

Source: Researcher' Computation, 2025

The average score for RI, AIMC, RA and AIPE are 7.86, 9.1699, 10.9961 and 8.9653 with a standard deviation of 3.88683, 3.95641, 4.85647 and 4.07235 respectively.

Table 3: Correlations

		RI	AIMC	RA	AI[E
Pearson Correlation	RI	1.000	.670	–	–
	AIMC	.670	1.000	–	–
	RA	–	–	1.000	.560
	AIPE	–	–	.560	1.000
Sig. (1-tailed)	RI	–.	.000	–	–
	AIMC	.000	–.	–	–
	RA	–	–	–.	.000
	AIPE	–	–	.000	–.
N		259	259	259	259

Source: Researcher' Computation, 2025

The correlations between RI and AIMC and RA and AIPE are.670 and.560, respectively, indicating a significant and moderate positive connection. A p-value of.000 means the correlations are statistically significant at the 1% level ($p < 0.01$). This shows that RM and AI are positively related, implying that an increase in RA and RI correlate with an increase in AIPE and AIMC respectively.

Table 4: Model Summary

	Mod el	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2
Hyp 1	1	.670 ^a	.449	.447	2.89009	.449	209.644	1	257
Hyp 2	1	.560 ^a	.314	.311	4.03037	.314	117.603	1	257

a. Predictors: (Constant), AIMC

a. Predictors: (Constant), AIPE
Source: Researcher' Computation, 2025

The Model summary table displays the regression model findings. The R values of .670 and .560, indicating a significant and moderate positive correlation between the predictor factors and the dependent variables. R^2 (.449 and .314) indicates that the independent variables explain 44.9% and 31.4% of the variances in the dependent variables, respectively. The F-statistics (209.644 and 117.603) are both quite high and statistically significant, showing that the model is well fitted.

Table 5: ANOVA

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	1751.085	1	1751.085	209.644	.000 ^b
	Residual	2146.629	257	8.353		
	Total	3897.714	258			
1	Regression	1910.325	1	1910.325	117.603	.000 ^b
	Residual	4174.671	257	16.244		
	Total	6084.996	258			

a. Dependent Variable: RI &

b. Predictors: (Constant), AIMC & AIPE

Source: Researcher' Computation, 2025

The ANOVA test determines whether the regression model adequately explains the variation in the dependent variable. Both models are statistically significant ($p = .000$ and $.000$), indicating that the independent factors have a significant impact on the dependent variables.

Table 6: Coefficients

Model		Unstandardized Coefficients		Unstandardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1.	(Constant)	1.819	.454		4.006	.000
	AIMC	.658	.045	.670	14.479	.000
1.	(Constant)	5.006	.607		8.253	.000
	AIPE	.668	.062	.560	10.844	.000

a. Dependent Variable: RI

a. Dependent Variable: RA

Source: Researcher' Computation, 2025

This table shows the regression coefficients for two models. The constants (intercepts) are 1.819 and 5.006. This suggests that when AIMC and AIPE are zero, the dependent variables have predicted values of 1.819 and 5.006, respectively. A one-unit rise in AIMC and AIPE resulted in 0.658 and 0.668 unit increases in the dependent variables. Finally, both models are statistically significant ($p < .001$), indicating that AIMC and AIPE are good predictors of their dependent variables.

Conclusion and Recommendations

The study used statistical models to examine the relationship between AI and Risk Management (RM). Objective one revealed a strong positive correlation between AIMC and Risk Identification (RI) ($r = 0.670$, $p < 0.01$). The model's F-statistic (117.603, $p < 0.01$) confirms the statistical significance of the relationship. This suggests that organizations with advanced AI-driven management systems are better equipped to identify risks efficiently.

Based on objective two, the study found a moderate but significant positive correlation between Artificial Intelligence Personnel Experts (AIPE) and Risk Assessment (RA) ($r = 0.560$, $p < 0.01$). AIPE enhances RA by improving analytical capabilities, predictive accuracy, and overall risk management efficiency.

This study recommended that organizations should emphasize AI-driven risk management techniques to reduce possible hazards effectively.

To retain skilled individuals, policymakers should improve access to information, mentorship, and career development programs.

Organizations should develop strategic initiatives to enhance intellectual mobility within local economies, reducing the need for migration.

Organizations can improve risk identification efficiency, accuracy, and predictive capabilities by investing in AI-driven risk monitoring tools and predictive analytics.

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