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Impact of Artificial Intelligence-Driven Project Management on Operational Performance in Oil and Gas Projects: A Structural Equation Modeling Approach

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	Abstract
Dr. Muhammad Asad Akram Bhatti Center for Research and Development, Minhaj University Lahore, Lahore, Pakistan, Email: asadbhatti42@gmail.com **Ahmed Tanveer Cheema (Corresponding Author)** Master of Business Administration, University of Bedfordshire, United Kingdom, Email: cheems@gmail.com	The oil and gas industry is a capital-intensive, high-risk sector in which project delays, cost overruns, and unmanaged operational risk carry substantial financial and safety consequences. Artificial intelligence (AI) is increasingly promoted as a lever for improving project management practice, yet the mechanisms and boundary conditions through which AI-driven project management (AI-PM) translates into operational performance (OP) remain insufficiently tested in this sector. Drawing on the resource-based view and dynamic capabilities theory, this study develops and tests a structural model in which project risk management (PRM) mediates, and organizational readiness (OR) moderates, the relationship between AI-PM and OP. Survey data were collected from 285 professionals working across the upstream, midstream, and downstream segments of the oil and gas value chain and analyzed using partial least squares structural equation modeling (PLS-SEM). The measurement model demonstrated adequate reliability, convergent validity, and discriminant validity. The structural model explained 41.1% of the variance in operational performance and 23.7% of the variance in project risk management, with acceptable predictive relevance. All five hypothesized relationships were supported: AI-PM positively affected OP directly and indirectly through PRM, and organizational readiness positively moderated the AI-PM-OP relationship. The findings suggest that AI-driven project management is most beneficial when it is embedded in strong risk management routines and supported by organizational readiness, offering both theoretical extensions to technology-performance research and practical guidance for oil and gas project organizations.
Keywords:	artificial intelligence, project management, operational performance, project risk management, organizational readiness, oil and gas, PLS-SEM

Introduction

The global oil and gas industry continues to operate under conditions of extreme capital intensity, technical complexity, and price volatility, all of which magnify the consequences of project management failure. Megaprojects in exploration, production, and downstream processing routinely experience schedule delays and cost overruns that erode shareholder value and, in the most severe cases, compromise safety and environmental performance. Against this backdrop, artificial intelligence has emerged as one of the most consequential technological developments affecting project-based organizations, with applications spanning predictive maintenance, automated scheduling, risk forecasting, and real-time decision support across the upstream, midstream, and downstream value chain (Mardanov et. al., 2026).

Industry evidence indicates that AI adoption in oil and gas has moved from isolated pilot programs toward enterprise-scale deployment, with predictive maintenance and digital twin initiatives now central to how supermajors and national oil companies pursue operational efficiency gains (Mardanov et. al., 2026; Al-Rbeawi, 2023). At the same time, practitioner-oriented literature emphasizes that AI tools such as automated verification, dynamic scheduling, and live analytics are reshaping how project managers plan, monitor, and control complex engineering, procurement, and construction (EPC) work. However, the diffusion of these tools into everyday project management practice does not automatically translate into improved operational outcomes; the mechanisms linking AI-driven project management to operational performance, and the organizational conditions under which this relationship is strongest, remain only partially understood (Bashir & Cheema, 2025; Ljarwan et. al., 2025).

A growing stream of research has examined AI applications in project risk management, showing that machine learning, natural language processing, and explainable AI techniques can improve risk identification, assessment, and response across complex, capital-intensive projects (Badhon et al., 2025). Parallel work on megaproject governance suggests that AI-enabled contractual knowledge management can strengthen risk allocation and reduce ambiguity in EPC settings (Malatesta & Mancini, 2025). Yet few studies have integrated these insights into a single structural model that simultaneously tests the direct effect of AI-driven project management on operational performance, its indirect effect through project risk management, and the moderating role of organizational readiness, and fewer still have done so within the specific context of oil and gas projects.

This study addresses that gap by developing and empirically testing a structural equation model of AI-driven project management (AI-PM), project risk management (PRM), organizational readiness (OR), and operational performance (OP) among project professionals in the oil and gas industry. The study is guided by the following research questions: (1) Does AI-driven project management have a significant positive effect on operational performance in oil and gas projects? (2) Does project risk management mediate the relationship between AI-driven project management and operational performance? (3) Does organizational readiness moderate the relationship between AI-driven project management and operational performance?

The remainder of this paper is organized as follows. Section 2 reviews the literature on AI-driven project management, project risk management, organizational readiness, and operational performance, and develops the study hypotheses. Section 3 describes the research design, sample, measures, and analytical approach. Section 4 presents the results of the measurement and structural model assessment and discusses their implications in light of prior literature. Section 5 concludes with theoretical and practical implications, limitations, and directions for future research.

2. Literature Review

2.1 Artificial Intelligence-Driven Project Management

AI-driven project management (AI-PM) refers to the systematic use of machine learning, natural language processing, optimization algorithms, and related analytics to support planning, scheduling, monitoring, and decision-making across the project lifecycle. In the oil and gas context, AI applications extend from automated seismic interpretation and drilling optimization in upstream operations to pipeline integrity analytics in midstream operations and process control in downstream refining (Mardanov et. al., 2026; Al-Rbeawi, 2023). Beyond these technical applications, AI is increasingly embedded directly in project management workflows through tools that support automated verification, dynamic scheduling, resource forecasting, and live analytical dashboards, allowing project managers to respond to emerging issues with greater speed and precision. Industry-focused analyses of AI implementation in the sector report measurable operational gains, including reductions in unplanned downtime and maintenance cost, when AI tools are deployed as an integrated capability rather than a stand-alone technology (Ljarwan et. al., 2025).

2.2 Project Risk Management

Project risk management (PRM) encompasses the systematic identification, assessment, response planning, and monitoring of risks that threaten project cost, schedule, quality, or safety objectives. In complex engineering and construction settings, AI technologies, including machine learning, computer vision, and knowledge-based reasoning, have been shown to strengthen each stage of the risk management lifecycle by improving the speed and accuracy of risk identification and by enabling more proactive response strategies (Badhon et. al., 2025). In megaproject and EPC environments specifically, AI-enabled contractual knowledge management has been proposed as a mechanism for reducing ambiguity in risk allocation and strengthening risk governance structures (Malatesta & Mancini, 2025). These findings support the theoretical expectation that AI-driven project management capabilities not only directly affect performance but also strengthen an organization's project risk management practices, which in turn protect operational outcomes.

2.3 Organizational Readiness

Organizational readiness (OR) refers to the extent to which an organization possesses the behaviors, resources, governance structures, and cultural conditions necessary to successfully adopt and scale a new technology or practice. Readiness is typically conceptualized along internal capability dimensions, such as strategy clarity, data infrastructure, talent, and governance, together with external alignment considerations (Sarstedt et. al., 2022; AlGhanem & Mendy, 2024). Evidence from technology adoption research consistently shows that organizations with higher readiness translate technology investment into performance improvement more effectively than organizations that adopt the same technology without corresponding organizational preparation, a pattern that is consistent with dynamic capabilities theory, in which the ability to reconfigure resources and routines around a new capability determines whether that capability generates competitive advantage (Bhatti & Cheema, 2025; Barney, 1991).

2.4 Operational Performance

Operational performance (OP) in the oil and gas context is typically assessed in terms of cost efficiency, schedule adherence, production reliability, safety outcomes, and asset uptime. Because the sector's value creation rests on a capital-intensive, tightly coupled chain of activities, even incremental improvements in operational reliability and efficiency can generate substantial financial and strategic benefits when scaled across large asset bases (Mardanov et. al., 2026). AI-enabled predictive maintenance and process optimization initiatives have been associated with measurable reductions in unplanned downtime and maintenance cost in large oil and gas operators, providing an evidentiary basis for expecting a positive relationship between AI-driven project management and operational performance (Ljarwan et. al., 2025).

2.5 Hypothesis Development and Conceptual Framework

Building on technology adoption theory (Venkatesh et. al., 2003), the resource-based view (Barney, 1991), and dynamic capabilities theory (Teece et. al., 1997), this study conceptualizes AI-driven project management as a technological resource whose performance effects depend on the risk management routines through which it is exercised and the organizational readiness conditions under which it is deployed. The conceptual framework, therefore, specifies AI-PM as the primary exogenous construct, PRM as a mediating mechanism, OR as a moderating condition, and OP as the ultimate outcome. Formally, the study tests the following hypotheses:

H1: Artificial Intelligence-Driven Project Management has a significant positive effect on Operational Performance in oil and gas projects.

H2: Artificial Intelligence-Driven Project Management has a significant positive effect on Project Risk Management.

H3: Project Risk Management has a significant positive effect on Operational Performance.

H4: Project Risk Management mediates the relationship between Artificial Intelligence-Driven Project Management and Operational Performance.

H5: Organizational Readiness positively moderates the relationship between Artificial Intelligence-Driven Project Management and Operational Performance.

3. Methodology

3.1 Research Design

This study adopted a quantitative, cross-sectional survey design to test the hypothesized structural relationships among AI-PM, PRM, OR, and OP. A structured questionnaire operationalized each construct using multi-item, reflective indicators adapted from established project management, technology adoption, and organizational readiness scales, measured on five-point Likert-type response formats.

3.2 Sample and Data Collection

Data were collected from 285 professionals employed across the upstream, midstream, and downstream segments of the oil and gas value chain, using a purposive sampling strategy targeting respondents with direct project management, engineering, or digital transformation responsibilities. Table 3.1 summarizes the composition of the final sample. Respondents were fairly distributed across value-chain segments, with upstream professionals forming the largest group, and across organizational roles spanning project management, technical, and digital transformation functions. The sample also reflected a range of professional experience and organizational types, including international oil companies, national oil companies, and EPC contractors or service providers, supporting the generalizability of the findings across the sector.

Table 3.1 Respondent Profile

Characteristic	Category	n	%
Value-chain segment	Upstream	128	44.9%
	Midstream	61	21.4%
	Downstream	96	33.7%
Role	Project Manager / PMO	94	33.0%
	Engineer / Technical Lead	112	39.3%
	Digital/AI Transformation Staff	79	27.7%
Years of experience	< 5 years	52	18.2%
	5–10 years	103	36.1%
	11–20 years	88	30.9%
	> 20 years	42	14.7%
Organization type	IOC / Supermajor	87	30.5%
	National Oil Company (NOC)	104	36.5%
	EPC Contractor / Service Provider	94	33.0%

3.3 Measures

AI-Driven Project Management, Project Risk Management, Organizational Readiness, and Operational Performance were each measured with multiple reflective indicators reflecting the definitions outlined in Section 2. Item wording drew on prior technology adoption and project management instruments, adapted to the oil and gas project context and refined through expert review prior to full-scale data collection.

3.4 Analytical Approach

The measurement and structural models were estimated using partial least squares structural equation modeling (PLS-SEM), a variance-based approach well suited to complex models involving mediation and moderation with a formative or predictive orientation (Hair et. al., 2022). Following current best-practice guidelines, the measurement model was first assessed for indicator reliability, internal consistency reliability (Cronbach's alpha and composite reliability), and convergent validity (average variance extracted, AVE), before discriminant validity was evaluated using the heterotrait-monotrait ratio of correlations (HTMT), which has been shown to outperform the Fornell-Larcker criterion in detecting discriminant validity problems (Hair & Alamer, 2022). The structural model was then evaluated using bootstrapped path coefficients (5,000 resamples), coefficients of determination (R^2), and the Q^2 predictive relevance statistic derived from blindfolding procedures, consistent with recommended PLS-SEM reporting practice (Hair et. al., 2024; Richter et. al., 2022). Mediation was tested using the indirect-effect approach with bootstrapped confidence intervals, and moderation was tested using an interaction term between the standardized organizational readiness and AI-PM indicators.

4. Results and Discussion

4.1 Measurement Model Assessment: Reliability and Convergent Validity

Table 4.1 presents the reliability and convergent validity statistics for the four latent constructs following item purification. All constructs retained between five and six items, with standardized loadings ranging from 0.688 to 0.861, exceeding the conventional 0.70 threshold for acceptable indicator reliability, with the small number of loadings between 0.688 and 0.70 retained on the basis of their contribution to content validity and composite reliability. Cronbach's alpha values ranged from 0.834 (Project Risk Management) to 0.872 (AI-Driven Project Management), and composite reliability (CR) values ranged from 0.883 to 0.902, both comfortably above the 0.70 benchmark and indicating strong internal consistency reliability across all constructs. Average variance extracted (AVE) values ranged from 0.567 (Organizational Readiness) to 0.607 (AI-Driven Project Management), all exceeding the 0.50 threshold recommended by Hair et. al. (2022), confirming that each construct's indicators share, on average, more variance with their respective latent construct than with measurement error. Taken together, these results support the reliability and convergent validity of the measurement model.

Table 4.1 Reliability and Convergent Validity

Construct	Items retained	Loading range	Cronbach's α	CR	AVE
AI-Driven Project Management (AI-PM)	6	0.712–0.861	0.872	0.902	0.607
Project Risk Management (PRM)	5	0.703–0.845	0.834	0.883	0.601
Organizational Readiness (OR)	6	0.688–0.832	0.841	0.887	0.567
Operational Performance (OP)	6	0.695–0.849	0.858	0.895	0.588

4.2 Discriminant Validity

Discriminant validity was assessed using the heterotrait-monotrait ratio of correlations (HTMT), presented in Table 4.2. All HTMT values fell well below the conservative threshold of 0.85, ranging from 0.441 (Project Risk Management-Organizational Readiness) to 0.634 (Project Risk Management-Operational Performance). Because every HTMT ratio remains below the recommended cutoff, the results indicate that each construct is empirically distinct from the others and that discriminant validity is established. The comparatively higher HTMT ratio between Project Risk Management and Operational Performance (0.634), while still well within acceptable limits, is consistent with the conceptual proximity of the two constructs implied by Hypothesis 3, in which risk management practice is expected to be a proximal driver of operational outcomes.

Table 4.2 Discriminant Validity: HTMT Ratios

	AI-PM	PRM	OR	OP
AI-PM	—			
PRM	0.612	—		
OR	0.487	0.441	—	
OP	0.598	0.634	0.452	—

4.3 Explained Variance and Predictive Relevance

Table 4.3 reports the coefficients of determination (R^2), adjusted R^2, and Q^2 predictive relevance statistics for the two endogenous constructs. AI-Driven Project Management explained 23.7% of the variance in Project Risk Management (adjusted $R^2 = 0.234$), a moderate effect indicating that AI-enabled tools account for a meaningful, though partial, share of the variation in how effectively project teams manage risk, leaving room for other antecedents such as contractual governance or team experience. The full structural model, incorporating AI-PM, PRM, and the OR-x-AI-PM interaction term, explained 41.1% of the variance in Operational Performance (adjusted $R^2 = 0.404$), which represents a substantial effect for a multi-construct behavioral model in a complex operational setting. Both endogenous constructs recorded positive Q^2 values obtained through the blindfolding procedure (0.152 for PRM and 0.268 for OP), confirming that the structural model possesses adequate predictive relevance for both outcomes, consistent with PLS-SEM reporting conventions (Hair et. al., 2024).

Table 4.3 Explained Variance and Predictive Relevance

Endogenous construct	R^2	Adjusted R^2	Q^2
Project Risk Management (PRM)	0.237	0.234	0.152
Operational Performance (OP)	0.411	0.404	0.268

4.4 Path Coefficients and Hypothesis Testing

Table 4.4 presents the standardized path coefficients, t-values, p-values, and 95% bootstrapped confidence intervals for each hypothesized relationship, and Table 4.5 summarizes the corresponding hypothesis testing decisions.

Table 4.4 Path Coefficients and Hypothesis Testing

Path	Hyp.	β	t-value	p-value	Supported?
AI-PM → OP	H1	0.284	4.66	< .001	Yes
AI-PM → PRM	H2	0.487	8.40	< .001	Yes

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Path	Hyp.	β	t-value	p-value	Supported?
PRM → OP	H3	0.362	5.66	< .001	Yes
AI-PM → PRM → OP	H4	0.398	4.29	< .001	Yes
OR × AI-PM → OP	H5	0.129	2.35	.019	Yes

Table 4.5 Hypothesis Testing Summary

Hypothesis	Relationship	Result
H1	AI-PM → Operational Performance	Supported
H2	AI-PM → Project Risk Management	Supported
H3	Project Risk Management → Operational Performance	Supported
H4	PRM mediates AI-PM → Operational Performance	Supported
H5	Organizational Readiness moderates AI-PM → Operational Performance	Supported

4.5 Discussion of the Structural Results

Hypothesis 1 was supported: AI-driven project management exerted a significant, positive direct effect on operational performance ($\beta = 0.284$, $t = 4.66$, $p < .001$). This result corroborates industry-level evidence that AI-enabled tools such as predictive maintenance, digital twins, and dynamic scheduling are associated with measurable operational gains in the oil and gas sector (Mardanov et. al., 2026; Ljarwan et. al., 2025), and extends this evidence to the specific context of project management practice rather than plant-level operations alone. The moderate effect size suggests that AI-PM is a meaningful but partial driver of operational performance, consistent with the view that technology adoption alone is rarely sufficient to generate performance gains without complementary organizational and risk management mechanisms.

Hypothesis 2 received the strongest support in the model: AI-driven project management had a substantial positive effect on project risk management ($\beta = 0.487$, $t = 8.40$, $p < .001$), the largest path coefficient in the structural model. This finding aligns closely with research showing that machine learning, natural language processing, and explainable AI techniques materially strengthen risk identification, assessment, and response processes in complex projects (Badhon et. al., 2025), and with evidence that AI-enabled contractual knowledge management can reduce risk allocation ambiguity in EPC settings (Malatesta & Mancini, 2025). The comparatively large magnitude of this path indicates that, within the oil and gas project context sampled here, AI's most immediate organizational contribution is to the rigor and responsiveness of risk management practice rather than to operational outcomes directly.

Hypothesis 3 was supported: project risk management had a significant positive effect on operational performance ($\beta = 0.362$, $t = 5.66$, $p < .001$), the second-largest path in the model. This is consistent with long-standing project management theory holding that disciplined risk identification and response planning protect cost, schedule, and safety outcomes, and it reinforces the conceptual logic that in capital-intensive, hazard-prone environments such as oil and gas, risk management functions as a critical operational safeguard rather than an administrative formality.

Hypothesis 4 was supported: the indirect effect of AI-driven project management on operational performance through project risk management was significant (indirect $\beta = 0.398$, $t = 4.29$, $p < .001$, 95% CI [0.101, 0.257]), confirming that project risk management partially mediates the AI-PM-OP relationship. Because the direct effect (H1) remained significant alongside the indirect effect, the pattern is best characterized as complementary partial mediation: AI-driven project management improves operational performance both directly, likely through efficiency and decision-support mechanisms, and indirectly, by strengthening the risk management routines through which project teams anticipate and respond to threats to cost, schedule, and safety (Baron & Kenny, 1986). This dual pathway is consistent with the theoretical framing of AI-PM as a resource that is most valuable when embedded in operational routines, echoing the resource-based view's emphasis on rare and difficult-to-imitate resource-routine bundles rather than technology in isolation (Barney, 1991).

Hypothesis 5 was supported: organizational readiness significantly and positively moderated the relationship between AI-driven project management and operational performance ($\beta = 0.129$, $t = 2.35$, $p = .019$, 95% CI [0.021, 0.238]). Although the interaction effect was smaller in magnitude than the main effects, its significance indicates that the performance benefit of AI-PM is not uniform across organizations: firms with stronger internal capabilities, governance structures, and change-readiness extract a greater operational return from the same AI-enabled project management practices. This finding is consistent with dynamic capabilities theory, which holds that the ability to reconfigure resources and routines around a new capability determines whether that capability translates into competitive advantage (Teece et. al., 1997), and with technology-readiness research showing that adoption outcomes depend heavily on organizational preparedness rather than on the technology itself (Sarstedt et. al., 2022; AlGhanem & Mendy, 2024).

Overall, the pattern of results, a strong AI-PM to PRM path, a strong PRM to OP path, a moderate direct AI-PM to OP path, significant partial mediation, and a significant but smaller moderation effect, paints a coherent picture in which AI-driven project management functions primarily as an enabler of stronger risk management practice, which then acts as the more proximal driver of operational performance, while organizational readiness determines how fully that potential is realized. This nuanced structure has practical implications discussed further in Section 5: oil and gas organizations seeking to maximize the performance returns from AI investment should prioritize integrating AI tools into risk management workflows and should invest in organizational readiness, rather than treating AI adoption as a stand-alone operational intervention.

5. Conclusion

5.1 Summary of Findings

This study developed and tested a structural equation model examining how AI-driven project management affects operational performance in oil and gas projects, both directly and through the mediating mechanism of project risk management, under the moderating condition of organizational readiness. Using survey data from 285 professionals and PLS-

SEM analysis, all five hypotheses were supported. AI-driven project management had a significant positive direct effect on operational performance and an even stronger effect on project risk management, project risk management in turn significantly improved operational performance and partially mediated the AI-PM-OP relationship, and organizational readiness significantly strengthened the AI-PM-OP relationship.

5.2 Theoretical Implications

The study contributes to the technology-performance literature by demonstrating that AI's operational value in project-based, high-risk industries operates substantially through its effect on risk management practice rather than through direct efficiency gains alone. This extends resource-based view and dynamic capabilities perspectives on technology adoption by empirically situating project risk management as a mediating routine and organizational readiness as a boundary condition within a single integrated model, addressing calls in the literature for more rigorous empirical tests of proposed AI value-creation pathways (Mardanov et. al., 2026).

5.3 Practical Implications

For practitioners, the findings suggest that oil and gas organizations should not evaluate AI-driven project management tools in isolation from risk management practice; rather, the strongest performance returns are likely to come from embedding AI capabilities directly within risk identification, assessment, and response workflows. Additionally, because organizational readiness significantly conditions the AI-PM-OP relationship, organizations should invest deliberately in governance structures, digital talent, and change-readiness alongside AI tool deployment, rather than assuming that technology acquisition alone will generate proportional performance gains.

5.4 Limitations and Future Research

This study is subject to several limitations. The cross-sectional design limits causal inference, and future research employing longitudinal or quasi-experimental designs would strengthen claims about the direction of the hypothesized relationships. The sample, while spanning the three value-chain segments and multiple organization types, was drawn using a purposive strategy and may not fully represent the global oil and gas project management population. Finally, because all constructs were assessed through self-reported survey measures, future studies could complement these findings with objective operational indicators, such as documented cost variance, schedule performance indices, or safety incident data, to further validate the proposed model.

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