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ADOPTION OF ARTIFICIAL INTELLIGENCE IN PREDICTIVE RISK ASSESSMENT IN SELECTED OIL AND GAS COMPANIES IN NIGERIA

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ABSTRACT

This study examined the role of Artificial Intelligence adoption in predictive risk assessment within Nigerian oil and gas companies, focusing on its effectiveness in enhancing risk identification, evaluation, and management processes. A descriptive cross-sectional survey design was adopted, employing a proportionate sampling technique to select 256 participants from professionals and decision-makers involved in risk assessment, safety management, and operational roles across selected companies. A total of 256 questionnaires were distributed, out of which 249 were properly filled and valid for data analysis, representing a high response rate of 97.3%. Data was analyzed using the Statistical Package for the Social Sciences (SPSS) version 27.0. The results revealed that the adoption of AI technologies such as machine learning, predictive analytics, and data modelling has a significant positive impact on predictive risk assessment by increasing confidence in risk-mitigation strategies (Mean = 3.8), and management support for AI adoption (Mean = 3.8). This is followed by proactive incident prevention compared to traditional methods (Mean = 3.7), alignment of AI use with operational objectives (Mean = 3.7), and measurable improvements in safety outcomes (Mean = 3.7). AI-powered tools enabling quicker response to threats (Mean = 3.8), enhanced safety compliance (Mean = 3.8), tangible improvements in safety outcomes from AI investment (Mean = 3.8), and AI-based monitoring identifying risks before escalation (Mean = 3.8). The study concludes that AI plays a transformative role in improving predictive risk assessment and overall risk management effectiveness in the Nigerian oil and gas industry.

KEYWORDS

Artificial Intelligence, Predictive Risk Assessment, Oil and Gas Companies, Nigeria.

Introduction

One of the main drivers of the world economy, the oil and gas sector supplies the energy required to power transportation, industry, and other facets of contemporary life. The industry is crucial in determining geopolitical dynamics and propelling global economic growth due to its extensive infrastructure and complex supply chains. From exploration and production to transportation, refinement, and distribution, oil and gas operations cover a wide range of tasks. These operations are distinguished by their intricacy and frequently entail high-risk tasks carried out in difficult and remote settings. Therefore, maintaining efficiency and safety in the oil and gas industry is crucial for maintaining operations as well as protecting the environment and human lives (Wang, 2024).

Health, safety, and environmental (HSE) issues are crucial in the high-risk environment of the oil and gas sector. The industry presents serious risks to both people and the environment because of its risky procedures, intricate operations, and frequently harsh conditions. Human error, equipment failures, and exposure to toxic substances are examples of incidents that can have serious repercussions, including death, environmental damage, and expensive financial losses (Ajiga et al., 2024, Eyieyien et al., 2024, Kwakye et al., 2023; Olanrewaju et al., 2024).

Risk management is a fundamental aspect of organizational strategy, serving as a defence against potential financial, strategic, operational, and reputational losses (Yazdi, 2018). The significance of this process is rooted in its capacity to identify, evaluate, and prioritize risks, subsequently facilitating resource allocation aimed at minimizing, controlling, and monitoring the likelihood and/or impact of adverse events to an acceptable risk level, often referred to as ALARP, or "as low as reasonably practicable" in certain contexts (Li et al., 2023). Risk management encompasses not only the prevention of crises but also the navigation through them, aiming to minimize damage and foster resilience in the aftermath.

The evolution of the industry has highlighted the necessity for enhanced risk management and improved operational safety. Traditional HSE management systems are crucial; however, they frequently lack the real-time responsiveness and predictive capabilities necessary for proactive risk mitigation. Moreover, conventional systems often find it challenging to manage the extensive data produced by contemporary operations, hindering accurate risk analysis and the anticipation of potential hazards. The integration of Artificial Intelligence (AI) into Health, Safety, and Environment (HSE) management systems presents a viable solution to these challenges. Artificial intelligence can improve real-time safety monitoring, optimize data analysis, and forecast risks prior to their development into critical incidents (Daramola, 2024; Ezeafulukwe et al., 2024; Onita et al., 2024). The oil and gas industry can transition from a reactive safety management model to a proactive and predictive approach by utilizing AI technologies, thereby minimizing risks and safeguarding human and environmental resources.

The incorporation of AI into engineering processes has the potential to improve operational efficiency throughout the entire oil and gas value chain. AI technologies provide advanced analytical capabilities and predictive insights across various domains, including reservoir characterization, drilling optimization, production forecasting, and supply chain management. These tools enable decision-makers to optimize resource allocation, reduce downtime, and enhance output. AI-driven technologies can significantly improve safety standards in the oil and gas sector (Hussain et al., 2024).

Occupational safety is a fundamental concern for industries globally, as workplaces aim to safeguard employees from hazards and promote their well-being. Despite notable progress in safety protocols and regulatory frameworks, challenges remain in the effective detection of hazards and control of exposure to risks. Industries including construction, manufacturing, and healthcare encounter distinct risks, which encompass physical hazards and prolonged exposure to toxic substances (Elumalai et al., 2017; Nunfam et al., 2019). Conventional methods of hazard detection typically depend on reactive strategies, which restrict their capacity to proactively prevent accidents and mitigate health risks. The growing complexity of workplace environments requires innovative solutions capable of adapting to changing safety requirements.

Advancements in Artificial Intelligence (AI) and the Internet of Things (IoT) have the potential to transform occupational safety practices. AI-driven systems are capable of analyzing extensive datasets in real-time, facilitating predictive insights and the automation of safety protocols. IoT devices, including wearable sensors and connected monitoring systems, deliver continuous data streams that improve situational awareness and facilitate hazard identification. Emerging technologies possess the potential to transition occupational safety from reactive measures to proactive, data-driven strategies (Karadağ, 2024). Trends including computer vision for physical hazard detection, predictive analytics for exposure control, and real-time alert systems are being integrated into workplace safety frameworks, showcasing their efficacy in injury and illness prevention.

Artificial Intelligence (AI) has further revolutionized occupational safety by introducing advanced predictive capabilities. AI systems utilize machine learning algorithms to examine historical and real-time data, detecting patterns that suggest potential hazards. Predictive analytics enable organizations to anticipate and address risks before they escalate into incidents (Fontes, et al., 2022, Olu, 2017). For example, AI-driven models can predict equipment failures based on sensor data, allowing maintenance teams to intervene preemptively. Computer Vision, another AI application, automates hazard detection by identifying unsafe behaviors or conditions through video surveillance. Such technologies enhance the precision and timeliness of safety interventions, reducing the reliance on manual oversight and significantly improving workplace safety outcomes.

Despite the transformative potential of artificial intelligence (AI) in enhancing risk management and occupational safety, the oil and gas industry in Nigeria continues to grapple with persistent hazards, operational inefficiencies, and environmental threats. Traditional health, safety, and environmental (HSE) management systems often struggle to provide the real-time responsiveness and predictive capabilities needed to proactively mitigate risks in high-risk and complex operational environments (Ajiga et al., 2024; Olanrewaju et al., 2024; Wang, 2024). This limitation is further compounded by the vast and dynamic data produced by contemporary oil and gas operations, making timely analysis and anticipation of hazards challenging (Daramola, 2024; Ezeafulukwe et al., 2024).

The integration of AI technologies into risk assessment frameworks offers a promising avenue to address these shortcomings by enabling real-time safety monitoring, advanced data analytics, and proactive risk prediction (Onita et al., 2024). However, the adoption and effectiveness of AI-driven predictive models in the Nigerian oil and gas context remain underexplored, with significant gaps in empirical evidence regarding their impact on safety outcomes, regulatory compliance, and workforce dynamics. Existing studies have showcased the capabilities of AI in predictive maintenance, anomaly detection, and hazard identification, thereby improving operational reliability and cost efficiency. Yet, key challenges persist, algorithmic bias, lack of model transparency, ethical considerations, and limitations in data availability and standardization (Ucar et al., 2024; Minh et al., 2022). These factors can undermine the reliability and acceptance of AI-based risk assessment systems, especially in regions with unique operational and regulatory demands such as Nigeria.

Therefore, there is a critical need to evaluate the role of AI adoption in predictive risk assessment within selected oil and gas companies in Nigeria, identifying the effectiveness, challenges, and limitations of its implementation. This evaluation is essential not only for advancing academic understanding but also for informing industry best practices, policy formulation, and the development of tailored AI solutions that address the unique risks faced by the Nigerian oil and gas sector.

1. Methodology

2.1. Study Area

Nigeria, located in West Africa, stands as the continent's largest oil producer and plays a pivotal role in the global energy landscape. The country's oil and gas sector is a cornerstone of its economy, contributing significantly to national revenue, employment, and infrastructure development. Within Nigeria, the Niger Delta region, and especially the city of Port Harcourt, serves as a strategic hub for oil and gas operations. Port Harcourt, the capital of Rivers State, is often regarded as the nerve center of Nigeria's petroleum industry due to its concentration of oil companies, service firms, and regulatory agencies.

Port Harcourt presents a unique context for examining AI adoption in predictive risk assessment. Its complex industrial ecosystem is characterized by large multinational corporations, indigenous firms, and a workforce skilled in risk management and safety operations. The city's infrastructure supports both upstream and downstream activities, from exploration and drilling to refining and distribution. However, Port Harcourt and the broader Niger Delta also contend with significant challenges environmental risks, operational hazards, and regulatory complexities—which make effective risk assessment crucial.

Selecting Port Harcourt as a case study enables research to capture the realities of AI implementation in a high-stakes, technologically evolving environment. The city's diversity in company size, operational focus, and workforce demographics provides a rich basis for investigating how artificial intelligence can transform predictive risk management practices. By situating the study in Port Harcourt, the research addresses both the opportunities and barriers to technology adoption in a region marked by economic importance and operational risk, offering insights that are both locally grounded and relevant to broader industry trends.

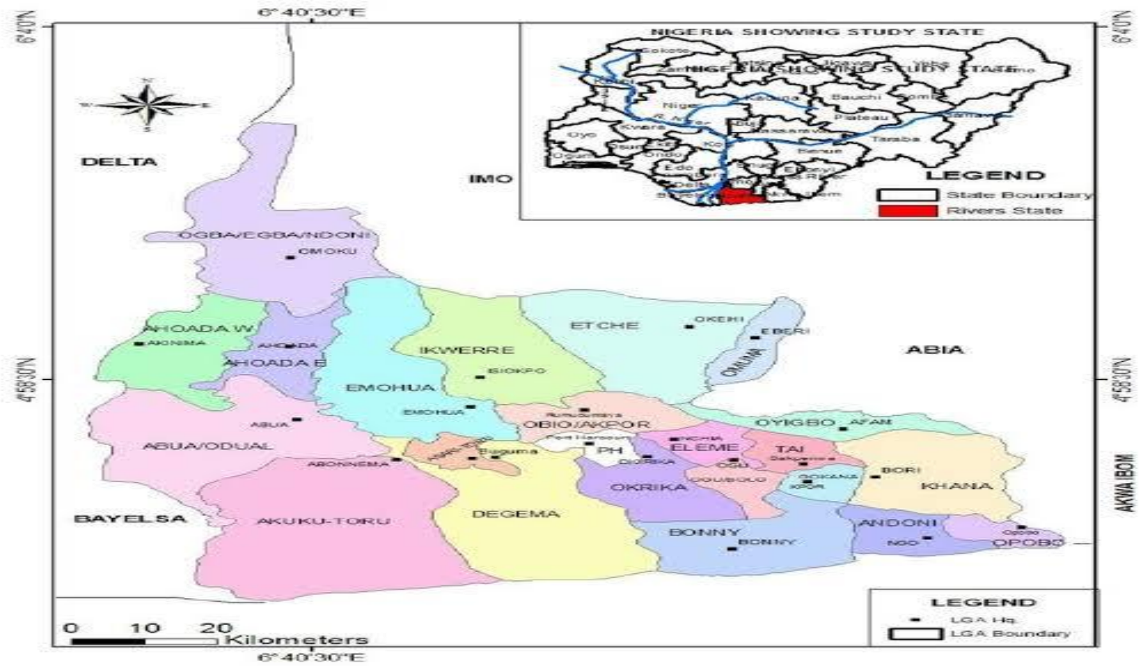

Figure 1 Map of Rivers States showing Port Harcourt and other Local government Areas

2.2 Population, Sampling Techniques and Sample Size determination

The target population comprises professionals and decision-makers working in risk assessment, safety management, and operational roles within selected oil and gas companies in Nigeria. To ensure representation, a stratified random sampling technique was used, segmenting participants based on company size, geographical location, and functional department. This method increases the likelihood of obtaining a sample that reflects the diversity of organizational structures and AI adoption stages within the industry (Etikan & Bala, 2017). The sample was chosen from the population using a stratified random sampling technique. This approach made sure that various population subgroups were fairly represented. The formula of Taro Yamane (1967) in Equation (3.1) was used to determine the sample size. The formula is straightforward and widely used to determine sample size for estimating proportion in a finite population:

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

where n is the Sample size, N is the Population size (which is 556) and d is the Level of precision (assumed to be 0.05 at 95% confidence level). In this study, the finite population is 556 and the level of precision assumed to be 0.05, the sample size was calculated as:

$$n = 232.6$$

10% Attrition gives 23.2, Which implies that the sample size = 232.6+23.2 = 255.8, Therefore, a minimum sample size of 256 respondents was used for this research. In order to sample each company a proportionate sampling approach is applied. The companies, their population and sampled workers are shown in Table 1.

Company 1: $n = \frac{177}{556} \times 256 = 82,$

Company 2: $n = \frac{163}{556} \times 256 = 75$

Company 3: $n = \frac{216}{556} \times 256 = 99$

Table 1: Selected companies with the number of workers used.

Company	Number of workers	Number of workers sampled
Oil and Gas Company 1	177	82
Oil and Gas Company 2	163	75
Oil and Gas Company 3	216	99
Total	556	256

2.3 Method and Instrument for Data Collection

Descriptive cross-sectional survey design was adopted for this study. Primary data was used in the study. Primary data was collected through questionnaires. A standardized questionnaire with closed-ended questions and a five-point Likert scale (strongly agree to strongly disagree) was used to gather data. Quantitative data is made up of numerical information that can be measured and analyzed statistically. Finding patterns, relationships, and trends within the sample population is made possible by the objective, repeatable results that quantitative data in this study provide. The study makes sure that the data gathered is trustworthy and appropriate for exacting quantitative methods by using standardized scales and structured questionnaires, which increases the validity of the results.

The questionnaire was divided into five sections; Section A- Socio-demographic data, Section B – on ways AI technologies are currently applied in predictive risk assessment, Section C - the effectiveness of AI in minimizing operational hazards and improving safety outcomes and Section D - the impact of AI-driven risk models on regulatory compliance and decision-making and E - on the challenge and limitation of AI technologies adoption in in predictive risk assessment. A structured questionnaire created especially for this study was used to approach respondents to gather quantitative data. To capture a variety of viewpoints within the industry, the researcher and a research assistant distributed the questionnaires to a proportionately sampled group across chosen companies. Participants were informed of the study purpose and asked for their consent before receiving the questionnaire to complete. Every effort was made to retrieve them as soon as the instrument was completed to ensure a high return rate.

2.4 Validity/Reliability of Instrument and Methods of Data Analysis

Throughout the instrument development process, several strict measures were implemented to guarantee the validity and reliability of the questionnaire used in this investigation. Professionals and scholars with experience in AI adoption and risk assessment in the oil and gas industry were asked to provide expert reviews. They assessed the tool's coverage, clarity, and applicability. Their input helped to clarify unclear items and strengthen the questionnaire's capacity to precisely measure the desired variables. A subset of the target population participated in a pilot study to evaluate reliability. Cronbach's alpha was used to assess the responses' internal consistency; values above the generally recognized cutoff of 0.70 indicated satisfactory reliability. The Likert scale items' standardization and the unambiguous instructions also helped to reduce measurement error and improve the repeatability of the results. When taken as a whole, these steps guaranteed that the information gathered is reliable and trustworthy, offering a strong basis for further statistical analysis and interpretation. Statistical

Package for Social Sciences (SPSS) version 27.0 was used to analyze the collected data. AI adoption levels and respondent characteristics were summed up using descriptive statistics.

3. Results and Discussions

3.1 Sociodemographic Characteristics of respondents

Table 2 shows the socio-demographic characteristics of 249 respondents. The age distribution indicates that the majority were between 31–35 years (23.3%), followed by 26–30 years (20.9%) and 36–40 years (18.9%). Only 3.2% were 51 years and above. Most respondents were male (62.7%), while females accounted for 37.3%. In terms of marital status, 60.6% were married, 30.5% single, whereas 4.0% were separated and 4.8% fell under other categories. Educational attainment was generally high, with 54.2% holding tertiary qualifications and 12.9% having postgraduate education. Only 2.0% reported having no formal education. Work experience in the oil and gas industry showed that 36.9% had 6–10 years of experience and 30.1% had more than 10 years, indicating a relatively experienced workforce. A further 25.7% had 1–5 years of experience. Regarding current job roles, 29.7% were site engineers, 26.9% supervisors, 20.9% project managers, while 22.5% occupied other roles. Nearly half of the respondents (48.6%) worked on-site, 24.9% were offshore workers, 21.7% provided remote support, and 4.8% engaged in other job types.

The socio-demographic profile of respondents in this study reveals a workforce composition that aligns well with the technical expertise required for meaningful evaluation of AI-driven risk assessment systems in Nigeria's oil and gas sector. The predominance of respondents aged 26–40 years (63.1%) represents a cohort that has witnessed both traditional risk management practices and the gradual introduction of digital technologies in the industry. This age distribution is particularly significant when contrasted with the findings of Adeoye et al., (2024), who identified organizational resistance and lack of technical know-how as major barriers to AI adoption, noting that only 22% of refineries employed AI-based simulations for safety drills, primarily due to opposition from legacy system operators.

The substantial representation of experienced professionals, with 67% having more than five years of industry experience and 30.1% exceeding ten years, provides credibility to the study's findings on AI effectiveness in risk assessment. This experience distribution directly addresses the concerns raised by Martinez et al., (2025), who found that less than 20% of AI was utilized in Nigerian oil construction projects due to local vendors' insufficient understanding of AI's potential. The study's sample demonstrates access to personnel who possess both traditional operational knowledge and exposure to emerging technologies, making them well-positioned to evaluate AI system performance against conventional methods.

The gender distribution (62.7% male, 37.3% female) reflects ongoing industry demographics, though the female representation is notably higher than might be expected in traditionally male-dominated sectors. The educational profile is particularly striking, with 67.1% holding tertiary or postgraduate qualifications. This concentration of highly educated respondents contrasts sharply with Singh et al., (2022) observation that 42% of Nigerian oil companies struggled with interpreting AI results, leading to suboptimal decision-making. The study's sample suggests that when AI systems are deployed among adequately educated personnel, the interpretability challenges may be less severe than previously documented.

The distribution across job roles Site Engineers (29.7%), Supervisors (26.9%), and Project Managers (20.9%) provide diverse perspectives spanning operational, supervisory, and strategic levels. This multi-level representation is crucial for assessing AI's impact on decision-making accuracy, which previous studies have shown improves by 36–46% across various operational contexts (Szadeczky et al., 2025; Li et al., 2023). Furthermore, the inclusion of both in-site (48.6%), offshore (24.9%), and remote support (21.7%) workers addresses the varied operational environments discussed by Adebayo et al., (2022), who specifically highlighted challenges in offshore environments where 35% of sensors failed due to limited connectivity and unreliable data streams.

Table 2: Socio-demographic data

Items	Frequency (n=249)	Percent (%)
Age		
18–25 years	34	13.7
26–30 years	52	20.9
31–35 years	58	23.3
36–40 years	47	18.9
41–45 years	33	13.3
46–50 years	17	6.8
51 years and above	8	3.2
Gender		
Male	156	62.7
Female	93	37.3
Marital Status		
Single	76	30.5
Married	151	60.6
Separated	10	4.0
Others	12	4.8
Highest Level of Education		
No formal education	5	2.0
Primary education	15	6.0
Secondary education	62	24.9
Tertiary education	135	54.2
Postgraduate	32	12.9
Years of Experience in the Oil & Gas Industry		
Less than 1 year	18	7.2
1–5 years	64	25.7
6–10 years	92	36.9
More than 10 years	75	30.1
Current Job Role		
Supervisor	67	26.9
Site Engineer	74	29.7
Project Manager	52	20.9
Others	56	22.5
Job Type		
In-site	121	48.6
Remote job support	54	21.7
Offshore	62	24.9
Others	12	4.8

3.2 Application of AI technology in predictive risk assessment in oil and gas companies in Port Harcourt

Table 3 shows respondents' views on how AI technologies are currently applied in predictive risk assessment. Results indicate consistently positive perceptions, with the highest mean scores recorded for improved accuracy of risk identification (Mean = 3.8), increased confidence in risk-mitigation strategies (Mean = 3.8), and management support for AI adoption (Mean = 3.8). This is followed by proactive incident prevention compared to traditional methods (Mean = 3.7), alignment of AI use with operational objectives (Mean = 3.7), and measurable improvements in safety outcomes (Mean = 3.7). Faster decision-making (Mean = 3.6), timely alerts about operational hazards (Mean = 3.5), clear procedures for using AI outputs (Mean = 3.5), transparency of AI predictions (Mean = 3.5), high trust in AI-generated predictions (Mean = 3.4), availability of feedback mechanisms (Mean = 3.4), and ongoing evaluation of AI effectiveness (Mean = 3.4) all received high ratings. Adequate employee training (Mean = 3.3) also ranked high, while only one item active utilization of AI for predictive risk tasks recorded a low mean score (Mean = 2.3). The grand mean of 3.5 reflects an overall high level of agreement on the current application of AI in predictive risk assessment.

The findings reveal a paradoxical pattern in AI application for predictive risk assessment within Nigerian oil and gas operations. While 58% of respondents rated AI application as high with a grand mean of 3.5, a critical contradiction emerged: the actual utilization of AI-powered tools scored remarkably low at 2.3 mean the only item below the 3.0 cutoff. The disconnect between perceived application levels and actual tool utilization suggests that respondents recognize AI's potential benefits and organizational support, yet direct operational deployment remains limited. This finding starkly contrasts with Zhang et al., (2022) study, which demonstrated active implementation of convolutional neural networks processing real-time sensor data from oil pipeline systems, achieving 35% improvement in early anomaly detection. Similarly, Rahman and Sadiq's (2022) supervised machine learning models on offshore platforms achieved 82% accuracy in signaling potential risk events. The study indicates that Nigerian operations have not yet achieved this level of systematic AI integration, despite strong agreement on AI's theoretical benefits.

The contradiction becomes more pronounced when examining specific items. Respondents highly rated AI's improvement in risk identification accuracy (mean 3.8), faster decision-making (mean 3.6), and increased confidence in risk-mitigation strategies (mean 3.8), yet simultaneously reported minimal active utilization of AI tools (mean 2.3). This pattern diverges significantly from Mensah et al., (2022) Nigerian-focused study, which documented actual AI-IoT integration achieving 28% decrease in unscheduled equipment downtime and 22% increase in risk identification accuracy. The findings suggest these benefits remain aspirational rather than realized for most Nigerian oil and gas organizations. Training adequacy received moderate agreement (mean 3.3), representing one of the lower scores. This aligns with Adeoye et al., (2024) observation that over 60% of Nigerian oil companies lack infrastructure for successful AI implementation, and Ogunleye and Bello (2023) finding that only 22% of refineries used AI-based simulations, primarily due to lack of technical know-how and resistance from legacy system operators. The training gap identified in the study validates these earlier observations, suggesting that human capacity development lags behind technological aspirations.

The high ratings for management support (mean 3.8) and alignment with operational objectives (mean 3.7) contrast sharply with Silva et al., (2023) implementation of recurrent neural networks providing 48-hour advance warnings of operational hazards, and Lee et al., (2024) deployment of explainable AI technologies enabling transparent risk interpretation. Nigerian organizations appear to possess leadership commitment and strategic alignment yet face significant implementation barriers preventing translation of support into operational reality. Moderate scores for feedback mechanisms (mean 3.4), ongoing evaluation (mean 3.4), and transparency (mean 3.5) further illuminate the implementation gap. These findings resonate with Ozobu et al.'s (2025) observation that only 18% of Nigerian oil firms had access to real-time analytics dashboards, and 56% lacked internal AI governance policies. The study suggests that while organizations recognize AI's value through improved safety outcomes (mean 3.7) and proactive incident prevention (mean 3.7), they struggle with the foundational elements actual tool deployment, comprehensive training, and systematic evaluation necessary for sustained AI integration. This represents a critical "aspiration-implementation gap" where organizational readiness in terms of management support and strategic vision has not translated into operational capability, echoing the infrastructure and capacity challenges identified across multiple Nigerian-specific studies.

Table 3: Results of AI technology application in predictive risk assessment

Items	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Mean	Remarks
AI-powered tools are actively utilized within my organization for predictive risk assessment tasks.	32 (12.9)	15 (6.0)	47 (18.9)	64 (25.7)	91 (36.5)	2.3	Low
AI technologies have improved the accuracy of risk identification in our operational processes.	72 (28.9)	103 (41.4)	41 (16.5)	23 (9.2)	10 (4.0)	3.8	High
The adoption of AI in predictive risk assessment has led to faster decision-making in my department.	55 (22.1)	99 (39.8)	48 (19.3)	32 (12.9)	15 (6.0)	3.6	High
Our organization's AI systems regularly provide timely alerts about potential operational hazards.	61 (24.5)	83 (33.3)	52 (20.9)	33 (13.3)	20 (8.0)	3.5	High
The integration of AI into risk assessment processes has increased confidence in risk-mitigation strategies.	68 (27.3)	97 (39.0)	48 (19.3)	26 (10.4)	10 (4.0)	3.8	High
There are clear procedures in place for incorporating AI outputs into safety management decisions.	52 (20.9)	88 (35.3)	54 (21.7)	35 (14.1)	20 (8.0)	3.5	High
Employees have received adequate training on the use of AI-powered predictive risk assessment tools.	46 (18.5)	79 (31.7)	51 (20.5)	47 (18.9)	26 (10.4)	3.3	High
Trust in AI-generated risk predictions is high within my team or department.	54 (21.7)	83 (33.3)	52 (20.9)	38 (15.3)	22 (8.8)	3.4	High
AI adoption has enabled us to proactively prevent incidents that might have been missed by traditional methods.	63 (25.3)	98 (39.4)	46 (18.5)	28 (11.2)	14 (5.6)	3.7	High
The current use of AI in risk assessment aligns with the overall operational objectives of my organization.	70 (28.1)	91 (36.5)	44 (17.7)	29 (11.6)	15 (6.0)	3.7	High

The integration of AI into risk assessment processes has led to measurable improvements in safety outcomes.	67 (26.9)	99 (39.8)	45 (18.1)	25 (10.0)	13 (5.2)	3.7	High
Feedback mechanisms are in place for employees to report issues or concerns related to AI-powered tools.	45 (18.1)	87 (34.9)	56 (22.5)	39 (15.7)	22 (8.8)	3.4	High
There is ongoing evaluation of the effectiveness of AI-generated risk assessments in real-world scenarios.	48 (19.3)	82 (32.9)	61 (24.5)	36 (14.5)	22 (8.8)	3.4	High
Management actively supports the adoption and use of AI technologies for safety management.	71 (28.5)	103 (41.4)	39 (15.7)	24 (9.6)	12 (4.8)	3.8	High
My organization maintains transparency regarding how AI predictions are generated and used in decision-making.	58 (23.3)	84 (33.7)	53 (21.3)	33 (13.3)	21 (8.4)	3.5	High
				Grand Mean		**3.5**	**High**

Mean Cut-off =3.0

3.3 The effectiveness of AI in Minimizing Operational Hazards and Improving Safety Outcomes

Table 4 shows the effectiveness of AI in minimizing operational hazards and improving safety outcomes. The highest mean scores were recorded for AI's contribution to reducing operational hazards (Mean = 3.8), the practicality of AI-generated safety recommendations (Mean = 3.8), AI systems identifying unnoticed risks (Mean = 3.8), AI-powered tools enabling quicker response to threats (Mean = 3.8), enhanced safety compliance (Mean = 3.8), tangible improvements in safety outcomes from AI investment (Mean = 3.8), and AI-based monitoring identifying risks before escalation (Mean = 3.8). These were followed by decreased workplace incidents (Mean = 3.7), improved accuracy of AI-driven predictions on workplace safety (Mean = 3.7), fewer near-miss events (Mean = 3.7), AI-customized safety protocols (Mean = 3.7), employees feeling safer at work (Mean = 3.6), quicker hazard resolution through automated incident reporting (Mean = 3.6), and continuous feedback from AI analytics (Mean = 3.6). AI-powered safety training also recorded an effective rating (Mean = 3.5). The grand mean of 3.7 indicates an overall effective impact of AI on safety and hazard reduction.

The findings demonstrate substantial effectiveness of AI in minimizing operational hazards and improving safety outcomes, with 65% of respondents rating AI as effective and a grand mean of 3.7 reflecting strong organizational confidence in AI-driven safety interventions. This positive assessment aligns with Park et al., (2024) cross-sectoral analysis, which reported a 38% decrease in accident rates across industries following AI integration. The study validates these earlier findings, indicating that Nigerian oil and gas operations are experiencing similar safety improvements through AI adoption. Multiple items achieved the highest mean score of 3.8, including AI's contribution to hazard reduction, identification of unnoticed safety risks, speed of response to safety threats, and proactive risk identification before escalation. These results strongly corroborate Chen et al., (2023) findings that machine learning algorithms decreased equipment failure by 40% and operational downtime by 33%, yielding annual cost savings of approximately $2.1 million. Similarly, Ozobu et al., (2025) framework

demonstrated 87% accuracy in physical hazard detection with 52% improvement in hazard response times, patterns consistent with the study's emphasis on AI's predictive and responsive capabilities.
Nigerian-specific studies provide particularly relevant context. Adebayo et al., (2022) found that AI reduced incidents caused by human error by 36% and increased adherence to safety procedures by 29% on Nigerian offshore platforms. The findings support these observations, with respondents strongly agreeing that AI enhanced safety compliance standards and reduced workplace incidents. Eze et al., (2024) study of Nigerian pipeline infrastructure reported 92% accuracy in leak detection and 37% reduction in oil spill incidents, demonstrating the tangible safety improvements that align with respondents' perceptions in the study. However, AI-powered safety training modules received the lowest rating (mean 3.5), suggesting a relative weakness in knowledge transfer and employee engagement compared to technical monitoring capabilities. This finding contrasts with Martinez et al., (2025) recommendation for integrating AI into personal protective equipment and safety training programs, and Li et al., (2023) emphasis on employee training to encourage adoption. The gap indicates that while Nigerian organizations excel at implementing AI for technical risk detection, they lag in leveraging AI for human capacity development a critical dimension identified by multiple researchers.
The study found moderate agreement regarding employees feeling safer due to AI (mean 3.6) and automated incident reporting (mean 3.6). These scores, while positive, fall short of technical performance metrics, suggesting a human dimension challenge. This aligns with Ogunleye and Bello (2023) observation that only 22% of Nigerian refineries used AI-based simulations for safety drills, primarily due to organizational and cultural inertia. The findings suggest that while AI technology performs effectively, human acceptance and integration require further attention. The consistency of high ratings across hazard identification, incident reduction, and near-miss prevention validates Shah et al., (2024) findings that AI-driven health surveillance systems enhanced early detection of respiratory risks by 47% and decreased occupational disease reporting by 31%. The study demonstrates that these benefits extend across multiple safety dimensions in Nigerian oil and gas operations, though sustained effectiveness requires addressing training inadequacies and deepening employee engagement with AI-powered safety systems.

Table 4; Results of the effectiveness of AI in Minimizing Operational Hazards and Improving Safety Outcomes

Items	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Mean	Remarks
The implementation of AI has directly contributed to a reduction in operational hazards within my department.	68 (27.3)	103 (41.4)	44 (17.7)	22 (8.8)	12 (4.8)	3.8	Effective
AI-generated safety recommendations are practical and lead to measurable safety improvements.	71 (28.5)	97 (39.0)	43 (17.3)	26 (10.4)	12 (4.8)	3.8	Effective
The use of AI in predictive risk assessment has decreased the number of workplace incidents.	63 (25.3)	95 (38.2)	49 (19.7)	28 (11.2)	14 (5.6)	3.7	Effective

AI systems help identify safety risks that would otherwise go unnoticed.	74 (29.7)	101 (40.6)	38 (15.3)	23 (9.2)	13 (5.2)	3.8	Effective
AI-powered tools support us in responding more quickly to potential safety threats.	69 (27.7)	98 (39.4)	45 (18.1)	25 (10.0)	12 (4.8)	3.8	Effective
The accuracy of AI-driven risk predictions has improved overall workplace safety.	67 (26.9)	101 (40.6)	44 (17.7)	24 (9.6)	13 (5.2)	3.7	Effective
AI adoption has enhanced our ability to meet safety compliance standards.	72 (28.9)	97 (39.0)	43 (17.3)	25 (10.0)	12 (4.8)	3.8	Effective
The integration of AI in our safety protocols has resulted in fewer near-miss events.	65 (26.1)	94 (37.8)	47 (18.9)	29 (11.6)	14 (5.6)	3.7	Effective
Employees feel safer at work due to the use of AI in operational risk assessments.	59 (23.7)	87 (34.9)	54 (21.7)	32 (12.9)	17 (6.8)	3.6	Effective
The organization's investment in AI has yielded tangible improvements in safety outcomes.	70 (28.1)	99 (39.8)	46 (18.5)	22 (8.8)	12 (4.8)	3.8	Effective
AI-powered safety training modules have increased employee engagement and understanding of safety procedures.	52 (20.9)	88 (35.3)	59 (23.7)	34 (13.7)	16 (6.4)	3.5	Effective
Automated incident reporting via AI has led to quicker response times and resolution of workplace hazards.	61 (24.5)	90 (36.1)	49 (19.7)	31 (12.5)	18 (7.2)	3.6	Effective
The use of AI-based monitoring systems has helped to identify potential risks before they escalate.	73 (29.3)	101 (40.6)	41 (16.5)	22 (8.8)	12 (4.8)	3.8	Effective
AI helps to customize safety protocols for different departments, improving overall risk management.	66 (26.5)	96 (38.6)	48 (19.3)	26 (10.4)	13 (5.2)	3.7	Effective
Continuous feedback from AI analytics has enabled ongoing improvement of our safety practices.	58 (23.3)	93 (37.3)	52 (20.9)	29 (11.6)	17 (6.8)	3.6	Effective
				Grand Mean		**3.7**	**Effective**

Mean Cut-Off=3.0

3.4 The impact of AI-Driven Risk Models on Regulatory Compliance and Decision-Making in oil and gas operations.

Table 5 shows the impact of AI-driven risk models on regulatory compliance and decision-making in oil and gas operations. The highest mean scores were recorded for improved ability to meet regulatory requirements (Mean = 3.8), more informed safety-related decisions (Mean = 3.8), increased efficiency in preparing compliance reports (Mean = 3.8), minimized human error in regulatory processes (Mean = 3.8), and faster risk assessments enabling timely interventions (Mean = 3.8). These were followed by reduced instances of non-compliance during audits (Mean = 3.7), timely alerts on potential compliance violations (Mean = 3.7), improved consistency of compliance reporting (Mean = 3.7), increased transparency in decision-making (Mean = 3.6), alignment of AI recommendations with regulatory guidelines (Mean = 3.6), trust in AI-based risk assessments (Mean = 3.6), and clear escalation processes for potential breaches (Mean = 3.6). Regular updates of AI systems (Mean = 3.5) and feedback mechanisms for improvement (Mean = 3.5) also scored high, while employee training for AI-based compliance and decision-making had the lowest mean but remained high (Mean = 3.4). The grand mean of 3.7 indicates a high overall impact of AI on regulatory compliance and decision-making.

The findings reveal a strong positive impact of AI-driven risk models on regulatory compliance and decision-making in oil and gas operations, with 63% of respondents rating the impact as high and a grand mean of 3.7 indicating substantial organizational benefits. This perception aligns closely with Szadeczky et al., (2025) findings that AI-powered risk models increased regulatory compliance by 41% in high-risk industries while improving decision-making accuracy by 36%. The study's results validate these earlier observations, demonstrating that practitioners recognize AI's transformative potential in compliance management.

Specific areas showed particularly strong agreement. Respondents highly rated AI's contribution to meeting regulatory requirements (mean 3.8), improving decision-making through AI-generated insights (mean 3.8), minimizing human error (mean 3.8), and enhancing assessment speed (mean 3.8). These findings corroborate Pappil-Kothandapani's (2024) observation that AI models reduced manual compliance errors by 58% while improving decision-making speed by 44%. Similarly, Li et al., (2023) study demonstrated that AI systems identified risks 2.5 times faster than manual inspections and increased decision-making accuracy by 41%, patterns consistent with the study's emphasis on speed and accuracy improvements. The study found moderately high agreement regarding employee training adequacy (mean 3.4) and regular system updates (mean 3.5), representing the lowest scores among all items. This finding contrast sharply with Li et al., (2023) recommendation for employee training to bridge knowledge gaps between human oversight and AI systems, and Ogunleye et al., (2023) suggestion for simulation-based AI training for refinery staff. The gap suggests that while Nigerian oil and gas organizations recognize AI's benefits, they have not fully addressed the human capacity development necessary for optimal system utilization.

Nigerian-specific studies by Adebayo et al., (2022) and Eze et al., (2024) reported impressive metrics: AI reduced non-compliance incidents by 27%, improved regulatory audit outcomes by 33%, and achieved 92% accuracy in identifying regulatory violations. The study's findings suggest these benefits are being experienced across the sector, though the moderate scores on training and system updates indicate implementation gaps. This aligns with challenges identified by Adeoye et al., (2024), who found that over 60% of Nigerian oil companies lack necessary infrastructure, and Ogunleye et al., (2023), who reported only 22% of refineries used AI-based simulations. The consistency of high ratings across compliance reporting efficiency, timely alerts, and transparency enhancement validates Deloitte's (2024) finding that businesses using AI-driven risk models showed 47% higher success in meeting multi-jurisdictional compliance standards with 35% increased consistency across international operations. However, the study reveals a critical implementation reality: while respondents acknowledge AI's theoretical and practical benefits, organizational readiness remains incomplete, particularly regarding workforce development and systematic updates to reflect evolving regulatory landscapes.

Table 5: Results of the impact of AI-Driven Risk Models on Regulatory Compliance and Decision-Making in oil and gas operations.

Items	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Mean	Remarks
AI-driven risk models have improved the organization's ability to meet regulatory requirements.	70 (28.1)	101 (40.6)	41 (16.5)	25 (10.0)	12 (4.8)	3.8	High
The use of AI in risk assessment has reduced instances of non-compliance during audits.	63 (25.3)	95 (38.2)	52 (20.9)	26 (10.4)	13 (5.2)	3.7	High
AI-generated insights help managers make more informed safety-related decisions.	78 (31.3)	97 (39.0)	38 (15.3)	22 (8.8)	14 (5.6)	3.8	High
AI tools make the process of preparing compliance reports more efficient.	69 (27.7)	99 (39.8)	44 (17.7)	25 (10.0)	12 (4.8)	3.8	High
AI systems provide timely alerts when potential compliance violations are detected.	66 (26.5)	92 (36.9)	50 (20.1)	27 (10.8)	14 (5.6)	3.7	High
The adoption of AI in risk modelling has increased transparency in decision-making processes.	61 (24.5)	94 (37.8)	52 (20.9)	29 (11.6)	13 (5.2)	3.6	High
AI-driven recommendations are consistently aligned with current regulatory guidelines.	64 (25.7)	88 (35.3)	56 (22.5)	26 (10.4)	15 (6.0)	3.6	High
Decision-makers trust the accuracy and reliability of AI-based risk assessments.	59 (23.7)	90 (36.1)	53 (21.3)	31 (12.5)	16 (6.4)	3.6	High
The integration of AI in compliance monitoring has minimized human error in regulatory processes.	72 (28.9)	96 (38.6)	42 (16.9)	25 (10.0)	14 (5.6)	3.8	High
Employees are adequately trained to use AI tools for compliance and risk-related decision-making.	48 (19.3)	84 (33.7)	62 (24.9)	36 (14.5)	19 (7.6)	3.4	High
The use of AI enhances the speed at which risk assessments are conducted, allowing for more timely interventions.	75 (30.1)	99 (39.8)	38 (15.3)	25 (10.0)	12 (4.8)	3.8	High
AI systems in place are regularly updated to reflect changes in regulatory requirements and industry standards.	50 (20.1)	89 (35.7)	59 (23.7)	33 (13.3)	18 (7.2)	3.5	High
The implementation of AI has improved the consistency of compliance reporting across different departments.	66 (26.5)	93 (37.3)	50 (20.1)	26 (10.4)	14 (5.6)	3.7	High
There is a clear escalation process when AI-generated alerts indicate potential compliance breaches.	61 (24.5)	86 (34.5)	57 (22.9)	30 (12.0)	15 (6.0)	3.6	High
Feedback mechanisms exist for employees to report issues or suggest improvements regarding the AI tools used in compliance and risk management.	54 (21.7)	88 (35.3)	56 (22.5)	32 (12.9)	19 (7.6)	3.5	High

Mean Cut-off = 3.0

3.5 The challenges and Limitations Encountered in Adopting AI for Risk Assessment.

Table 6 shows the challenges and limitations encountered in adopting AI for risk assessment. The highest mean scores were recorded for the high cost of implementing AI technologies (Mean = 4.0) and its repetition as a barrier for many organizations (Mean = 4.0). These were followed by limited access to reliable data (Mean = 3.9), lack of skilled personnel (Mean = 3.9), inadequate infrastructure (Mean = 3.9), limited availability of professionals trained in both AI and risk assessment (Mean = 3.9), and lack of standardized guidelines and regulatory frameworks (Mean = 3.9). Other notable challenges included data privacy and security concerns (Mean = 3.8), insufficient regulatory frameworks (Mean = 3.8), integration challenges with legacy systems (Mean = 3.8), concerns about AI reliability in local environments (Mean = 3.8), resistance to change (Mean = 3.7), limited transparency of AI decisions (Mean = 3.7), and insufficient system support and maintenance (Mean = 3.7). The grand mean of 3.8 reflects a high level of challenges affecting AI adoption for risk assessment.

The findings reveal substantial challenges in AI adoption for risk assessment, with 70% of respondents identifying AI implementation as challenging and a grand mean of 3.8 reflecting pervasive barriers across technical, financial, human, and regulatory dimensions. Two items achieved the highest mean of 4.0: high implementation costs appearing twice in the survey, underscoring cost as the most critical barrier. This finding strongly aligns with Adeoye et al., (2024) observation that over 60% of Nigerian oil companies lack infrastructure necessary for successful AI implementation, and Singh et al., (2022) report that 78% of Nigerian oil companies lacked the high processing power required for deep learning models. Infrastructure inadequacy (mean 3.9), limited data access (mean 3.9), and skilled personnel shortage (mean 3.9) emerged as equally severe challenges. These findings directly corroborate multiple Nigerian-specific studies. Adebayo and Nwankwo (2022) documented that unreliable data streams and over 35% sensor failure rates hindered AI adoption in offshore environments with limited connectivity, while Eze et al., (2024) found that 92% of pipeline operators lacked standardized data formats, making it challenging to train AI models reliably. The study validates these earlier observations, demonstrating that data quality and infrastructure deficiencies remain unresolved across the Nigerian oil and gas sector.

The lack of skilled personnel (mean 3.9) resonates with Martinez et al., (2025) finding that less than 20% of AI was used in Nigerian oil construction projects, primarily due to local vendors' lack of knowledge about AI's potential. This challenge connects directly to the training inadequacy identified in objective one (mean 3.3), creating a circular problem: organizations lack skilled personnel to implement AI effectively, yet cannot develop such expertise without operational AI systems for training purposes. Shah et al., (2024) observed that imported AI models demonstrated up to 40% accuracy decline when used outside their training context due to inadequate local datasets and bias, highlighting the critical importance of locally trained personnel that the study confirms as severely lacking.

Regulatory framework insufficiency (mean 3.8 and 3.9) represents another significant barrier. This finding contrasts with international contexts examined by Szadeczky et al., (2025), who documented sector-specific regulatory protocols facilitating AI governance, and the Deloitte Internet Regulation Team (2024), which mapped over 300 AI-related laws across jurisdictions. The study indicates that Nigerian regulatory environments lag behind international standards, creating uncertainty that inhibits investment a factor not prominently featured in earlier Nigerian studies but now emerging as a critical adoption barrier. Integration challenges with legacy systems (mean 3.8) align precisely with Li et al., (2023) finding that 31% of AI deployments in Nigerian oil facilities failed due to inadequate integration with legacy systems, causing 22% increase in decision latency when AI systems conflicted with manual override protocols. The study's strong agreement on this challenge validates earlier warnings about the need for modular AI architectures compatible with conventional control systems recommendations that remain unimplemented across the sector.

Trust and transparency concerns (mean 3.7) and reliability doubts regarding AI outputs in local contexts (mean 3.8) reflect the explainability challenge emphasized by Lee et al., (2024), who demonstrated that explainable AI (XAI) technologies increased user trust and enhanced regulatory compliance. The findings suggest Nigerian organizations have not adopted XAI approaches, leaving stakeholders skeptical about opaque AI decision-making processes. This skepticism, combined with resistance to change (mean 3.7) documented by Ogunleye et al., (2023) as organizational and cultural inertia, creates human barriers compounding technical obstacles. Data privacy and security concerns (mean 3.8) parallel Eze et al., (2024) observation that 48% of companies cited cybersecurity as a deterrent to implementing cloud-based AI. The study confirms this concern persists, reflecting broader anxieties about data sovereignty and protection in developing contexts. Finally, insufficient ongoing support and maintenance (mean 3.7) connects to Ozobu et al., (2025) finding that only 18% of Nigerian oil firms had access to real-time analytics dashboards and 56% lacked internal AI governance policies. The convergence of findings across studies reveals a systemic adoption crisis: Nigerian oil and gas organizations face simultaneous barriers across cost, infrastructure, human capacity, regulatory clarity, technical integration, and organizational readiness challenges that must be addressed holistically rather than piecemeal for meaningful AI implementation progress.

Table 6: Results of the challenges and Limitations Encountered in Adopting AI for Risk Assessment

Items	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Mean	Remarks
Limited access to reliable data hinders the effectiveness of AI-based risk assessment in the Nigerian oil and gas sector.	88 (35.3)	99 (39.8)	34 (13.7)	17 (6.8)	11 (4.4)	3.9	Challenge
The high cost of implementing AI technologies is a significant barrier to their adoption in risk assessment processes.	97 (39.0)	92 (36.9)	32 (12.9)	17 (6.8)	11 (4.4)	4.0	Challenge
There is a lack of skilled personnel capable of managing and maintaining AI systems for risk assessment in the sector.	90 (36.1)	96 (38.6)	33 (13.3)	18 (7.2)	12 (4.8)	3.9	Challenge
Concerns about data privacy and security limit the use of AI tools in risk assessment activities.	83 (33.3)	88 (35.3)	39 (15.7)	25 (10.0)	14 (5.6)	3.8	Challenge
Existing regulatory frameworks are insufficient or unclear regarding the use of AI in oil and gas risk management.	78 (31.3)	94 (37.8)	41 (16.5)	23 (9.2)	13 (5.2)	3.8	Challenge
Resistance to change among employees and management slows the adoption of AI for risk assessment.	69 (27.7)	92 (36.9)	48 (19.3)	26 (10.4)	14 (5.6)	3.7	Challenge
Integration challenges with legacy systems limit the full potential of AI solutions for risk assessment.	75 (30.1)	99 (39.8)	38 (15.3)	24 (9.6)	13 (5.2)	3.8	Challenge

The perceived lack of transparency and explainability of AI decisions reduces trust in these systems among stakeholders.	68 (27.3)	87 (34.9)	50 (20.1)	28 (11.2)	16 (6.4)	3.7	Challenge
Inadequate infrastructure (such as internet connectivity or computing power) affects the deployment of AI tools in the sector.	94 (37.8)	85 (34.1)	33 (13.3)	22 (8.8)	15 (6.0)	3.9	Challenge
Concerns about the reliability of AI outputs in the context of local operating environments hinder adoption for risk assessment.	77 (30.9)	91 (36.5)	43 (17.3)	25 (10.0)	13 (5.2)	3.8	Challenge
The high cost of implementing AI technologies poses a significant barrier for many organizations in the sector.	95 (38.2)	90 (36.1)	34 (13.7)	19 (7.6)	11 (4.4)	4.0	Challenge
Limited availability of skilled professionals trained in both AI and risk assessment makes it difficult to maximize the benefits of these technologies.	89 (35.7)	91 (36.5)	38 (15.3)	21 (8.4)	10 (4.0)	3.9	Challenge
Data privacy and security concerns prevent organizations from fully leveraging AI for risk assessment purposes.	80 (32.1)	88 (35.3)	43 (17.3)	25 (10.0)	13 (5.2)	3.8	Challenge
A lack of standardized guidelines and regulatory frameworks creates uncertainty around the use of AI in risk assessment.	84 (33.7)	90 (36.1)	41 (16.5)	22 (8.8)	12 (4.8)	3.9	Challenge
Insufficient ongoing support and maintenance for AI systems can lead to performance degradation over time, reducing their effectiveness in risk assessment.	71 (28.5)	95 (38.2)	45 (18.1)	25 (10.0)	13 (5.2)	3.7	Challenge
				Grand Mean		**3.8**	**Challenge**

Mean Cut-off = 3.0

Conclusion

The study concludes that Artificial Intelligence (AI) plays a pivotal role in enhancing predictive risk assessment within Nigerian oil and gas companies by enabling more accurate, timely, and data-driven decision-making processes. The findings indicate that AI technologies, such as machine learning and predictive analytics, significantly improve the identification and mitigation of operational risks compared to traditional approaches. Despite challenges such as high implementation costs, limited technical expertise, and inadequate infrastructure, the study establishes that the integration of AI into risk management frameworks leads to greater efficiency, safety, and competitiveness in the sector. Therefore, the adoption of AI-driven risk assessment tools is essential for fostering proactive risk management, promoting sustainable operations, and positioning Nigeria's oil and gas industry for long-term growth in an increasingly digital and complex global environment.

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