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HUMAN-ARTIFICIAL INTELLIGENCE SUPERVISION AND INSPECTION PERFORMANCE OF OIL AND GAS FIRMS IN NIGERIA

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Abstract: The study was on the relationship between Human - Artificial Intelligence supervision and inspection performance of oil and gas firms in Rivers State, Nigeria. AI tool adoption Level and Human Supervisor Competence were used to operationalised Human - Artificial Intelligence supervision and inspection accuracy and operational efficiency were used to measured inspection performance. Technology Acceptance Model was underpinned the study. Cross-sectional survey design was used in data collection at a spot. The accessible population was 1,800 individuals and the sample size was 317 respondents at a 95% confidence level and a 5% margin of error from the accessible population of 1,800. Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed to analysed the hypotheses. The findings revealed that there is a significant influence of Human - Artificial Intelligence supervision on inspection performance of oil and gas firms in Rivers State, Nigeria. The study concluded that Human-Artificial Intelligence supervision had positive impact on inspection performance of oil and gas firms in Rivers State, Nigeria. The study suggests that AI technology should not be treated as a substitute for human supervision. Oil and gas firms should pursue an integrated approach in which AI provides analytical and predictive capabilities, competent human supervisors provide contextual judgement and accountability, and organisational factors provide the infrastructure and management support necessary for the two to work effectively together.

Keywords: Human-Artificial Intelligence Supervision, Inspection Performance, AI tool adoption Level, Human Supervisor Competence, Inspection Accuracy, Operational Efficiency.

1.0 Introduction

The global oil and gas industry is undergoing a profound technological transformation driven by the integration of artificial intelligence (AI) into core operational and supervisory functions. Inspection and safety management that was long dependent on manual processes and the experiential judgement of human supervisors are increasingly augmented by AI-powered sensing, machine learning-based anomaly detection and intelligent decision-support systems (Odili et al., 2024). This transition presents both opportunities and challenges for organisations seeking to improve inspection performance while managing complex human-machine interactions in high-risk environments. Oil and gas firms operating in this region face persistent operational challenges including pipeline corrosion, equipment failure, environmental incidents and regulatory scrutiny from the Nigerian Upstream Petroleum Regulatory Commission (NUPRC). These challenges are compounded by ageing infrastructure, skilled workforce shortages and the demanding ecological conditions of the Niger Delta environment (Odili et al., 2024).

Despite significant investments in AI - based inspection technologies by oil and gas firms operating in Rivers State, inspection-related incidents, pipeline failures and compliance shortfalls continue to represent major operational and reputational risks for the industry. The 2024 operational safety statistics published by the Nigerian Upstream Petroleum Regulatory Commission (NUPRC) indicated alarming rates of hydrocarbon spills which are caused by Sabotage (67.29%), Equipment failure (4.02%), Corrosion (64%), Operational/Maintenance Error (2.50%) and regulatory non-conformances attributable in part to inadequacies in inspection processes is alarming and worrisome (Statisense, 2025). A critical dimension of this problem lies in the uneven and often poorly managed integration of *AI inspection tools into existing supervisory workflows*. Many firms have procured AI - enabled inspection platforms without adequately addressing the human factors that determine their effective use. Supervisors may lack the technical competence to interpret AI - generated diagnostics leading to over reliance on automated outputs without appropriate critical scrutiny (Jung & Yang, 2025).

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The emergence of AI technologies specifically designed for oil and gas inspection including non-destructive testing (NDT) automation, machine vision systems, drone based surveillance and corrosion prediction algorithms offers transformative potential for improving inspection accuracy, operational efficiency and safety outcomes (Khalaf et al., 2024). Khalaf et al. (2024) documented that AI-based corrosion monitoring systems achieve defect detection rates significantly exceeding those of conventional manual methods, while Usman et al. (2025) demonstrated that machine learning models applied to pipeline corrosion prediction substantially reduce the risk of undetected failures that could precipitate major incidents. However, the deployment of these technologies does not occur in isolation from the human supervisory workforce. Human supervisors remain central to inspection operations, providing contextual judgement, interpreting AI-generated alerts, making safety-critical decisions and managing the interface between automated systems and broader organisational protocols. The level of synergy between human supervisors and AI tools is therefore a critical determinant of actual inspection performance (Liu & Li, 2025; Fiegler-Rudol et al., 2025).

Existing literature has predominantly examined AI adoption in oil and gas from technical and economic perspectives (Mardanov et al., 2026; Povaos et al., 2025; Enholm et al., 2022) with comparatively less attention paid to the supervisory and organisational dimensions of AI integration in inspection intensive contexts. This research addresses these gaps by investigating how the three dimensions of Human - AI supervision (AI Tool Adoption Level, and Human Supervisor Competence) influence inspection performance in oil and gas firms in Rivers State. The aim of this study is to examine the relationship between Human - Artificial Intelligence supervision and inspection performance of oil and gas firms in Rivers State, Nigeria. Specifically, the study seeks to:

i. assess the effect of AI Tool Adoption Level on inspection accuracy in oil and gas firms in Rivers State.

ii. ascertain the effect of AI Tool Adoption Level on operational efficiency in oil and gas firms in Rivers State.

iii. examine the effect of Human Supervisor Competence on inspection accuracy in oil and gas firms in Rivers State.

iv. determine the effect of Human Supervisor Competence on operational efficiency in oil and gas firms in Rivers State.

1.1 Research Hypotheses

The following hypotheses are formulated to guide the quantitative component of the study:

H^1: AI Tool Adoption Level has no significant positive effect on inspection accuracy in oil and gas firms in Rivers State.

H^2: AI Tool Adoption Level has no significant positive effect on operational efficiency in oil and gas firms in Rivers State.

H^3: Human Supervisor Competence has no significant positive effect on inspection accuracy in oil and gas firms in Rivers State.

H^4: Human Supervisor Competence has no significant positive effect on operational efficiency in oil and gas firms in Rivers State.

2.0 Literature Review

2.1. Inspection Performance

Inspection Performance in oil and gas operations constitutes a multidimensional construct encompassing the accuracy of hazard identification, the efficiency of inspection processes, and the safety outcomes attributable to inspection activities (Khalaf et al., 2024). The multidimensional operationalisation adopted in this study reflects both a theoretical synthesis of prior literature and alignment with the practical concerns of oil and gas operators and regulators. Treating inspection performance as a single unidimensional construct would obscure important trade-offs and complementarities among its components, making it impossible to assess whether Human–AI supervision interventions generate balanced improvements or concentrated improvements in some dimensions at the expense of others (Odili et al., 2024; Khalaf et al., 2024). The safety performance literature in oil and gas has increasingly emphasised the importance of distinguishing between leading and lagging safety performance indicators (Liu & Li, 2025). Leading indicators such as the frequency of near-miss reporting, the completion rate of AI-flagged maintenance actions, and the timeliness of inspection follow-up on AI-generated alerts measure proactive safety behaviours and process characteristics that predict future incident rates but are not themselves incidents (Odili et al., 2024). Lagging indicators such as the frequency and severity of reportable incidents, the rate of regulatory compliance violations, and the number of unplanned shutdowns attributable to equipment failures that inspection should have prevented measure the safety outcomes that inspection systems exist to prevent, but provide information only after failures have occurred (Liu & Li, 2025; Jung & Yang, 2025).

2.1.1 Inspection Accuracy

Inspection Accuracy is defined as the precision and reliability of fault detection, defect identification, and compliance audit outcomes (Liu & Li, 2025). It encompasses both the true positive rate (the proportion of actual defects correctly identified) and the false negative

rate (the proportion of defects the inspection system fails to detect). In safety-critical inspection, the false negative rate is of primary concern, since undetected defects generate catastrophic failure modes (Khalaf et al., 2024). Khalaf et al. (2024) demonstrated that AI-based corrosion monitoring systems achieve substantially higher fault detection rates than conventional manual methods, particularly for sub-surface and micro-scale defects. Usman et al. (2025) demonstrated that machine learning algorithms achieve 89.3% prediction accuracy versus 67.1% for conventional deterministic models — a 22.2 percentage-point improvement with direct implications for maintenance scheduling and incident prevention in Nigerian pipeline networks. Liu and Li (2025) found that poorly designed Human–AI interfaces can decrease inspection accuracy relative to manual inspection by generating false alarms that divert supervisory attention, producing opaque outputs, or creating cognitive overload. These findings underscore that inspection accuracy is not a simple function of AI system capability but an emergent property of the Human–AI supervisory dyad.

2.1.2 Operational Efficiency

Operational Efficiency is conceptualised as the resource effectiveness of inspection processes, encompassing inspection cycle time, cost per inspection unit, and coverage completeness. In oil and gas operations, inspection efficiency has direct implications for asset availability — inspections that require asset shutdown create production losses that may be substantial relative to the inspection cost itself. Mardanov et al. (2026) documented that AI-integrated inspection workflows reduce inspection cycle times substantially and enable concurrent monitoring of multiple assets, with their panel data analysis of 112 firms demonstrating measurably lower inspection costs per unit of coverage for higher AI integration firms. Povaos et al. (2025) found that autonomous drone inspection platforms reduced offshore structure inspection times by factors of five to ten relative to rope-access manual inspection, while simultaneously improving coverage completeness. Saudi Aramco's AI deployment reportedly doubled annual technology value realisation from $2 billion in 2023 to $4 billion in 2024, with predictive maintenance contributing significantly to these gains. The application of AI in robotic inspection has cut inspection cycle times by nearly 40% across industry adopters, according to market analysis data referenced in the academic literature (Povaos et al., 2025).

2.2. Human–Artificial Intelligence Supervision

Human–AI supervision represents a new paradigm of organisational oversight in which intelligent automated systems and human agents jointly perform functions traditionally executed by humans alone (Chowdhury et al., 2022; Liu & Li, 2025). Unlike fully autonomous AI systems that remove human agency from the supervisory loop, and unlike traditional manual supervision that offers no computational augmentation, Human–AI supervision occupies an intermediate and evolving space that preserves human accountability while leveraging computational capabilities for pattern recognition, anomaly detection and real-time monitoring at scales and speeds beyond unaided human capacity (Povaos et al., 2025). This collaborative model is particularly salient in safety-critical industries such as oil and gas, where the consequences of supervisory failure are potentially catastrophic; where regulatory frameworks mandate human accountability for safety outcomes and where the volume and complexity of monitoring data increasingly exceed the cognitive limits of individual human supervisors (Liu & Li, 2025). The concept of Human–AI supervision draws theoretical grounding from multiple disciplines. From cognitive science and human factors engineering, it inherits attention to the design of human–machine interfaces, the management of situation awareness and the mitigation of cognitive overload (Fiegler-Rudol et al., 2025; Haney et al., 2024). From organisational psychology, it draws on the literature on team cognition, distributed decision-making and the social dynamics of technology adoption (Chowdhury et al., 2022; Liu & Li, 2025).

2.2.1 AI Tool Adoption Level

AI Tool Adoption Level captures the extent to which AI-powered technologies are embedded in inspection and supervisory workflows (Usman et al., 2025). As a construct, it encompasses both the range of AI technologies deployed across different inspection tasks and the depth of integration; the degree to which AI outputs are systematically incorporated into inspection decision-making rather than treated as optional supplementary information (Liu & Li, 2025). Khalaf et al. (2024) documented a wide range of AI technologies relevant to oil and gas inspection, including machine learning algorithms for corrosion monitoring, computer vision systems for structural integrity assessment, drone-based aerial inspection platforms and digital twin environments. The measurement of AI Tool Adoption Level requires attention to both breadth and depth. Breadth refers to the variety of inspection tasks for which AI tools are deployed; depth refers to the degree of workflow integration from AI outputs that are consulted occasionally and optionally to systems where AI alerts trigger mandatory human review protocols, to environments where AI recommendations are systematically logged, validated, and fed back into model improvement cycles (Povaos et al., 2025). Mardanov et al. (2026) suggests that depth of integration is a stronger predictor of performance outcomes than breadth of deployment, with firms achieving measurably lower inspection costs per unit of coverage and shorter inspection cycles.

2.2.2 Human Supervisor Competence

Human Supervisor Competence encompasses the technical skills, domain knowledge, AI literacy, and professional

training of supervisors engaged in AI-augmented inspection processes (Fiegler-Rudol et al., 2025). As AI systems become more sophisticated and their outputs more consequential for safety and operational decisions, the competence requirements of human supervisors are not reduced but transformed (Jung & Yang, 2025). The supervisor who can effectively oversee AI-augmented inspection must possess not only traditional domain expertise in oil and gas integrity management but also AI-specific competencies the ability to interpret probabilistic model outputs, to recognise AI system limitations, to exercise contextual judgement when AI recommendations conflict with experiential knowledge, and to provide high-quality feedback that enables AI systems to improve over time (Fiegler-Rudol et al., 2025; Jung & Yang, 2025). Jung and Yang (2025) identified human competence as the central moderating factor in the safety performance of Human–Robot collaborative systems, demonstrating across manufacturing and process industry firms that supervisors with higher technical proficiency and a better understanding of AI system limitations generate significantly fewer safety incidents. This finding has a critical implication: investing in advanced AI systems without simultaneously investing in supervisor competence may not only fail to yield performance benefits but may actively generate new safety risks. Romeo and Lacko (2026) highlighted that human competence gaps represent the most frequently cited barrier to successful AI integration in organisations, particularly in developing economy contexts where training infrastructure for AI literacy is limited.

2.3 Theoretical Framework

The Technology Acceptance Model (TAM) and its extensions address the individual-level cognitive and motivational processes that determine whether and how effectively human supervisors adopt and use AI inspection tools. The Technology Acceptance Model (TAM), originally developed by Davis (1989) and subsequently extended by Venkatesh and Davis (2000) and Venkatesh et al. (2003), is among the most widely applied and empirically validated frameworks in information systems research. TAM posits that two primary beliefs (perceived usefulness (PU) and perceived ease of use (PEOU)) are the fundamental determinants of an individual's intention to adopt and effectively use a new technology. Davis (1989) validated these constructs in his foundational study using a sample of IBM users (n=40) and MBA students (n=152), demonstrating that PU consistently exerted a stronger effect on adoption intention than PEOU; a finding replicated across hundreds of subsequent applications.

In the context of this study, TAM explains the AI Tool Adoption Level dimension by predicting that supervisors and technicians are more likely to adopt and effectively use AI inspection tools that they perceive as genuinely improving inspection outcomes (PU) and that are technically accessible and operationally straightforward (PEOU). Supervisors who experience AI tools as generating useful, actionable insights will develop stronger adoption intentions and deeper integration of AI tools into their inspection workflows. Conversely, supervisors who perceive AI tools as technically opaque or unreliable will adopt them superficially if at all (Khalaf et al., 2024; Odili et al., 2024). A meta-analysis by Schepers and Wetzels (2007), cited in Venkatesh and Davis (2000) and Ibrahim et al. (2025), found that while PU and PEOU consistently predicted adoption intention across study contexts, the relative strength of each predictor varied substantially with industry context, technology type, and the voluntary versus mandatory character of the adoption decision.

2.4 Empirical Review

Odili et al. (2024) examined technology integration in Nigerian oil and gas operations with specific attention to corrosion and inspection management, finding that firms with higher technology integration achieved significantly better inspection accuracy and operational efficiency. However, only a minority of Nigerian firms had achieved deep AI integration, with persistent barriers [insufficient technical training (73% of respondents), inadequate digital infrastructure (68%), and inconsistent regulatory enforcement (52%)] constraining benefit realisation.

Ikegwuru et al. (2023) investigated AI implementation and organisational performance among mainstream Nigerian oil and gas companies, finding that AI adoption was positively associated with organisational performance but that benefits were partial and unevenly realised. Systematic AI integration in inspection-specific workflows remained underdeveloped. Human capital development was the most significant constraint, cited by 81% of respondents as a critical gap.

Attah et al. (2024) conducted a systematic literature review of AI applications in Nigeria's petroleum supply chain, concluding that significant knowledge gaps hinder practical application. They specifically noted that the majority of existing research focuses on developed economies with established digital infrastructure and fails to address the Nigerian operational context characterised by inconsistent power delivery, limited connectivity in remote areas, and variable technology adoption rates.

Masiko et al. (2022) examined the relationships among technology, human resource competencies, and productivity in Uganda's nascent petroleum industry through SEM, providing valuable comparative evidence from a West African context with significant parallels to Rivers State. Their analysis found that HR competencies fully mediate the technology-productivity relationship, providing empirical support for the prediction that AI tool adoption levels will generate inspection performance improvements only in

organisations that simultaneously invest in supervisor AI literacy and AI-specific competence development.

Romeo and Lacko (2026) provided the most comprehensive empirical synthesis, reviewing 147 empirical studies spanning multiple sectors and countries. Their meta-synthesis identified human factors, organisational culture, and infrastructure readiness as the three most consistently significant determinants of AI adoption outcomes. Infrastructure readiness was a significantly stronger predictor in developing economies than in OECD countries, directly constraining AI system operation where digital infrastructure is less developed.

3.0 Methodology

This study adopted cross-sectional survey design and data was collected at a time. The target population of this study comprises of the number of oil and gas firms in operating in Rivers State, Nigeria. Based on data from the Rivers State Oil Producers Trade Section (OPTS) membership register and the Nigerian Petroleum Exchange (NIPEX) contractor database, the estimated target population of qualifying personnel across upstream and downstream firms in Rivers State is approximately 2,400 individuals. This population includes supervisory personnel, inspection engineers, Health, Safety and Environment (HSE) officers, operations managers, and technical directors whose roles involve direct or indirect responsibility for inspection planning, execution, oversight, or performance management. The accessible population, defined as those reachable through formal company channels and willing to participate in academic research, is estimated at 1,800 individuals, accounting for access restrictions imposed by some firms on grounds of proprietary confidentiality and the known non-response rates characteristic of industrial survey research in Nigeria (Nwachukwu & Ihejirika, 2021). The sample size for the quantitative component is determined using the Krejcie and Morgan (1970) formula for finite populations, which yields a minimum sample of 317 respondents at a 95% confidence level and a 5% margin of error from the accessible population of 1,800. Accounting for an anticipated non-response rate of approximately 6%, a total of 337 questionnaires will be distributed across the study population.

This sample size exceeds the minimum threshold of 200 recommended for Partial Least Squares Structural Equation Modelling (PLS-SEM) with the number of constructs and indicators included in this study's measurement model (Hair et al., 2019), providing adequate statistical power for the planned analyses. Stratified random sampling was employed as the primary sampling technique to ensure proportional representation across firm types (upstream, downstream, service contractors), firm sizes (large, medium, small by employee count), and job functions (inspection engineers, HSE officers, operations supervisors, technical management). Construct validity will be assessed through exploratory factor analysis (EFA) during the pilot study, using a sample of 30 respondents drawn from the accessible population but excluded from the main study sample. Items with factor loadings below 0.50 or cross-loadings above 0.30 will be revised or removed (Hair et al., 2019). Convergent validity will be assessed by examining average variance extracted (AVE) values, with a threshold of AVE > 0.50, and discriminant validity will be assessed using the Heterotrait-Monotrait (HTMT) ratio criterion, with a threshold of HTMT < 0.85 (Henseler et al., 2015).

4.0 Results and Discussion

This section is concerned with the presentation of data, quantitative and qualitative data analysis. While the descriptive and univariate analysis was conducted using mean and standard deviation aided by excel; inferential analysis was conducted using the Partial Least Square Structural Equation Modelling aided by SMART PLS.

Table 4.1: Response Rate of Questionnaire

Questionnaire	Frequency	Percentage (%)
Number Administered	**337**	**100**
Number Retrieved	321	95.3
Number of Defected Responses	9	2.7
Number used	**312**	**92.6**

***Source**: Field Survey, 2026*

The table 4.1 shows the response rate of questionnaire administered for the study. In line with the sample size of the study, a total of three hundred and thirty-seven (337) copies of the questionnaire were administered; three hundred and twenty-one (321) were retrieved; this gave rise to 95.3% response rate. Out of this number, three hundred and twelve (312) was found to be useful for the analyses. This resulted to 92.6% valid response rate which was consequently used for analysis.

Demographic Data of Respondents

Table 4.2: Demographic attributes of respondents

Variables	Categories	Frequency	Percentage (%)
Role in organisation	HSE Personnel	41	13.1
	Operations Manager	109	34.9
	Technical Director	62	19.9
	Inspection Engineer	84	26.9
	Supervisory Personnel	16	5.2
Years of Experience	1 - 5 years	69	22.1
	6 - 10 Years	153	48.9
	11 - 14 Years	80	25.8
	15 Years and above	10	3.2
Operation Segment	Upstream	60	19.2
	Downstream	150	48.1
	Midstream	102	32.7
Adoption of AI Powered inspection tools/system			
	Full Adoption	82	26.2
	Partial Adoption	159	51.0
	Ongoing Deliberation	71	22.8
Training on AI inspection System			
	Yes, Regularly	161	51.6
	Yes, Sometimes	105	33.7
	Not Yet	46	14.7

Source: Survey Result Computations, 2026

Table 4.2 shows the demographic details of the respondents. The first demographic data sought to examine the role of the respondents in their various oil and gas organisations. The result showed that forty-one (41) respondents who accounted for about 13% of the respondents are HSE personnel, about 35% of the respondents are operations managers, technical directors amounted to about 19.9%. The result further revealed that about 26.9% of the respondents are inspection engineers while about 5% of the respondents are supervisory personnel.

The second result on the table revealed that the respondents' years of experience in the oil and gas industry. It was revealed that about 22.1% of the respondents have between 1-5 years of experience in the oil and gas industry. 153 respondents which accounted for about 48.1% of the respondents have between 6-10 years of experience, 25.8% of have between 11-15 years of experience while about 3.2% of the respondents have over 15 years of experience in the oil and gas industry.

The third result on the table gave details of the operational sections of the respondents in the oil and gas industry. The result showed that 60 respondents which accounted for about 16.2% of the study size have operate in the upstream sector of the oil and gas industry. The result further shows that 150 respondents (48.1%) operate in the downstream sector while 102 respondents (32.7%) operate in the midstream sector of the oil and gas industry.

Another notable insight that could be derived from this analysis is the organisations' level of AI powered inspection systems. The result showed that majority of the respondents affirmed that AI powered inspection system have been implemented in their respective oil and gas firms. Specifically, it was revealed that about 26% of the oil and gas firms have embraced full implementation of AI powered inspection system, about 51% have partial implementation while only about 22.8% of the oil and gas firms are in the planning stage of AI implementation.

Lastly, the fifth result on the demonstrated sought to examine the if training on AI inspection system has been

carried out in the oil and gas firms. The result showed that about 51.6% of the oil and gas firms conduct AI training regularly, 33.7% sometimes conduct AI training while the remaining 14.7% are yet to conduct AI training. This showed that most of the sampled oil and gas firms conduct training on AI inspection systems.

4.1. Bivariate Analysis (Inferential Statistics)

As earlier stated in the previous sections of this study, the bivariate analysis which involved the testing of hypothesis was using conducted Partial Least Square structural equation modelling (PLS-SEM) which was aided by SMARTPLS Version 4.0.9.9. This analysis was carried out in two stages namely, assessment of the measurement model and the assessment of structural model. Each of these analyses are put forward in the subsequent sections. The final Measurement Model improved not only the factor loadings of all research variables but also Cronbach alpha (α), composite reliability (CR), and average variance extracted (AVE). The findings may be seen in Table below.

Table 4.3: The Results of the Measurement Model Assessment with descriptive analysis and factor loadings

Constructs	Item Scale	Mean	S.D	Factor Loadings	Cronbach Alpha	CR	AVE	Sq. Root of AVE
AI Tool Adoption Level	My organisation has fully integrated AI-powered tools (e.g., machine vision, predictive analytics, drone inspection) into its routine inspection workflows.	3.97	.766	**0.802**	**0.808**	**0.904**	**0.611**	**0.781**
	AI inspection tools in my organisation are used consistently across all major asset categories, including pipelines, vessels, and structural equipment.	3.69	.849	**0.794**				
	The AI inspection systems used in my organisation generate outputs that are easily accessible to supervisory staff in real time.	4.01	.889	**0.799**				
	My organisation regularly updates its AI inspection tools to incorporate the latest algorithmic improvements and sensor data.	3.81	.873	**0.717**				
	The level of AI tool integration in my organisation's inspection processes has increased significantly over the past three years.	4.32	.803	**0.769**				
	AI tools in my organisation are perceived by inspection staff as genuinely improving the quality of inspection outcomes rather than merely replacing manual steps.	3.86	.803	**0.804**				
Human Supervisor Competence	I possess the technical skills necessary to interpret and act on the outputs generated by the AI inspection tools used in my organisation.	4.33	1.001	**0.741**	**0.889**	**0.908**	**0.623**	**0.789**
	I understand the operational limitations of the AI inspection systems I use, including the conditions under which they may generate inaccurate outputs.	4.08	.983	**0.739**				
	I have received adequate training to enable me to work effectively alongside AI inspection systems in my supervisory role.	3.97	.874	**0.883**				
	I am confident in my ability to override or supplement AI inspection recommendations when my professional judgement indicates that the AI output may be incorrect.	4.01	.926	**0.827**				
	My organisation invests in continuous	3.99	1.022	**0.719**				

	development of supervisors' competence in AI-integrated inspection methods.							
	I actively seek opportunities to improve my understanding of how AI inspection tools function, and how they can best be used in my work context.	4.25	.989	**0.812**				
Inspection Accuracy	AI-assisted inspection processes in my organisation helps to identify defects and non-conformances.	3.87	.823	**0.778**	**0.877**	**0.839**	**0.568**	**0.754**
	AI-assisted inspection has resulted to higher degree of accuracy than conventional manual methods.	3.94	1.008	**0.702**				
	The accuracy of our inspection has improved significantly since the integration of AI tools into supervisory workflows.	3.69	.988	**0.696**				
	AI enabled inspection system has helped to reduce error occurrences in supervisory workflows.	3.87	.823	**0.830**				
Operational Efficiency	The use of AI tools in inspection activities has reduced the incidence of missed defects or false-clear inspections in my organisation.	4.10	.991	**0.764**	**0.899**	**0.861**	**0.608**	**0.780**
	AI-assisted inspection processes have enabled my organisation to complete inspection cycles in significantly less time than before AI was adopted.	3.82	.953	**0.701**				
	Using AI inspection system, we have significantly reduced time lag and resource wastage in workflow stations.	4.00	.974	**0.810**				
	The use of AI inspection tools has reduced the overall cost of inspection activities in my organisation while maintaining or improving coverage quality.	4.10	.991	**0.849**				
	χ^2 (201) = 426.12 P = 0.001; CFI = 0.913, TLI = 0.897; SRMR = 0.05							
CFA Model Fit								

Source: Researchers' Computation, 2026 (Aided by SMARTPLS Version 4.1.1.8).

The descriptive evaluation and assessment of the study's measurement model is presented in the table 4.3. First, the CFA analysis revealed that all items comprising the research instrument possess factor loadings exceeded the minimum threshold of 0.50, as proposed by Fidell and Tabachnick (2007). As a result, the convergent validity was deemed adequate. In a similar vein, the composite reliability (CR) for each of the constructs are largely above the minimum threshold of 0.700. The obtained outcome demonstrates that the research instrument is reliable, as it meets the minimum requirement of 0.7 as proposed by Fornell and Lacker (1981) and Nunnally (1978). The implication of this connotes that each of the variables in the model are quite consistent with one another.

Table 4.4: Summary of Direct Relationship Results

S/n	Hypothesized Path	Path Coefficient (β)	P-Value	T Value	Decisions	R^2
1.	AI Adopt ->Ins. Acc	0.619***	0.000	2.115	Not Supported	0.383
2.	AI Adopt -> Opr. Eff.	0.687***	0.000	3.026	Not Supported	0.472
4.	Hum Sup C ->Ins. Acc	0.547***	0.000	4.473	Not Supported	0.299
5.	Hum Sup C -> Opr. Eff.	0.483***	0.000	3.944	Not Supported	0.233

***P<0.001 **P<0.01 *P<0.05

Source: The Researcher's Computation (2026) from Path Analysis Result (Aided by SMARTPLS 4.1.1.8).

Summarily, the analysis revealed that there is significant positive relationship between Human - Artificial Intelligence supervision and inspection performance of oil and gas firms in Rivers State, Nigeria. Although the result portrayed that AI adoption and Human Supervision have a positive impact on inspection performance. The result clearly demonstrates that both AI and Human supervision may not be fully efficient, rather a right complementary of both human effort and AI system may yield better outcome.

4.2: Discussion of Findings

This section discussed the stated results and findings of the study on the relationship between human-artificial intelligence supervision and inspection performance in Oil and gas firms in Rivers State.

AI tool adoption level significantly and positively correlates with inspection performance and as such enhances indices such as inspection accuracy, operational efficiency.

The result from the test of analysis identified AI tool adoption level as having a significant impact on inspection performance and as such enhancing outcomes such as inspection accuracy, operational efficiency and incident/accident reductions. On this basis, the null hypotheses one, and two were rejected, as the results revealed that there was a significant relationship between AI tool adoption level related activities and the measures of inspection performance (inspection accuracy, and operational efficiency). The results showed that AI tool adoption level contributed towards the degree to which the oil and gas firms is able to attract and retain its services, drives the uniformity and uniqueness of their productive capacity and also their reputation and positioning within the Rivers State and the world at large. The findings reiterate the views of scholar such as Khalaf et al. (2024) findings documented consistent accuracy improvements of between 15% and 40% over conventional methods, with significant variability in performance outcomes linked to data quality, sensor calibration, and the competence of human operators. Usman et al. (2025) applied multiple machine learning methods to pipeline corrosion prediction in Nigerian oil and gas contexts, benchmarking Random Forest, Support Vector Machine, and Deep Learning approaches against conventional deterministic corrosion models using SCADA system operational data. Random Forest achieved a mean prediction accuracy of 89.3% across test datasets compared to 67.1% for conventional deterministic models, a 22.2 percentage-point improvement.

Human supervisor competence has a significant and positive influence on inspection performance and as such enhances indices such as inspection accuracy, operational efficiency and incident/accident reductions.

The evidence on the association between human supervisor competence and inspection performance was also observed to be significant; with human supervisor competence having a significant impact on inspection accuracy and operational efficiency. As such, the null hypothesis three and four, of significant relationship was rejected. This went to indicates that human supervisor competence contributed significantly as a predictor of inspection performance and that it enhances its features such as inspection accuracy, and operational efficiency. The result from this finding aligns with that of Jung and Yang (2025) found that competence training programmes specifically designed for AI-integrated work environments generated approximately three times larger safety performance improvements per unit of training investment than generic technical training. Song et al. (2024) found a dual-pathway effect in which AI technology use both enhances safety performance and potentially degrades it through cognitive resource depletion and role stress. Their mediation analysis found that role clarity, the degree to which supervisors have a clear understanding of their responsibilities in the human–AI inspection workflow was a significant buffer of the negative cognitive depletion pathway. Haney et al. (2024) found that trust calibration is dynamic and context-sensitive varying with the supervisor's prior experience with the AI system, their knowledge of specific AI failure modes and the organisational climate surrounding AI tool use.

5.0 Conclusions and Recommendations

Based on the findings of this study, we therefore conclude that: Premised on the facts presented in the previous chapter,

it was avowed that the outcomes of the present study were consistent with the plethora of previous studies as witnessed in discussion of findings, whereby all observed indicators of human-artificial intelligence supervision were seen to contribute towards inspection performance. Hence, in conclusion, it is stated that oil and gas firms' initiatives using AI tool adoption level will enhance results such as inspection accuracy, and operational efficiency in Oil and gas firms in Rivers State. From the findings, it was gathered that there is a positive and strong significant relationship between human supervisor competence and inspection performance in Oil and gas firms in Rivers State.

In line with the stated findings and conclusion for this study, the following recommendations are highlighted:

i. The study suggests that AI technology should not be treated as a substitute for human supervision. Oil and gas firms should pursue an integrated approach in which AI provides analytical and predictive capabilities, competent human supervisors provide contextual judgement and accountability, and organisational factors provide the infrastructure and management support necessary for the two to work effectively together.
ii. Oil and gas firms should strengthen the adoption and integration of AI inspection tools. Management Oil and gas firms should invest in appropriate AI-enabled inspection technologies such as predictive analytics, computer vision, intelligent monitoring systems, drones and automated anomaly-detection tools. However, adoption should be integrated into existing inspection procedures rather than treated as a standalone technological investment.
iii. Oil and gas firms should establish continuous AI and digital-technology training programmes for human supervisors. Supervisors should receive regular training on AI literacy, interpretation of AI-generated inspection results, data analysis, anomaly detection and the limitations of AI systems. This will enable supervisors to combine technological outputs with professional judgement effectively.
iv. Oil and gas firms should develop formal human-AI collaboration protocols. Organisations should clearly define which inspection tasks are performed by AI systems, which require human judgement and where human verification is mandatory. Such protocols can reduce ambiguity and promote effective coordination between inspectors and AI systems.
v. Management of Oil and gas firms should establish mandatory human verification of critical AI-generated inspection decisions. AI-generated alerts and recommendations involving safety-critical equipment should be reviewed by qualified personnel before major operational decisions are made. This approach preserves human accountability while allowing organisations to benefit from AI's analytical capabilities.

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