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Appraisal of Artificial Intelligence for Smart Project Management in the oil and gas Sector of the Niger Delta, Nigeria

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Abstract

This study investigated the role of artificial intelligence (AI) in enhancing project management within the oil and gas sector of the Niger Delta, Nigeria. The research was motivated by the need to evaluate how AI adoption can improve efficiency, safety, and overall performance in an industry facing persistent operational challenges. The study focused on three objectives: to assess the extent of AI adoption in project management practices, to identify barriers hindering effective integration, and to determine performance areas most improved through targeted AI application. A quantitative research design was adopted. The study population comprised 550 staff, with a sample size of 232 determined using Yamane's formula. A multi-stage sampling technique ensured proportional representation, and the survey data were complemented by secondary information from company and regulatory reports. Findings indicate that AI adoption is progressing but uneven across companies. Shell PLC's AI-driven risk modeling increased from 25% in 2020 to 50% in 2024, while Dagrow Resources expanded from 5% to 65% over the same period, consistent with survey responses yielding a moderate grand mean of 3.35 on a 5-point Likert scale. Barriers to adoption were also identified. NNPC's digital readiness improved from 2.5 to 3.6, compared to Shell's consistently high baseline of 4.2–4.5, while regulatory approval timelines averaged over 145 days. Survey evidence reinforced these barriers, producing a high overall mean of 4.15. Performance improvements were most notable in downtime reduction and asset integrity, with Shell reducing downtime from 5% to 18% and Dagrow from 0% to 28%, supported by a grand mean of 4.22 from survey data. Hypothesis testing confirmed that adoption levels remained moderate and that barriers significantly hindered integration. The study concludes that AI has strong transformative potential for project management in Nigeria's oil and gas sector, but its full realization requires sustained organizational investment and enabling institutional reforms.

Keywords: *Artificial intelligence; Project management; Oil and gas sector; Niger Delta; Adoption barriers; Operational performance; Digital transformation.*

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Introduction

Artificial intelligence (AI) refers to computer systems designed to perform tasks that typically require human intelligence, including learning, reasoning, and problem solving (Al-Mashaqbeh, 2021). AI has increasingly shaped global industries by enabling automation, predictive analytics, and optimization in complex organizational settings. In project management, AI is recognized as a transformative tool capable of improving efficiency, decision-making, and risk assessment (Khan *et al*., 2023). As industries face greater competition, tighter deadlines, and pressure for cost optimization, the application of AI in project management has attracted growing scholarly and practical interest. Globally, the oil and gas industry represents a sector where project management is central to operational and financial outcomes. This industry is characterized by high capital intensity, complex technical requirements, and exposure to geopolitical and environmental risks. Effective project management is therefore critical to balancing productivity, safety, and profitability. AI has been adopted internationally to address challenges such as project scheduling, supply chain optimization, and predictive maintenance (Memon *et al*., 2023). Researchers have noted that the use of AI in oil and gas project management can reduce uncertainties and improve decision quality, particularly in large-scale projects (Ogbonna & Jimoh, 2023).

Despite its potential, AI adoption in project management has been uneven across regions. Scholars have observed that while advanced economies have embraced AI for digital transformation, many developing countries continue to face structural and organizational barriers (Adegbite *et al.*, 2023). Factors such as inadequate infrastructure, limited digital skills, and financial constraints slow down technology integration. In the African context, the oil and gas sector plays a dominant economic role, yet faces difficulties in adapting to rapid technological shifts. Nigeria, being the largest oil producer in Africa, provides a particularly important case for examining these dynamics.

The Nigerian oil and gas sector has historically underpinned national economic performance. Revenues from oil exports account for a substantial share of government income and foreign exchange earnings. However, project execution in the sector has often been affected by cost overruns, delays, and operational inefficiencies (Abubakar & Mohammed, 2022). These challenges are linked to both internal factors, such as weak organizational practices, and external conditions, including regulatory uncertainty and security risks. AI presents opportunities to address such inefficiencies by enhancing project planning, monitoring, and resource allocation. Yet, the extent of its adoption in the Nigerian context remains limited.

Studies have noted that organizational culture plays a significant role in shaping the integration of new technologies. For instance, Ogbonna and Jimoh (2023) observed that resistance to change and insufficient top management support can undermine digital adoption. In the Nigerian oil and gas industry, hierarchical structures and rigid organizational norms may further complicate AI integration. Economic conditions, including fluctuating oil prices and investment pressures, also affect the willingness of firms to commit resources to innovative tools (Adegbite *et al*., 2023).

Technological readiness is another factor influencing AI adoption in project management. Research has shown that inadequate digital infrastructure and poor data quality constrain effective implementation of AI solutions (Memon *et al*., 2023). In Nigeria, limitations in broadband penetration, cybersecurity frameworks, and data governance have been cited as major challenges to digital transformation. These conditions hinder the development of AI-driven project management systems that rely on large-scale, high-quality data.

Policy environments further shape the prospects for AI adoption. Although Nigeria has made policy commitments to digital innovation, regulatory inconsistencies and fragmented institutional frameworks reduce the effectiveness of such initiatives. Scholars have stressed that coherent policy frameworks and industry-specific guidelines are necessary to create an enabling environment for AI integration (Abubakar & Mohammed, 2022). Without strong policy alignment, project managers and organizations may find it difficult to justify investments in AI tools.

Overall, while AI holds considerable promise for improving project management outcomes in the oil and gas sector, adoption in Nigeria is constrained by organizational, economic, technological, and policy-related barriers. The literature has not sufficiently addressed how these factors intersect to influence the extent of AI use in project management. In particular, the specific project performance areas where AI can create the most significant improvements remain underexplored.

Statement of the Problem

The oil and gas sector plays a pivotal role in global energy supply and economic stability. In Nigeria, the industry provides most government revenue and foreign exchange, yet it is characterized by operational inefficiencies, project delays, and cost overruns that reduce competitiveness and limit contributions to national development. These persistent challenges highlight the need for innovative approaches that can strengthen project management practices and improve outcomes in a high-risk and capital-intensive industry.

Artificial intelligence has emerged as a powerful tool for enhancing project management by enabling predictive analytics, risk detection, and real-time decision support (Khan *et al*., 2023). Internationally, firms have adopted AI to improve efficiency and reduce uncertainty in large projects (Memon *et al*., 2023). However, evidence suggests that Nigerian oil and gas organizations lag behind in leveraging AI technologies effectively. Ogbonna and Jimoh (2023) noted that adoption rates remain low, with significant organizational and technical barriers limiting integration into project management workflows.

Despite growing recognition of AI's potential, systematic evidence on its application within Nigerian oil and gas project management remains limited. Scholars have observed that most studies focus on AI in technical operations such as exploration and drilling, leaving project management applications underexplored (Adegbite *et al*., 2023). The absence of empirical studies assessing adoption levels, barriers, and specific performance areas affected creates a significant knowledge gap.

This gap is problematic because ineffective project management undermines Nigeria's ability to maximize returns from oil and gas investments. Without clear insights into how AI adoption could address inefficiencies, project risks remain high, and opportunities for cost savings and improved performance are lost. Stakeholders including policymakers, industry leaders, and citizens face continued exposure to the economic vulnerabilities created by weak project delivery. Addressing this problem requires targeted investigation into the extent of AI adoption, the barriers to integration, and the project performance areas where AI could provide the greatest improvements in Nigeria's oil and gas sector.

Aim and Objectives of the Study

The aim of the study is Leveraging artificial intelligence for smarter project management in Nigerian oil and gas sector. The specific objectives of the study are to;

i. To assess the adoption of artificial intelligence tools in project management practices within the Nigerian oil and gas sector.
ii. To ascertain the key barriers hindering effective integration of artificial intelligence into project management workflows in the Nigerian oil and gas sector.
iii. To identify project management performance areas that could be most improved through targeted application of artificial intelligence.
iv. To propose best practices in artificial intelligence adoption in the Nigerian Oil and Gas sector.

Research Questions

The following research questions are designed to guide the investigation into artificial intelligence adoption and its impact on project management in the Nigerian oil and gas sector:

i. To what areas of project management has adopted artificial intelligence (AI) in Nigerian oil and gas sector?
ii. What are the key barriers hindering the effective integration of artificial intelligence into project management workflows in the Nigerian oil and gas sector?
iii. Which project management performance areas have the greatest potential for improvement through targeted application of artificial intelligence?
v. What best practices in artificial intelligence are in the Nigerian Oil and Gas sector?

Statement of Hypotheses

Based on the research questions, the following null hypotheses are formulated to allow statistical testing and structured analysis of the study variables:

i. Artificial intelligence has no significant influence on project management in the oil and gas sector.
ii. The barriers have no significant influence on the adoption of artificial intelligence in project management within the oil and gas sector.
iii. Targeted application of artificial intelligence does not significantly influence project management performance in the oil and gas sector.

Scope of the Study

This study focuses on examining the adoption of artificial intelligence in project management practices within oil and gas sector in the Niger Delta, Nigeria. The research investigates three key dimensions: the extent of adoption of AI tools, the organizational and technical barriers that constrain integration, and the project management performance areas that may benefit most from targeted application. The scope is thus limited to the intersection of AI and project management rather than broader technical applications in exploration, drilling, or production.

The geographical focus of this study is the Niger Delta region, which hosts the majority of Nigeria's oil and gas operations. This area comprises states such as Rivers, Bayelsa, Delta, Akwa Ibom, and Edo. The selection of this region is based on the fact that the sample companies operate primarily within it, with their respective projects distributed across various locations. The region's complex socio-economic environment and the critical need for enhanced project delivery and risk management further justify its choice as the focal area of the research.

The study is limited to the upstream and midstream segments of the oil and gas industry, covering activities such as exploration, production, transportation, and processing. Key operational facilities considered include flowstations, gas plants, terminals, and pipeline systems. The research excludes downstream marketing and retail operations.

The temporal scope of the study covers the period from 2020 to 2025, aligning with recent advances in digital transformation and AI adoption trends.

Review of Related Literature

Conceptual Review

The conceptual review provides the foundation for situating this study within existing academic and professional discourses. It clarifies the key constructs that guide the investigation and establishes their relevance to the research context. Two interrelated concepts are central to this study. The first is artificial intelligence in project management, which highlights the role of digital technologies in reshaping project processes, decision-making, and organizational practices. The second is project management performance in the oil and gas sector, which underscores the multidimensional nature of project outcomes in a capital-intensive, high-risk industry. Reviewing these concepts is essential to understanding how technological innovation intersects with performance imperatives.

Artificial Intelligence in Project Management

Artificial intelligence (AI) refers to the development of systems capable of performing tasks that traditionally require human intelligence, such as reasoning, learning, and decision-making (Borges *et al*., 2021). In project management, AI encompasses a range of technologies that support planning, monitoring, and control of projects by automating processes, analyzing large datasets, and generating predictive insights. The relevance of AI to project management lies in its ability to address increasing project complexity, enhance efficiency, and improve decision accuracy. In resource-intensive industries such as oil and gas, these capabilities are particularly significant because projects involve high risks, large budgets, and strict timelines (Abdelgawad *et al*., 2022).

The use of AI in project management has been conceptualized in several dimensions, including scheduling, cost estimation, risk assessment, and performance monitoring. Sahu and Shrivastava (2023) explained that AI tools such as machine learning models can optimize scheduling by predicting potential delays and recommending corrective actions. Similarly, predictive analytics can enhance cost estimation accuracy by identifying historical cost drivers and adjusting forecasts accordingly (Liu *et al*., 2021). Risk management also benefits from AI applications, as algorithms are able to detect early warning signals and assess probabilities of project failures with greater precision than traditional methods (Sun *et al*., 2021). These functions collectively highlight how AI transforms project management from a reactive to a proactive discipline.

Several scholars have emphasized the growing integration of AI technologies into decision-making processes. Chan and Olawumi (2022) noted that project managers increasingly rely on AI-enabled decision support systems that synthesize data from multiple sources. These systems reduce reliance on subjective judgment and improve transparency in decision-making. However, while the promise of AI is widely acknowledged, concerns remain about overdependence on automated systems. Borgi and Boughzala (2021) argued that AI applications require continuous oversight to ensure alignment with organizational goals and contextual realities. This perspective underscores the balance needed between human expertise and machine intelligence.

In addition to operational functions, AI influences the strategic dimensions of project management. Abdelgawad *et al*. (2022) observed that AI adoption supports alignment between project execution and organizational strategy by providing real-time performance metrics and scenario analyses. Such integration strengthens the ability of managers to evaluate trade-offs and make strategic adjustments. At the same time, AI adoption reshapes organizational structures by demanding new skill sets, such as data literacy and algorithmic oversight, among project management professionals (Ghosh, 2021). This shift suggests that AI is not only a technical tool but also a driver of organizational change.

The application of AI in project management has also raised debates around ethical and contextual challenges. Ethical concerns include issues of data privacy, accountability, and algorithmic bias, which can affect the legitimacy of AI-driven decisions (Rahman *et al*., 2023). Contextual barriers such as limited infrastructure, inadequate investment, and workforce resistance are particularly salient in developing countries (Olawumi *et al*., 2023). These challenges highlight that AI adoption is not purely a technological issue but one embedded in social, cultural, and institutional contexts. The Nigerian oil and gas sector reflects many of these complexities, as it combines global competitiveness with local constraints in infrastructure and governance.

For stakeholders, the implications of AI in project management are far-reaching. Policymakers must consider how regulatory frameworks can support innovation while safeguarding ethical standards. Practitioners need to evaluate how AI tools can be integrated into workflows without undermining professional judgment. Communities and investors benefit from more efficient and transparent project outcomes, which can enhance social trust and economic returns. At the same time, gaps in empirical understanding remain, especially regarding how AI adoption interacts with contextual barriers and organizational practices in specific industries and regions.

In sum, artificial intelligence in project management represents a rapidly evolving concept that encompasses technical, strategic, and ethical dimensions. The literature demonstrates both the transformative potential of AI and the challenges associated with its integration.

Project Management Performance in the Oil and Gas Sector

Project management performance refers to the extent to which projects achieve their intended objectives within established parameters such as scope, cost, time, quality, and stakeholder satisfaction (PMI, 2021). In the oil and gas sector, project performance is a particularly critical issue due to the capital-intensive nature of operations, the complexity of project activities, and the sector's exposure to political, economic, and environmental risks (Ali *et al*., 2021). Performance in this context is not only measured by efficiency in execution but also by how effectively projects contribute to long-term strategic goals, regulatory compliance, and sustainability objectives. This makes the study of project management performance in the oil and gas industry especially relevant to countries like Nigeria, where the sector plays a central role in economic development.

Several scholars have emphasized that project performance in oil and gas depends on the interaction of technical, organizational, and external environmental factors. Mensah and Ametepe (2021) noted that cost overruns, schedule delays, and quality shortfalls have historically been pervasive in oil and gas projects globally. These inefficiencies were often attributed to inadequate project planning, poor risk management, and insufficient stakeholder engagement. Similarly, Akinwale (2022) argued that in developing countries, infrastructural gaps and governance challenges exacerbated performance deficits, limiting the ability of project teams to deliver expected outcomes. These observations underscored that performance in oil and gas project management is influenced by both internal managerial practices and external systemic conditions.

Performance evaluation frameworks in this sector have increasingly moved beyond the traditional iron triangle of cost, time, and scope. Rahman *et al*. (2023) observed that contemporary frameworks also incorporated dimensions such as health, safety, environmental compliance, and stakeholder satisfaction. This shift reflected growing recognition that oil and gas projects operate in sensitive socio-political environments where community expectations and environmental considerations play a decisive role. Omotayo and Kulatunga (2020) explained that in contexts like Nigeria, where host community relations are delicate, stakeholder trust is essential for successful project delivery. Consequently, performance assessment now requires a more holistic perspective that balances operational efficiency with broader societal and environmental outcomes.

The literature has also highlighted significant regional disparities in project performance outcomes. In advanced economies, technological advancements, stringent regulatory systems, and mature project management cultures have supported relatively higher performance benchmarks (Lopez *et al*., 2021). In contrast, developing countries often reported recurring issues such as procurement inefficiencies, regulatory bottlenecks, and capacity limitations (Ebekozien & Aigbavboa, 2021). Nigerian oil and gas projects have frequently been cited as facing persistent challenges in meeting deadlines and budgets, with performance indicators often falling below global averages (Okoro *et al*., 2023). These disparities suggest that context-specific factors must be critically considered when analyzing project performance in the oil and gas sector.

Recent studies have emphasized the importance of digital technologies and advanced methodologies in improving project management performance. Adepoju and Afolabi (2022) noted that digital project management tools enhanced transparency and coordination, leading to improved outcomes in complex oil and gas projects. Similarly, Olaoye and Adeniyi (2021) argued that performance could be enhanced by adopting integrated project delivery models that promote collaboration across stakeholders. However, barriers such as inadequate digital infrastructure, limited technical expertise, and resistance to organizational change continue to limit the uptake of these innovations in the Nigerian context. These constraints highlight the need for context-sensitive strategies to strengthen project management performance.

The implications of project performance for stakeholders in the oil and gas industry are far-reaching. Poor project outcomes can result in wasted resources, reduced investor confidence, environmental hazards, and social unrest in host communities (Chukwu & Adebayo, 2022). Conversely, effective project management performance can contribute to economic growth, sustainable energy development, and improved community relations. Policymakers require performance insights to design supportive regulatory frameworks, while practitioners benefit from adopting best practices that enhance efficiency and accountability. For communities and investors, improved performance translates into greater trust, reduced conflicts, and long-term returns.

Theoretical Framework

The theoretical framework provides the foundation for interpreting how artificial intelligence adoption can be understood and examined within project management in the oil and gas sector. It draws upon established theories that explain technology acceptance, resource utilization, and innovation diffusion. The Technology Acceptance Model clarifies the role of user perceptions in shaping attitudes and behavioral intentions toward new systems. The Resource-Based View emphasizes the strategic importance of internal capabilities and resources in sustaining performance advantages. The Diffusion of Innovation Theory explains the process through which new technologies spread within organizations and industries.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) was first introduced by Davis in 1986 and formally developed in 1989 to explain user acceptance of new technologies. The model was built on the theory of reasoned action, which argued that user behavior is shaped by attitudes and intentions (Fishbein & Ajzen, 1975). Davis proposed that two central constructs, perceived usefulness and perceived ease of use, determine the extent to which individuals are willing to adopt a technology. Perceived usefulness refers to the belief that technology enhances performance, while perceived ease of use reflects the belief that the technology reduces effort (Davis, 1989). Together, these perceptions influence users' attitudes and intentions toward technology adoption.

The model provided a framework for predicting user acceptance of digital tools across multiple contexts. It explained technology adoption not only through technical efficiency but also through the perceptions and motivations of the users themselves (Venkatesh & Davis, 2000). Later extensions of TAM incorporated variables such as social influence, facilitating conditions, and organizational context, which allowed researchers to account for broader factors in technology use (Venkatesh *et al*., 2003). Recent studies have continued to validate the model's relevance, particularly in relation to artificial intelligence applications in management, healthcare, and finance (Marangunić & Granić, 2021).

In the context of this study, TAM is relevant because it provides a structured approach to understanding how project managers and stakeholders in the oil and gas sector accept or resist artificial intelligence. The sector is heavily reliant on data-driven decision-making, and the successful integration of AI systems depends on user perceptions of their usefulness and ease of use. If project managers perceive AI to significantly enhance cost efficiency, scheduling accuracy, or risk management, they are more likely to adopt it as part of their project management practices (Okundaye *et al*., 2023). Conversely, if AI is perceived as complex or difficult to integrate with existing processes, adoption may remain limited.

The use of TAM in this study is justified for several reasons. First, it directly addresses the human and organizational dimensions of technology adoption, which are central to the research problem. Second, it offers a robust and widely tested theoretical framework that has been successfully applied to various emerging technologies, including AI. Third, its constructs allow the study to measure perceptions and attitudes that shape adoption behavior in a structured manner. This is particularly important in the Nigerian oil and gas sector, where technological investments must align with human resource capacities and organizational cultures (Adeleke & Ojo, 2022).

By applying TAM, this study can explore how perceptions of AI influence project management performance and highlight the conditions under which adoption can succeed. The model does not assume that technology adoption is automatic but instead underscores the importance of user attitudes and contextual barriers. This makes it an appropriate theoretical lens for examining the dynamics of AI integration into project management practices in a sector that is both technologically intensive and operationally complex.

Resource-Based View (RBV)

The Resource-Based View (RBV) was developed by Wernerfelt in 1984 and later expanded by Barney in 1991 to explain how organizations achieve and sustain competitive advantage through their internal resources. The theory posits that firms gain advantage when they possess resources that are valuable, rare, inimitable, and non-substitutable. These resources can be tangible, such as physical assets, or intangible, such as knowledge, skills, and technological capabilities (Barney, 1991). The RBV framework shifts attention from external industry factors to internal organizational strengths as the foundation of performance.

The model emphasizes that not all resources lead to advantage. Instead, only those that meet the VRIN criteria can provide long-term benefits. A resource is valuable if it enables the firm to exploit opportunities or neutralize threats. It is rare if few competitors possess it. It is inimitable if it cannot be easily replicated, and it is non-substitutable if no equivalent resource can replace it (Wernerfelt, 1984; Barney, 1991). This perspective allows researchers to evaluate why some organizations consistently outperform others despite operating in similar environments.

In recent years, scholars have applied the RBV to examine the role of digital technologies, data analytics, and artificial intelligence in strengthening organizational capabilities. For example, Alvarenga *et al*. (2020) noted that digital transformation initiatives can become a source of sustained advantage only when they are embedded within unique organizational practices and cultures. In the project management field, AI tools are increasingly regarded as strategic resources that can enhance predictive accuracy, optimize scheduling, and improve decision-making processes (Afonin *et al*., 2022). However, their impact depends on the firm's ability to integrate them effectively with existing knowledge, skills, and structures.

Within the oil and gas sector, RBV provides a useful lens for analyzing project management performance. The sector is capital-intensive and technologically demanding, which makes the quality of internal resources critical. Access to advanced project management technologies, specialized human expertise, and robust organizational systems determines whether firms can manage risks, control costs, and deliver projects successfully. Adeleke and Ojo (2022) argued that in developing economies such as Nigeria, firms often struggle to leverage technological resources effectively due to gaps in human capacity and institutional frameworks. This makes the evaluation of resources, both human and technological, central to understanding performance outcomes.

The relevance of RBV to this study lies in its ability to frame artificial intelligence not merely as a technological tool but as a strategic organizational resource. AI systems can be valuable and rare if they enhance project performance beyond industry norms. They can be inimitable when developed with proprietary data and expertise. They can also be non-substitutable when no alternative resource provides equivalent decision-making power. By applying RBV, the study can analyze how AI adoption contributes to project management performance through the alignment of technology with other critical organizational resources.

RBV is therefore appropriate because it situates the integration of AI within the broader resource landscape of oil and gas firms. It underscores the importance of both tangible and intangible resources in shaping project outcomes and highlights the need for organizations to develop capabilities that maximize the value of technological investments. This perspective supports the study's focus on linking technology adoption with project management performance in a sector where resource configuration is central to competitiveness.

Diffusion of Innovation Theory (DOI)

The Diffusion of Innovation (DOI) Theory was originally developed by Rogers in 1962 to explain how new ideas, technologies, or practices spread within a social system. The theory emphasizes the process by which innovations are communicated through specific channels over time and adopted by individuals, groups, or organizations (Rogers, 2003). It identifies key adopter categories, including innovators, early adopters, early majority, late majority, and laggards, which reflect the varying speeds and motivations of adoption. The DOI framework provides insights into the factors that influence the acceptance or resistance of technological innovations in diverse contexts.

The theory posits that five characteristics of an innovation influence its rate of adoption. These are relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2003). Relative advantage refers to the degree to which an innovation is seen as superior to existing practices. Compatibility describes how well the innovation aligns with current values, experiences, and needs. Complexity reflects the perceived difficulty in using the innovation. Trialability refers to the extent to which it can be experimented with before full adoption, while observability captures how visible its benefits are to others. Each of these factors shapes decision-making about whether to adopt or reject a new technology.

Recent studies have extended the DOI framework to digital and organizational innovations. For instance, Fichman *et al*. (2021) argued that the successful diffusion of emerging technologies depends not only on the technical merits of the innovation but also on organizational culture and external environmental pressures. Similarly, Al-Kahtani and Al-Dahash (2022) highlighted that in industries such as oil and gas, the pace of technological adoption is often slower due to regulatory requirements, cost concerns, and risk aversion. These findings suggest that the diffusion of AI in project management may face barriers beyond technical readiness, including institutional and cultural dynamics.

In the context of the oil and gas sector, DOI is useful in understanding the uneven patterns of AI adoption across firms and projects. The sector is known for its conservative approach to technology, often prioritizing safety and cost over rapid innovation (Olawale & Adeniran, 2021). In such an environment, firms may adopt AI tools only after their value has been demonstrated in other industries or contexts. This pattern aligns with Rogers' adopter categories, where firms in the sector may be positioned more toward the late majority or laggard groups.

The relevance of DOI to this study lies in its ability to explain why adoption levels of AI tools vary within project management practices. It provides a framework for analyzing how organizational decision-makers evaluate the advantages, risks, and cultural fit of AI solutions. By focusing on diffusion processes, the theory also draws attention to communication channels, leadership influence, and peer benchmarking, all of which shape adoption in practice.

The theory is therefore appropriate because it helps to interpret both the drivers and the barriers of AI integration in project management workflows.

By applying DOI, this study can frame the adoption of AI not only as a technical process but also as a social and organizational one. This perspective supports a deeper understanding of why some organizations in the Nigerian oil and gas sector may integrate AI tools successfully while others remain hesitant.

Empirical Review of Related Works

Bodea, Mitea, and Stanciu (2020) in "Artificial Intelligence Adoption in Project Management: Main Drivers, Barriers and Estimated Impact" sought to examine the adoption of AI in project management processes. The study employed a global survey administered by IPMA and PwC Romania to project managers across diverse industries between March and August 2020. Respondents represented varied organizational contexts, though the exact sample size was not detailed. Data collection centered on structured questionnaires, with results analyzed through descriptive and comparative approaches. Findings indicated that technological readiness, management support, and perceived usefulness strongly influenced adoption. However, resistance to change, cost implications, and lack of skilled personnel limited widespread integration.

Zenteno, Vintimilla, and Espinoza (2024) in "The Impact of Artificial Intelligence on Project Management" investigated AI adoption in Ecuador with a focus on organizational readiness. The research targeted large institutions, emphasizing organizations with more than 200 employees, and used surveys distributed to educators, department heads, and researchers. Quantitative and qualitative data were gathered and analyzed through mixed-method approaches to identify adoption barriers and opportunities. The study revealed that although financial and technical resources favor larger organizations, constraints such as limited managerial support, technological gaps, and budget restrictions impede full adoption. Respondents expressed optimism for AI expansion within five years, though significant uncertainties persist. The authors concluded that successful integration requires not only technical capacity but also policy and institutional support, making the findings highly relevant for resource-intensive industries like oil and gas.

Ibadildin and Kenzhin (2025) conducted "Artificial Intelligence in Project Management: A Bibliometric Analysis" to trace the evolution of AI applications in project delivery. The study applied bibliometric analysis to 51,752 patents, 5.5 million Google Scholar records, and over 436,000 Web of Science publications between 2001 and 2024. The review mapped global contributions, focusing on leading countries, trending topics, and interdisciplinary collaborations. Findings highlighted a steep rise in AI-related project management research after 2019, driven by digital transformation imperatives following COVID-19 disruptions. Emerging applications were evident in risk management, scheduling, and resource allocation. However, the analysis underscored persistent gaps in practical implementation and ethical regulation. The authors concluded that while global uptake has accelerated, applied methodologies remain fragmented, particularly in industries requiring high accountability, such as energy and oil.

Aliyeva (2024) in "Artificial Intelligence in the Oil Industry" examined the transformative influence of AI on production efficiency and market competitiveness. Using industry reports and secondary data, the paper analyzed how big data and machine learning tools are being applied to exploration, drilling, and production optimization. The review noted that 36 percent of oil companies had adopted AI-based big data technologies, while 38 percent intended to integrate them within the next five years. The analysis emphasized that AI assists in identifying new drilling sites, automating exploration, and minimizing operational costs. Findings confirmed that data utilization remains limited, despite massive reserves of structured and unstructured datasets. The study concluded that without strategic AI integration, oil companies risk losing competitiveness in a market increasingly shaped by digital transformation.

Zolfagharinia, Ghezavati, and Rahmani (2021) in "Artificial Intelligence Applications in Project Scheduling and Risk Management" analyzed the practical implications of AI adoption for complex projects. The study focused on engineering and construction sectors, drawing data from case projects in Asia and Europe. Mixed methods were applied, combining simulations, interviews, and project records to evaluate AI-enhanced scheduling systems. Findings revealed that AI tools improved forecasting accuracy, reduced scheduling delays, and facilitated proactive risk identification. Yet, challenges in data quality, integration with legacy systems, and user resistance limited their effectiveness. The study concluded that while AI significantly enhances efficiency, adoption remains contingent on managerial commitment and sector-specific adaptation, factors that align closely with challenges in oil and gas project management environments.

Al-Emran, Mezhuyev, and Kamaludin (2022) explored "Determinants of Artificial Intelligence Adoption in Organizations" with the objective of clarifying behavioral and organizational drivers. The research was conducted in the Gulf region, drawing data from 327 professionals across technology-intensive sectors. Structured surveys were administered and analyzed using structural equation modeling. Results demonstrated that perceived usefulness, ease of use, and top management support strongly predicted adoption. However, cultural resistance and concerns over job displacement reduced acceptance levels. The study concluded that while technology readiness plays an important role, organizational culture remains decisive in adoption success. These findings are particularly relevant for oil and gas firms where hierarchical decision-making and cultural norms shape technology diffusion.

Ahuja and Thakur (2023) investigated "Artificial Intelligence for Sustainable Project Management in Energy Sectors" to assess how AI contributes to environmental and operational outcomes. The study used multiple case analyses of renewable and non-renewable energy projects in South Asia. Data were collected through semi-structured interviews with 48 project managers and supplemented by organizational reports. Findings highlighted that AI improved sustainability outcomes through predictive analytics, energy optimization, and waste reduction. Nevertheless, limited infrastructure, high costs, and inadequate policies restricted widespread deployment. The research concluded that while AI fosters sustainability, the institutional and financial barriers are more pronounced in resource-dependent sectors.

Wang and Chen (2023) conducted "Artificial Intelligence-Driven Decision Support in Oil and Gas Projects" to examine how AI systems improve managerial decisions. The study adopted a quantitative design, gathering survey data from 216 managers in large oil and gas companies in China. Data were analyzed using regression modeling to test associations between AI usage and decision-making quality. Results indicated that AI enhanced accuracy in project monitoring, facilitated real-time adjustments, and improved resource allocation efficiency. However, technical integration challenges and data privacy concerns emerged as barriers. The study concluded that AI has a measurable impact on decision quality, although benefits depend on the robustness of implementation frameworks.

The Research Gap

Recent empirical studies have demonstrated the growing role of artificial intelligence in enhancing project management practices across energy and technology-intensive industries. Researchers documented improvements in scheduling accuracy, risk assessment, sustainability outcomes, and decision-making efficiency through AI applications (Zolfagharinia *et al*., 2021; Ahuja & Thakur, 2023; Wang & Chen, 2023). Others emphasized organizational and cultural factors that influenced adoption, highlighting the central role of perceived usefulness, management support, and workforce attitudes (Al-Emran *et al*., 2022; Mensah *et al*., 2022). Collectively, these studies confirmed the potential of AI to transform project delivery but revealed limitations in scope, methods, and sector-specific analysis.

Despite these advances, several critical gaps remain unaddressed. First, much of the evidence has been drawn from general energy or technology sectors rather than the oil and gas industry, with only limited focus on the distinct challenges of project management in this highly capital-intensive and high-risk environment (Wang & Chen, 2023). Second, the reviewed studies relied heavily on case analyses and surveys without systematically measuring sector-specific adoption levels or linking them to performance outcomes. This leaves insufficient clarity on how adoption levels vary, what barriers predominate, and which performance areas could benefit most in the oil and gas sector. Third, most investigations have been concentrated in Asia and the Middle East, creating a geographic gap in evidence from African contexts, particularly Nigeria, where oil and gas projects dominate national economic activity.

Addressing these gaps is both timely and essential. Without empirical insights into AI adoption patterns and their implications for project management performance in Nigeria's oil and gas sector, managers and policymakers risk missed opportunities for efficiency, risk reduction, and sustainable operations. This study directly responds to the identified gap by examining adoption levels, barriers, and performance implications in the Nigerian context. In doing so, it provides evidence that is urgently needed to guide strategic decisions for industry stakeholders and to advance academic understanding of AI integration in project management.

Methodology

Research Design

This study adopted a quantitative research design, which emphasizes the collection and analysis of numerical data to test hypotheses and identify relationships among variables. Quantitative research design was described by Creswell and Creswell (2021) as a systematic approach that uses structured instruments to produce measurable and objective results. Similarly, Apuke (2017) noted that quantitative research is appropriate when the aim is to quantify patterns, test relationships, and generalize findings within a defined population. This design is most suitable for the present study because it enables the measurement of artificial intelligence adoption, identification of barriers, and assessment of its impact on project management performance in the Nigerian oil and gas sector.

Area of Study

The study was conducted within the Niger Delta of Nigeria, focusing on the oil and gas sector that dominates the nation's economy. Nigeria is located in West Africa, lying between latitudes 4°N and 14°N and longitudes 3°E and 15°E. It is bounded by Niger to the north, Chad to the northeast, Cameroon to the east, and Benin to the west, with the Atlantic Ocean forming its southern boundary. The country consists of both urban and rural environments, with major oil and gas activities concentrated in the Niger Delta region, which serves as the hub of exploration and production. This geographical setting is highly relevant because the oil and gas sector remains central to Nigeria's revenue generation and infrastructure development. Concentrating on this area enables an assessment of artificial intelligence adoption in a sector that faces complex project management challenges due to technological, environmental, and organizational constraints.

Source of Data

The study relied on both primary and secondary data to achieve its objectives. Primary data was obtained directly from four selected oil and gas companies in Nigeria, namely Shell PLC, ExxonMobil Corporation, NNPC Limited, and Dagrow Resources Limited. These organizations were chosen because of their strategic roles in exploration, production, and project management within the Nigerian oil and gas industry. The data collected from these

companies provided direct insights into the extent of artificial intelligence adoption, the barriers to its integration, and its potential influence on project management performance.
Secondary data was also utilized to complement and validate the primary information. Key sources included annual reports and regulatory publications from the Nigerian Upstream Petroleum Regulatory Commission (NUPRC) and the National Oil Spill Detection and Response Agency (NOSDRA). In addition, relevant scholarly literature and industry reports were reviewed to provide a broader context and support for the empirical analysis.

Population of the Study

The population of the study comprised project management personnel drawn from four selected oil and gas companies in Nigeria, namely Shell PLC, ExxonMobil Corporation, NNPC Limited, and Dagrow Resources Limited. These organizations were chosen because they represent both multinational and indigenous players in the industry, thereby ensuring diversity in operational scale and management practices. The focus on project management personnel was appropriate since they are directly involved in planning, executing, and monitoring projects where artificial intelligence adoption could play a transformative role. The population was stratified by company to ensure adequate representation. Shell PLC had 145 project management staff, ExxonMobil Corporation had 132, NNPC Limited had 178, and Dagrow Resources Limited had 95. This brought the total study population to 550 personnel across the four organizations.

Determination of Sample Size

The determination of the sample size for this study was guided by Yamane's (1967) formula for calculating sample size from a finite population. The formula is presented in equation (3.1).

$$n = \frac{N}{1 + N(e)^2} \qquad (i)$$

Where *n* is the sample size, *N* is the population size, and *e* is the level of precision (0.05 at 95% confidence level). Given a total population of 550 project management staff across the four selected companies, the sample size was computed to be 232 experts.

Sampling Technique

The study employed a multi-stage sampling technique to ensure representativeness and focus on the most relevant respondents. In the first stage, Bourley's proportional allocation formula (equation 3.2) was applied to distribute the sample size of 232 proportionately across the four companies according to the size of their project management staff.

$$n_i = \frac{N_i}{N} \times n \qquad (ii)$$

Where n_i is the sample size for each stratum, N_i is the population of each stratum, *N* is the total population, and *n* is the total sample size. This method ensured that larger firms contributed more respondents while smaller firms were adequately represented.

The second stage involved purposive sampling within each company to select experts directly engaged in project management. Table 3.1 presents the outcome of the proportional allocation.

Table 3.1: Proportional allocation of sample size across companies

Company	Population (N_i)	Sample Size (n_i)
Shell PLC	145	61
ExxonMobil Corporation	132	56
NNPC Limited	178	75
Dagrow Resources Limited	95	40
Total	550	232

This multi-stage approach ensured both proportional representation of the study population and the inclusion of respondents with the expertise necessary to provide reliable insights.

Instrument of Data Collection

The instruments of data collection for this study consisted of a structured questionnaire and documentary sources. The structured questionnaire was designed to generate quantitative data directly related to the research questions. It was organized into three clusters, with each cluster corresponding to one of the study's research questions. Each cluster contained six carefully constructed items aimed at assessing different components of the respective research question, resulting in a total of 18 items. The items were presented in a clear and concise format, using a five-point Likert scale ranging from "strongly disagree" to "strongly agree" to ensure uniformity and ease of analysis.

In addition to the questionnaire, documentary evidence was also utilized to strengthen the validity of the study. Documents reviewed included official reports and regulatory publications from the Nigerian Upstream Petroleum Regulatory Commission (NUPRC) and the National Oil Spill Detection and Response Agency (NOSDRA). These documents provided secondary data on trends, regulatory practices, and sectoral performance, which served as a valuable complement to the primary data obtained from respondents.

Validity of the Instrument

The validity of the research instrument was established using the Content Validity Index (CVI). The questionnaire was subjected to expert review by three scholars from the Department of Project Management, ESUT Business School, Enugu. Each expert assessed the relevance, clarity, and appropriateness of the items against the study objectives. The CVI was computed by dividing the number of items rated as relevant by the total number of items. Out of the 18 items, 16 were rated as highly relevant, resulting in a CVI of 0.89. Since this value exceeds the acceptable threshold of 0.70, the instrument was considered valid.

Reliability of the Instrument

Reliability of the instrument was determined through a pilot test. Twenty copies of the questionnaire were administered to 20 project management experts in Oando, a company outside the study area to minimize bias. Responses were analyzed using Cronbach's Alpha to measure internal consistency across the three clusters. The first cluster produced a coefficient of 0.82, the second cluster yielded 0.85, and the third cluster showed 0.79. The overall reliability index was 0.82, which is above the recommended 0.70 benchmark. These results indicated that the instrument possessed a high level of reliability and was suitable for the main study.

Method of Data Analysis

The study employed a combination of analytical, descriptive, and inferential statistical methods to analyze the data. Analytical techniques were applied to secondary data obtained from regulatory reports to provide context and support for the primary data. Descriptive statistics, including frequency distributions, percentages, means, and standard deviations, were used to summarize responses from the structured questionnaire. Inferential statistics were employed to test the study's hypotheses using a two-way one-sample t-test, which allowed examination of differences between observed values and hypothesized parameters. Microsoft Office Excel and IBM SPSS software were utilized to ensure accuracy, reliability, and efficiency in the data analysis process.

Data Presentation, Analysis and Discussion of Results

Data Presentation

This chapter presents the data collected in line with the three research questions that guided the study. Out of the 232 copies of the questionnaire distributed, 219 were duly completed and returned, representing a response rate of 94 percent. The data are presented in their curated form, sequentially according to the study's objectives, but without analysis at this stage.

Presentation of Field Data on First Research Question

To address the first research question; the extent to which artificial intelligence tools are currently adopted in project management practices within the Nigerian oil and gas sector; both industry reports and field survey responses were collated. Table 4.1 presents secondary data drawn from industry records, while Table 4.2 captures the perceptions of respondents based on the questionnaire survey.

Table 4.1: Industry report on extent of adoption of AI tools in project management practices within the Nigerian oil and gas sector

Company	Metric	2020	2021	2022	2023	2024
Shell PLC	% of Capital Projects Utilizing AI-Driven Risk Modeling	25%	30%	40%	45%	50%
ExxonMobil	% of Capital Projects Utilizing AI-Driven Risk Modeling	20%	25%	35%	42%	48%
NNPC Limited	% of Capital Projects Utilizing AI-Driven Risk Modeling	10%	15%	25%	35%	40%
Dagrow Resources	% of Capital Projects Utilizing AI-Driven Risk Modeling	5%	15%	40%	55%	65%
Shell PLC	% of Local IT Budget allocated to Digital/AI Initiatives	8.0%	8.5%	9.0%	9.5%	10.0%
ExxonMobil	% of Local IT Budget allocated to Digital/AI Initiatives	7.5%	8.0%	8.5%	9.0%	9.5%
NNPC Limited	% of Local IT Budget allocated to Digital/AI Initiatives	4.0%	4.5%	6.0%	7.5%	8.5%
Dagrow Resources	% of Local IT Budget allocated to Digital/AI Initiatives	2.5%	3.5%	5.0%	6.5%	7.0%

Source: NUPRC (2025)

Table 4.2: Survey data on extent of adoption of AI tools in project management practices within the Nigerian oil and gas sector (n = 219)

Item No	Item	VHE	HE	ME	LE	VLE
1	Current utilization of AI models for resource allocation and scheduling optimization in capital projects.	26	17	158	11	7
2	Extent of AI integration with existing sensor (IoT/SCADA) infrastructure for real-time data collection in project environments.	17	11	159	19	13
3	Extent of AI tool deployment for risk modeling and contingency planning in offshore and remote operations.	87	12	112	5	3

4	Frequency of using AI/Machine Learning for forecasting project duration and budget variance across multiple projects.	4	7	124	43	41
5	Extent of regulatory approval and formal qualification of novel AI-driven technologies for upstream projects by NUPRC.	117	14	83	3	2
6	Scale of AI adoption in automated facilities management and production platform operations for monitoring and control.	62	21	112	13	11

Source: NUPRC (2025)

Presentation of Field Data on Second Research Question

The second research question focused on identifying the key barriers hindering the effective integration of artificial intelligence into project management workflows. In this regard, company-level indicators of digital readiness and regulatory approval timelines are reported in Table 4.3. Complementing this, Table 4.4 presented primary field data from respondents regarding the perceived barriers to integration.

Table 4.3: Company data on key barriers hindering effective integration

Company	Metric	2020	2021	2022	2023	2024
Shell PLC	Digital Readiness Index of PM Workforce (Scale 1-5, 5=High)	4.2	4.3	4.4	4.5	4.5
ExxonMobil	Digital Readiness Index of PM Workforce (Scale 1-5, 5=High)	4.0	4.1	4.2	4.3	4.4
NNPC Limited	Digital Readiness Index of PM Workforce (Scale 1-5, 5=High)	2.5	2.7	3.0	3.3	3.6
Dagrow Resources	Digital Readiness Index of PM Workforce (Scale 1-5, 5=High)	1.8	2.0	2.2	2.4	2.6
Shell PLC	Average Days for Regulatory Approval of Novel Technology	180	170	160	150	145
ExxonMobil	Average Days for Regulatory Approval of Novel Technology	185	175	165	155	148
NNPC Limited	Average Days for Regulatory Approval of Novel Technology	190	180	170	160	155
Dagrow Resources	Average Days for Regulatory Approval of Novel Technology	195	185	175	165	160

Source: NUPRC (2025); IT Budget Report (2025)

Table 4.4: Field data on the key barriers hindering effective integration of artificial intelligence into project management workflows in the Nigerian oil and gas sector (n = 219)

Item No	Item	SA	A	U	D	SD
1	High initial implementation cost significantly hinders the financial feasibility of deploying new AI systems.	113	72	24	7	3
2	Organizational resistance to change within project teams complicates the workflow redesign necessary for AI integration.	87	70	44	11	7
3	Lack of stable, reliable power infrastructure significantly impedes the necessary computational performance for AI models.	137	40	37	3	2
4	Insufficient local expertise and soft skills (data science, digital security) limit the effective use of advanced AI solutions.	103	80	18	13	5
5	Reliance on legacy IT systems and fragmented data architecture prevents seamless AI integration with core business processes.	97	86	8	17	11
6	Procedural complexity and time taken for regulatory approvals constrain the rapid deployment of novel AI technologies in the sector.	79	84	24	19	13

Presentation of Field Data on Third Research Question

Finally, to address the third research question which sought to determine the project management performance areas that could be most improved through targeted application of artificial intelligence, the data are presented in two forms. Table 4.5 outlined company-level reports on targeted performance improvements, while Table 4.6 presented field responses reflecting the perspectives of project management staff on the performance areas most enhanced by AI adoption.

Table 4.5: Company report on targeted performance improvement areas

Company	Metric	2020	2021	2022	2023	2024
Shell PLC	% Reduction in Unplanned Project Downtime (Targeted Assets)	5%	8%	12%	15%	18%
ExxonMobil	% Reduction in Unplanned Project Downtime (Targeted Assets)	4%	7%	10%	14%	17%
NNPC Limited	% Reduction in Unplanned Project Downtime (Targeted Assets)	2%	4%	8%	13%	16%
Dagrow Resources	% Reduction in Unplanned Project Downtime (Targeted Assets)	0%	5%	15%	23%	28%
Shell PLC	Asset Integrity Improvement Index (Factor: Baseline=1.0)	1.05	1.08	1.10	1.12	1.15
ExxonMobil	Asset Integrity Improvement Index (Factor: Baseline=1.0)	1.04	1.06	1.09	1.11	1.14
NNPC Limited	Asset Integrity Improvement Index (Factor: Baseline=1.0)	1.02	1.04	1.07	1.10	1.13
Dagrow Resources	Asset Integrity Improvement Index (Factor: Baseline=1.0)	1.00	1.03	1.06	1.09	1.11

Sources: Dagrow Resources (2025); NNPC Limited (2025); Shell PLC (2025); ExxonMobil (2025)

Table 4.6: Field data on project management performance areas that could be most improved through targeted application of artificial intelligence (n = 219)

Item No	Item	SA	A	U	D	SD
1	Targeted AI deployment significantly reduces project downtime through predictive maintenance scheduling of critical equipment.	149	34	33	2	1
2	Application of AI models enhances project safety and health standards by improving the accuracy of incident and failure prediction.	113	69	29	5	3
3	AI-driven risk modeling provides high accuracy in assessing technical and cost risks for complex, high-capital projects.	134	45	35	3	2
4	Utilizing AI significantly improves accountability and reduces financial losses through enhanced hydrocarbon metering technology.	97	72	32	11	7
5	AI optimizes operational parameters to achieve measurable increases in hydrocarbon production efficiency during execution phases.	103	74	30	7	5
6	AI provides objective support for prioritization of project tasks and work packages, reducing human bias in decision-making.	73	64	58	13	11

Source: Author's computation using SPSS Version 23

Data Analysis

In this chapter, the data obtained in response to the three research questions are analyzed and interpreted. The analysis is conducted sequentially in line with the study's objectives, enabling clearer insights into the extent of artificial intelligence adoption, the barriers to its effective integration, and the performance areas most likely to benefit from its targeted application. The interpretation of results is guided by both analytical and descriptive approaches, with findings presented alongside the corresponding tables for ease of understanding.

Evaluation of Data Obtained on First Research

In addressing the first research question, which sought to determine the extent to which artificial intelligence tools are adopted in project management practices within the Nigerian oil and gas sector, both company records and field survey data were subjected to analysis. Table 4.7 presented the analysis of company reports, highlighting adoption trends and growth rates, while Table 4.8 provided statistical analysis of the survey responses on various dimensions of AI adoption.

Table 4.7: Analysis of company report on adoption of AI in the selected oil and gas companies' projects

Company	Metric	2020	2021	2022	2023	2024	Average Annual Growth Rate (AAGR)
Shell PLC	% of Capital Projects Utilizing AI-Driven Risk Modeling	25%	30%	40%	45%	50%	18.92%
ExxonMobil	% of Capital Projects Utilizing AI-Driven Risk Modeling	20%	25%	35%	42%	48%	24.38%
NNPC Limited	% of Capital Projects Utilizing AI-Driven Risk Modeling	10%	15%	25%	35%	40%	41.42%
Dagrow Resources	% of Capital Projects Utilizing AI-Driven Risk Modeling	5%	15%	40%	55%	65%	89.26%
Shell PLC	% of Local IT Budget allocated to Digital/AI Initiatives	8.0%	8.5%	9.0%	9.5%	10.0%	5.74%
ExxonMobil	% of Local IT Budget allocated to Digital/AI Initiatives	7.5%	8.0%	8.5%	9.0%	9.5%	6.27%
NNPC Limited	% of Local IT Budget allocated to Digital/AI Initiatives	4.0%	4.5%	6.0%	7.5%	8.5%	20.84%
Dagrow Resources	% of Local IT Budget allocated to Digital/AI Initiatives	2.5%	3.5%	5.0%	6.5%	7.0%	29.38%

The data in Table 4.7 show a steady increase in the adoption of AI-driven risk modeling across all four companies between 2020 and 2024. Shell PLC recorded a rise from 25 percent in 2020 to 50 percent in 2024, representing an average annual growth rate (AAGR) of 18.92 percent. This indicates a gradual but consistent adoption trend, reflecting Shell's strategic integration of AI into risk management processes.

ExxonMobil followed a similar pattern, growing from 20 percent in 2020 to 48 percent in 2024. Its AAGR of 24.38 percent suggests a slightly faster pace of adoption compared to Shell. This highlights a more aggressive approach by ExxonMobil toward embedding AI in capital project risk modeling within the Nigerian context. NNPC Limited demonstrated a more accelerated trajectory. Its adoption rate increased from 10 percent in 2020 to 40 percent in 2024, resulting in an AAGR of 41.42 percent. This growth suggests that NNPC is catching up rapidly, moving from a relatively low baseline toward stronger engagement with AI-enabled project management practices. Dagrow Resources displayed the most dramatic growth, rising from only 5 percent adoption in 2020 to 65 percent in 2024. The company's AAGR of 89.26 percent is significantly higher than that of the other firms. This indicates a transformational shift in its project management approach, likely driven by the need to overcome resource limitations through rapid technological adoption. The allocation of IT budgets to digital and AI initiatives also reveals important differences among the companies. Shell PLC allocated 8.0 percent in 2020, gradually increasing to 10 percent in 2024, with an AAGR of 5.74 percent. This reflects a conservative but steady investment approach. ExxonMobil followed closely, with allocations rising from 7.5 percent in 2020 to 9.5 percent in 2024, yielding an AAGR of 6.27 percent. Both multinational firms show incremental increases in digital investment, consistent with their established infrastructures and global standards.

By contrast, NNPC Limited demonstrated a sharper rise in budget allocation, moving from 4.0 percent in 2020 to 8.5 percent in 2024. Its AAGR of 20.84 percent reflects a strong institutional commitment to building AI capacity. Similarly, Dagrow Resources rose from 2.5 percent in 2020 to 7.0 percent in 2024, recording the highest budget growth rate at 29.38 percent. These figures indicate a more aggressive repositioning by indigenous companies, suggesting that they are striving to close gaps with their multinational counterparts by dedicating larger portions of their budgets to digital transformation.

Table 4.8: Statistical analysis on the extent of adoption of artificial intelligence tools in project management practices within the Nigerian oil and gas sector

Item No	Item	VHE	HE	ME	LE	VLE	Mean	Std. Dev.
1	Current utilization of AI models for resource allocation and scheduling optimization in capital projects.	26 (11.9%)	17 (7.8%)	158 (72.1%)	11 (5.0%)	7 (3.2%)	3.20	0.83
2	Extent of AI integration with existing sensor (IoT/SCADA) infrastructure for real-time data collection in project environments.	17 (7.8%)	11 (5.0%)	159 (72.6%)	19 (8.7%)	13 (5.9%)	3.00	0.83
3	Extent of AI tool deployment for risk modeling and contingency planning in offshore and remote operations.	87 (39.7%)	12 (5.5%)	112 (51.1%)	5 (2.3%)	3 (1.4%)	3.80	1.04
4	Frequency of using AI/Machine Learning for forecasting project duration and budget variance across multiple projects.	4 (1.8%)	7 (3.2%)	124 (56.6%)	43 (19.6%)	41 (18.7%)	2.50	0.90
5	Extent of regulatory approval and formal qualification of novel AI-driven technologies for upstream projects by NUPRC.	117 (53.4%)	14 (6.4%)	83 (37.9%)	3 (1.4%)	2 (0.9%)	4.10	1.02
6	Scale of AI adoption in automated facilities management and production platform operations for monitoring and control.	62 (28.3%)	21 (9.6%)	112 (51.1%)	13 (5.9%)	11 (5.0%)	3.50	1.11
	Grand mean/ Standard deviation						3.35	0.96

Source: Author's computation using SPSS Version 23

The descriptive analysis presented in Table 4.8 provide a coherent understanding of how artificial intelligence (AI) tools are being adopted in project management within the Nigerian oil and gas sector. The first theme relates to the actual use of AI tools in managing operations, including resource allocation, scheduling, and facilities management. A majority of respondents, 158 individuals representing 72.1 percent, indicated moderate engagement with AI for resource allocation and scheduling. A smaller proportion, 26 respondents (11.9 percent), reported very high engagement, while 7 respondents (3.2 percent) reported very low engagement. The mean of 3.20 and standard deviation of 0.83 suggest a modest level of adoption with relatively low variability, indicating a broad convergence of responses.

Similarly, AI adoption in facilities management and production platform monitoring showed stronger responses. Here, 112 participants, or 51.1 percent, indicated moderate use, while 62 respondents (28.3 percent) signaled very high adoption. With a mean score of 3.50 and standard deviation of 1.11, this pattern suggests growing reliance on

AI for operational oversight, although variation across organizations remains notable. Together, these results reveal that while adoption is not uniformly high, there is clear evidence of integration into routine operational workflows.

A second theme centers on the extent to which AI is integrated with digital infrastructures such as IoT and SCADA systems. In this area, 159 respondents (72.6 percent) indicated moderate use, whereas 17 respondents (7.8 percent) and 11 respondents (5.0 percent) reported very high and high levels of integration, respectively. By contrast, 13 respondents (5.9 percent) still reported very low engagement. The mean score of 3.00 and standard deviation of 0.83 reflect that integration with digital infrastructure remains at a moderate level overall, with relatively little variation. This indicates that while AI readiness exists, technical embedding into existing systems is still evolving.

A third theme emerges around the use of AI for managing risks and planning contingencies in challenging project environments. Here, adoption appears more advanced. Eighty-seven respondents (39.7 percent) indicated very high engagement, while 112 respondents (51.1 percent) reported moderate use. Only a small minority, 3 respondents (1.4 percent), indicated very low engagement. The mean of 3.80 and standard deviation of 1.04 point to a relatively high level of adoption, although the dispersion shows some firms are ahead of others. This evidence suggests that organizations perceive greater value in leveraging AI for risk-sensitive contexts such as offshore and remote operations.

Forecasting project timelines and budget variance through AI showed weaker adoption compared to other themes. A majority of respondents, 124 individuals (56.6 percent), indicated moderate use, while only 11 respondents (5.0 percent) reported high or very high engagement. On the other hand, 43 respondents (19.6 percent) and 41 respondents (18.7 percent) signaled low and very low usage. The mean score of 2.50 with a standard deviation of 0.90 indicates limited uptake, and the responses are moderately spread. This points to a significant gap in predictive analytics adoption, suggesting hesitancy or lack of maturity in applying AI for forward-looking project management tasks.

The final theme relates to the extent to which AI-driven technologies are formally approved and qualified by regulatory bodies. Here, the highest levels of agreement were recorded. A total of 117 respondents (53.4 percent) reported very high recognition, while 83 respondents (37.9 percent) indicated moderate acknowledgment of AI tools. Only 5 respondents (2.3 percent) reported disagreement. With a mean of 4.10 and standard deviation of 1.02, this pattern reflects substantial regulatory acceptance of AI tools within the sector, although variation remains in how individual companies perceive or experience this approval process.

The grand mean of 3.35 with a standard deviation of 0.96 suggests that adoption is overall moderate, with differences in maturity levels across application areas.

Evaluation of Data Obtained on Second Research

The second research question examined the key barriers hindering the effective integration of artificial intelligence into project management workflows. To analyze this, company data on workforce digital readiness and regulatory approval timelines are summarized in Table 4.9, whereas Table 4.10 presents the statistical analysis of field responses regarding financial, organizational, infrastructural, and regulatory barriers.

Table 4.9: Analysis of company report on key barriers hindering effective integration of AI into project management workflows in the Nigerian oil and gas sector

Company	Metric	2020	2021	2022	2023	2024	Absolute Change in Index (2020 to 2024)
Shell PLC	Digital Readiness Index of PM Workforce (Scale 1-5, 5=High)	4.2	4.3	4.4	4.5	4.5	+0.3
ExxonMobil	Digital Readiness Index of PM Workforce (Scale 1-5, 5=High)	4.0	4.1	4.2	4.3	4.4	+0.4

Company	Metric	2020	2021	2022	2023	2024	Absolute Change in Index (2020 to 2024)
NNPC Limited	Digital Readiness Index of PM Workforce (Scale 1-5, 5=High)	2.5	2.7	3.0	3.3	3.6	+1.1
Dagrow Resources	Digital Readiness Index of PM Workforce (Scale 1-5, 5=High)	1.8	2.0	2.2	2.4	2.6	+0.8
Shell PLC	Average Days for Regulatory Approval of Novel Technology	180	170	160	150	145	-35 Days
ExxonMobil	Average Days for Regulatory Approval of Novel Technology	185	175	165	155	148	-37 Days
NNPC Limited	Average Days for Regulatory Approval of Novel Technology	190	180	170	160	155	-35 Days
Dagrow Resources	Average Days for Regulatory Approval of Novel Technology	195	185	175	165	160	-35 Days

The digital readiness of project management (PM) workforces varied significantly across the four companies during the five-year period. Shell PLC and ExxonMobil consistently maintained high levels of readiness, with indices rising from 4.2 to 4.5 and from 4.0 to 4.4 respectively on a five-point scale. These incremental increases of +0.3 and +0.4 suggest that their project teams were already well-equipped digitally, requiring only marginal improvements to reach near-optimal levels of readiness. Such stability reflects sustained investment in workforce training and established organizational capacity to adopt new technologies.

By contrast, NNPC Limited and Dagrow Resources started from much lower baselines, with indices of 2.5 and 1.8 in 2020. NNPC improved more markedly, reaching 3.6 in 2024, which represents an absolute change of +1.1. Dagrow Resources also made progress, rising to 2.6 in 2024, though with a smaller improvement of +0.8. These results indicate that indigenous companies are in a process of gradual catch-up, but their workforce readiness still lags behind multinational peers. The gap suggests persistent structural and capability-related barriers to the seamless integration of AI technologies.

Regulatory approval timelines also revealed important constraints. Across all companies, the average days required for regulatory approval of novel technology remained lengthy, though slight improvements were evident. Shell reduced approval times from 180 days in 2020 to 145 days in 2024, representing a reduction of 35 days. ExxonMobil recorded the largest improvement, from 185 to 148 days, a decrease of 37 days. NNPC and Dagrow Resources both experienced similar reductions of 35 days, bringing approval times to 155 and 160 days, respectively, by 2024. Despite these improvements, the approval processes remain protracted, averaging close to five months even at their most efficient. This reflects a regulatory environment that continues to slow the timely deployment of AI innovations.

Table 4.10: Statistical analysis on the key barriers hindering effective integration of artificial intelligence into project management workflows in the Nigerian oil and gas sector

Item No	Item	SA	A	U	D	SD	Mean	Std. Dve.
1	High initial implementation cost significantly hinders the financial feasibility of deploying new AI systems.	113 (51.6%)	72 (32.9%)	24 (11.0%)	7 (3.2%)	3 (1.4%)	4.30	0.89
2	Organizational resistance to change within project teams complicates the workflow redesign necessary for AI integration.	87 (39.7%)	70 (32.0%)	44 (20.1%)	11 (5.0%)	7 (3.2%)	4.00	1.04
3	Lack of stable, reliable power infrastructure significantly impedes the necessary computational performance for AI models.	137 (62.6%)	40 (18.3%)	37 (16.9%)	3 (1.4%)	2 (0.9%)	4.40	0.88
4	Insufficient local expertise and soft skills (data science, digital security) limit the effective use of advanced AI solutions.	103 (47.0%)	80 (36.5%)	18 (8.2%)	13 (5.9%)	5 (2.3%)	4.20	0.98

Item No	Item	SA	A	U	D	SD	Mean	Std. Dev..
5	Reliance on legacy IT systems and fragmented data architecture prevents seamless AI integration with core business processes.	97 (44.3%)	86 (39.3%)	8 (3.7%)	17 (7.8%)	11 (5.0%)	4.10	1.11
6	Procedural complexity and time taken for regulatory approvals constrain the rapid deployment of novel AI technologies in the sector.	79 (36.1%)	84 (38.4%)	24 (11.0%)	19 (8.7%)	13 (5.9%)	3.90	1.16
	Grand mean/ Standard deviation						4.15	1.02

The descriptive survey data provided in Table 4.10 shed light on the barriers hindering the effective integration of artificial intelligence (AI) into project management workflows within the Nigerian oil and gas sector.

A central barrier identified is the financial burden associated with AI implementation. A total of 113 respondents (51.6 percent) strongly agreed and 72 respondents (32.9 percent) agreed that high initial costs constrain deployment. Together, this represents 185 participants, or 84.5 percent of the sample, underscoring the weight of financial feasibility concerns. Only 10 respondents (4.6 percent) disagreed or strongly disagreed. The mean score of 4.30 with a standard deviation of 0.89 indicates a strong central tendency toward agreement, with relatively low variation.

Another theme centers on organizational readiness and cultural acceptance. A combined 157 respondents (71.7 percent) either strongly agreed or agreed that resistance to change within project teams complicates AI integration. By contrast, only 18 respondents (8.2 percent) expressed disagreement. The mean score of 4.00 and standard deviation of 1.04 reflect moderately strong agreement but with slightly greater variability than financial concerns.

Infrastructure remains a critical obstacle, particularly regarding power supply. A large majority; 137 respondents (62.6 percent); strongly agreed that unstable power systems impede computational performance, with an additional 40 respondents (18.3 percent) in agreement. This translates to 177 participants (80.9 percent) acknowledging power-related limitations. Only 5 respondents (2.3 percent) disagreed. The mean score of 4.40, the highest among all items, demonstrates strong consensus, while the low standard deviation of 0.88 indicates limited variability in opinion.

A further barrier is the lack of skilled professionals in areas such as data science and digital security. A total of 183 respondents (83.5 percent) strongly agreed or agreed, while only 18 respondents (8.2 percent) were undecided and a small minority disagreed. The mean of 4.20 with a standard deviation of 0.98 reveals high levels of concern but with some variation in how acutely this issue is felt across different firms.

Technological compatibility was also identified as a major constraint. A combined 183 respondents (83.6 percent) strongly agreed or agreed that reliance on legacy systems and fragmented data architectures hinders AI integration. In contrast, 28 respondents (12.8 percent) disagreed or strongly disagreed. The mean score of 4.10 with a standard deviation of 1.11 highlights strong agreement but also indicates noticeable variation.

Finally, regulatory processes emerged as a recognized impediment. A total of 163 respondents (74.5 percent) strongly agreed or agreed that procedural complexity and long approval times constrain AI deployment. However, 32 respondents (14.6 percent) disagreed or strongly disagreed, reflecting some divergence in experience. The mean score of 3.90 with the highest standard deviation of 1.16 suggests relatively broad variation in responses.

The grand mean of 4.15 and standard deviation of 1.02 confirm that barriers are both significant and persistent.

Evaluation of Data Obtained on Third Research

Finally, the third research question explored the project management performance areas that could be most improved through the targeted application of artificial intelligence. Table 4.11 provides an analysis of company reports on performance improvement factors such as project downtime reduction and asset integrity enhancement. Complementing this, Table 4.12 presents statistical analysis of survey responses on the specific performance areas where AI is perceived to add the most value.

Table 4.11: Analysis of company report on project management performance areas that could be most improved through targeted application of artificial intelligence

Company	Metric	2020	2021	2022	2023	2024	Average Improvement Factor (AIF)
Shell PLC	% Reduction in Unplanned Project Downtime (Targeted Assets)	5%	8%	12%	15%	18%	11.6%
ExxonMobil	% Reduction in Unplanned Project Downtime (Targeted Assets)	4%	7%	10%	14%	17%	10.4%
NNPC Limited	% Reduction in Unplanned Project Downtime (Targeted Assets)	2%	4%	8%	13%	16%	8.6%
Dagrow Resources	% Reduction in Unplanned Project Downtime (Targeted Assets)	0%	5%	15%	23%	28%	14.2%
Shell PLC	Asset Integrity Improvement Index (Factor: Baseline=1.0)	1.05	1.08	1.10	1.12	1.15	1.10
ExxonMobil	Asset Integrity Improvement Index (Factor: Baseline=1.0)	1.04	1.06	1.09	1.11	1.14	1.09
NNPC Limited	Asset Integrity Improvement Index (Factor: Baseline=1.0)	1.02	1.04	1.07	1.10	1.13	1.07
Dagrow Resources	Asset Integrity Improvement Index (Factor: Baseline=1.0)	1.00	1.03	1.06	1.09	1.11	1.06

The results from Table 4.11 highlighted two distinct areas of performance improvement attributable to AI adoption: the reduction of unplanned project downtime and the enhancement of asset integrity.

The evidence shows that targeted AI deployment has contributed to measurable reductions in project downtime across all four companies, though at different rates. Shell PLC recorded a steady increase in downtime reduction, rising from 5 percent in 2020 to 18 percent in 2024, yielding an average improvement factor (AIF) of 11.6 percent. ExxonMobil followed closely, achieving a reduction from 4 percent to 17 percent over the same period, with an AIF of 10.4 percent.

NNPC Limited demonstrated a slower but consistent improvement, moving from 2 percent in 2020 to 16 percent in 2024, averaging 8.6 percent annually. Dagrow Resources, however, achieved the most dramatic gains, moving from no downtime reduction in 2020 to 28 percent by 2024, resulting in the highest AIF of 14.2 percent. This sharp rise suggests that smaller or less digitally mature firms, when adopting AI more aggressively, can realize significant performance benefits in a relatively short time.

The asset integrity indices reveal more gradual improvements across all companies, though the trends remain positive. Shell PLC improved from a baseline of 1.05 in 2020 to 1.15 in 2024, averaging 1.10 over the five-year period. ExxonMobil showed a similar pattern, rising from 1.04 to 1.14, with an average of 1.09.

By contrast, NNPC Limited improved from 1.02 to 1.13, while Dagrow Resources rose from a baseline of 1.00 to 1.11, averaging 1.07 and 1.06 respectively. These figures demonstrate that multinationals have consistently higher asset integrity indices compared to indigenous firms. However, the upward movement across all companies reflects the gradual but steady impact of AI in enhancing structural reliability and minimizing asset degradation.

Table 4.12: Statistical analysis on project management performance areas that could be most improved through targeted application of artificial intelligence

Item No	Item	SA	A	U	D	SD	Mean	Std. Dev.
1	Targeted AI deployment significantly reduces project downtime through predictive maintenance scheduling of critical equipment.	149 (68.0%)	34 (15.5%)	33 (15.1%)	2 (0.9%)	1 (0.5%)	4.50	0.81
2	Application of AI models enhances project safety and health standards by improving the accuracy of incident and failure prediction.	113 (51.6%)	69 (31.5%)	29 (13.2%)	5 (2.3%)	3 (1.4%)	4.30	0.88
3	AI-driven risk modeling provides high accuracy in assessing technical and cost risks for complex, high-capital projects.	134 (61.2%)	45 (20.5%)	35 (16.0%)	3 (1.4%)	2 (0.9%)	4.40	0.87
4	Utilizing AI significantly improves accountability and reduces financial losses through enhanced hydrocarbon metering technology.	97 (44.3%)	72 (32.9%)	32 (14.6%)	11 (5.0%)	7 (3.2%)	4.10	1.04
5	AI optimizes operational parameters to achieve measurable increases in hydrocarbon production efficiency during execution phases.	103 (47.0%)	74 (33.8%)	30 (13.7%)	7 (3.2%)	5 (2.3%)	4.20	0.95

6	AI provides objective support for prioritization of project tasks and work packages, reducing human bias in decision-making.	73 (33.3%)	64 (29.2%)	58 (26.5%)	13 (5.9%)	11 (5.0%)	3.80	1.12
	Grand mean/ Standard deviation						4.22	0.95

The results from Table 4.12 presented respondents' perceptions of the project management performance areas most improved through the targeted application of artificial intelligence (AI).

The most significant gains were reported in the area of predictive maintenance and downtime reduction. A total of 149 respondents (68.0 percent) strongly agreed and 34 respondents (15.5 percent) agreed that targeted AI deployment reduces downtime through proactive equipment maintenance. Only 3 respondents (1.4 percent) disagreed. With a mean score of 4.50 and a relatively low standard deviation of 0.81, this was the strongest area of consensus across all items. The result reflects the sector's recognition of AI's tangible contribution to operational continuity and cost savings through minimized equipment failures and delays.

Operational efficiency also extended to production optimization. Here, 103 respondents (47.0 percent) strongly agreed and 74 respondents (33.8 percent) agreed that AI enhances hydrocarbon production efficiency. Together, this accounted for 177 respondents (80.8 percent), while only 12 respondents (5.5 percent) expressed disagreement. A mean score of 4.20 and standard deviation of 0.95 confirm strong agreement with moderate variation. These findings demonstrate that operational improvements represent a core area where AI adoption is already producing measurable benefits.

A second major theme concerns workplace safety and project risk management. On safety, 113 respondents (51.6 percent) strongly agreed and 69 respondents (31.5 percent) agreed that AI enhances safety standards by predicting incidents and failures more accurately. This represents 182 respondents (83.1 percent) affirming safety benefits, while only 8 respondents (3.7 percent) expressed disagreement. The mean of 4.30 with a standard deviation of 0.88 underscores strong consensus and relatively low dispersion.

Risk management also attracted strong support. A combined 179 respondents (81.7 percent) strongly agreed or agreed that AI-driven risk modeling provides high accuracy in assessing technical and cost risks. By contrast, only 5 respondents (2.3 percent) disagreed. The mean of 4.40 with a standard deviation of 0.87 indicates broad acceptance of AI's value in addressing complex project risks. Collectively, these results point to risk and safety management as domains where AI is highly trusted to deliver value.

Another performance area concerns financial accountability through AI-enabled metering technologies. A total of 97 respondents (44.3 percent) strongly agreed and 72 respondents (32.9 percent) agreed that AI reduces financial losses and improves accountability. This represents 169 respondents (77.2 percent) in agreement, while 18 respondents (8.2 percent) disagreed. The mean score of 4.10 with a standard deviation of 1.04 shows solid consensus, though with a slightly higher variability than safety and downtime responses. This suggests that financial benefits are recognized but may depend on the maturity of technological deployment across firms.

The final theme relates to AI's role in improving decision-making and prioritization of project tasks. While 73 respondents (33.3 percent) strongly agreed and 64 respondents (29.2 percent) agreed with this benefit, a substantial proportion; 58 respondents (26.5 percent); remained undecided. An additional 24 respondents (10.9 percent) expressed disagreement. With a mean score of 3.80 and the highest standard deviation of 1.12, this item displayed the most variability in responses. The evidence suggests that while many recognize AI's potential in reducing human bias in decision-making, its application in this domain is less established and possibly limited by organizational culture or trust in AI-driven judgment.

With a grand mean of 4.22 and a standard deviation of 0.95, the results confirm that AI is widely perceived as a transformative tool for performance improvement, though its benefits are uneven across domains.

Test of Hypotheses

This presents the statistical testing of the study's hypotheses in order to validate or refute the assumptions formulated from the research questions. The analysis was conducted using the one-sample *t*-test, a method considered most appropriate for this study because it allows comparison between the observed sample means and the hypothetical mean values established for each research variable. The decision rule applied is as follows: if the calculated *t*-statistic is greater than the critical *t*-value at the 0.05 level of significance, the null hypothesis is rejected; otherwise, the null hypothesis is accepted.

Test of First Null Hypothesis

The first null hypothesis (H_{01}) stated that there is no significant level of adoption of artificial intelligence tools in project management practices within the Nigerian oil and gas sector. To test this, a one-sample *t*-test was conducted, and the results are presented in Table 4.13.

Table 4.13: Summary of one sample t-test on level of adoption of artificial intelligence tools

Degree of Freedom	Mean ($\bar{x}$)	Hypothetical Mean (μ)	Standard deviation	Critical t-value	t-statistic	Level of Significance
5	3.35	3.00	0.96	2.571	0.89	0.05

The result for H_{01} shows that the calculated *t*-statistic (0.89) is less than the critical *t*-value (2.571) at the 0.05 level of significance. This indicates that the difference between the observed mean adoption level (3.35) and the hypothetical mean (3.00) is not statistically significant. Therefore, the null hypothesis is accepted, implying that the extent of adoption of artificial intelligence tools in project management practices remains moderate and not yet at a level considered significantly high.

4.3.2 Test of Second Null Hypothesis

The second null hypothesis (H_{02}) proposed that organizational and technical barriers do not significantly hinder the integration of artificial intelligence into project management workflows in the Nigerian oil and gas sector. A one-sample *t*-test was applied to the data, with the outcome summarized in Table 4.14.

Table 4.14: Summary of one sample t-test on Organizational and technical barriers

Degree of Freedom	Mean ($\bar{x}$)	Hypothetical Mean (μ)	Standard deviation	Critical t-value	t-statistic	Level of Significance
5	4.15	3.00	1.02	2.571	2.76	0.05

For H_{02}, the computed *t*-statistic (2.76) exceeds the critical *t*-value (2.571) at the 0.05 significance level. This means the mean value (4.15) differs significantly from the hypothetical mean (3.00). Consequently, the null hypothesis is rejected. The implication is that organizational and technical barriers, such as high costs, infrastructural limitations, and regulatory delays, significantly hinder the effective integration of artificial intelligence into project management workflows within the Nigerian oil and gas sector.

Test of Third Null Hypothesis

The third null hypothesis (H_{03}) stated that the targeted application of artificial intelligence does not significantly improve project management performance areas in the Nigerian oil and gas sector. Using a one-sample *t*-test, the hypothesis was assessed, and the findings are reported in Table 4.15.

Table 4.15: Summary of one sample t-test on targeted application of artificial intelligence

Degree of Freedom	Mean ($\bar{x}$)	Hypothetical Mean (μ)	Standard deviation	Critical t-value	t-statistic	Level of Significance
5	4.22	3.00	0.95	2.571	3.15	0.05

The test result for H_{03} indicates that the calculated *t*-statistic (3.15) is greater than the critical *t*-value (2.571) at the 0.05 significance level. This demonstrates that the mean score (4.22) is significantly higher than the hypothetical mean (3.00). Therefore, the null hypothesis is rejected. The finding implies that targeted application of artificial intelligence significantly improves project management performance areas, particularly in reducing downtime, enhancing safety standards, and optimizing operational efficiency across the Nigerian oil and gas sector.

Discussion of Results

The findings demonstrate that the adoption of artificial intelligence in project management within Nigeria's oil and gas sector is advancing, though at varying speeds across companies and application domains. Adoption is strongest in risk modeling and operational oversight, aligning with global trends identified by Zolfagharinia *et al*. (2021), who reported efficiency gains in scheduling and risk management through AI. However, unlike the more mature ecosystems described in their case studies, adoption in Nigeria remains uneven, with multinational firms displaying steady integration and indigenous firms showing rapid but less stable progress. This reflects the diffusion of innovation theory, which emphasizes disparities in uptake depending on organizational resources and readiness.
Barriers to integration emerged as a critical theme, particularly financial constraints, infrastructural deficiencies, and limited human capacity. These findings are consistent with Bodea *et al*. (2020), who identified cost, resistance to change, and skill shortages as limiting factors in global AI adoption. Similarly, Zenteno *et al*. (2024) emphasized the role of managerial support and policy frameworks, both of which remain weak in Nigeria's context. The persistence of infrastructural barriers, such as unreliable power systems, marks a divergence from findings in regions with more advanced digital environments, suggesting that structural deficits exacerbate organizational challenges in resource-constrained settings. From a resource-based view, these barriers highlight weaknesses in internal capabilities that limit the translation of technological potential into performance outcomes.

In terms of performance improvements, the evidence shows significant benefits in reducing project downtime, enhancing safety, and improving asset integrity. These findings resonate with Wang and Chen (2023), who demonstrated measurable impacts of AI-driven decision support on efficiency and monitoring accuracy in Chinese oil and gas projects. The results also echo Ahuja and Thakur (2023), who emphasized sustainability and operational optimization as key contributions of AI in energy sectors. Yet, the relatively cautious uptake of predictive forecasting diverges from the bibliometric analysis of Ibadildin and Kenzhin (2025), which identified forecasting as a globally expanding area of AI application. This divergence suggests that while Nigerian firms recognize immediate operational benefits, more complex predictive uses remain underdeveloped due to technical integration gaps and regulatory inertia.

In a nutshell, the findings affirm the relevance of the Technology Acceptance Model, as perceived usefulness and managerial commitment drive adoption more strongly than infrastructural readiness. They also extend debates by showing how institutional weaknesses; particularly in regulation and power infrastructure; compound organizational challenges. These dynamics imply that for AI to fully realize its transformative potential in Nigeria's oil and gas sector, both internal capacities and external enabling environments must be strengthened.

Summary of Findings, Conclusion and Recommendations

Summary of Findings

i. Adoption of artificial intelligence in project management has increased steadily, with company records showing Shell PLC's AI-driven risk modeling rising from 25% in 2020 to 50% in 2024, while Dagrow Resources advanced from 5% to 65% over the same period; this growth pattern is consistent with the survey evidence that produced a moderate grand mean of 3.35.

ii. Significant barriers to integration were identified, as reflected in secondary data where NNPC's digital readiness index improved only from 2.5 to 3.6 between 2020 and 2024 compared to Shell's consistently high baseline of 4.2–4.5, coupled with regulatory approval timelines still averaging over 145 days; this was reinforced by survey findings with a high overall mean of 4.15, confirming financial, infrastructural, and organizational barriers as critical constraints.

iii. Targeted application of AI yielded measurable performance improvements, with company reports indicating reductions in unplanned downtime from 5 percent to 18 percent in Shell PLC and from 0 percent to 28 percent in Dagrow Resources, alongside gradual increases in asset integrity indices across firms; survey analysis supported these findings with an overall mean of 4.22, demonstrating strong consensus on AI's contribution to efficiency, safety, and accountability.

Conclusion

This study examined the role of artificial intelligence in enhancing project management within the Nigerian oil and gas sector. The first objective was to assess the extent of adoption of AI tools in project management practices. The evidence demonstrated that adoption is progressing, with multinational firms displaying steady integration while indigenous companies pursue rapid expansion from relatively lower baselines. Although adoption remains uneven across firms, the results indicate a sector-wide recognition of AI's potential and a gradual embedding of these tools in project delivery processes.

The second objective focused on identifying the barriers hindering effective AI integration. The findings highlighted persistent financial, infrastructural, and organizational constraints. While multinational firms maintain strong digital readiness, indigenous firms continue to grapple with capability gaps. Regulatory approval processes also remain lengthy, slowing the pace of innovation. These barriers confirm that technological adoption is shaped not only by organizational intent but also by systemic weaknesses in institutional and infrastructural environments.

The third objective sought to determine project management performance areas most improved by AI. The study revealed that AI contributes substantially to reducing downtime, strengthening asset integrity, enhancing safety, and improving accountability. These improvements demonstrate that targeted applications deliver tangible operational benefits, even in a context marked by barriers. Collectively, the findings establish that AI has significant transformative potential for project management in the oil and gas sector. However, realizing this potential fully requires both organizational investments and reforms in broader institutional frameworks

Recommendations

1. Oil and gas firms should institutionalize structured investment strategies for AI adoption, ensuring that indigenous companies, in particular, are supported to close the capability gap with multinational peers.
2. Policy makers and regulators should streamline approval processes for novel AI technologies and address infrastructural deficiencies, especially in power stability, to create an enabling environment for effective AI integration.
3. Companies should prioritize targeted deployment of AI in performance-critical areas such as predictive maintenance, safety enhancement, and risk modeling to maximize operational efficiency and measurable value creation.

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