



The Impact of Artificial Intelligence Adoption on Project Success in the Oil and Gas Industry: The Mediating Roles of Project Risk Management and Decision Quality

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ABSTRACT

Artificial intelligence (AI) adoption has become a strategic priority across the global oil and gas industry, yet the mechanisms through which AI adoption translates into improved project success remain incompletely understood. This paper examines the relationship between AI adoption and project success in oil and gas projects, focusing on the mediating roles of project risk management and decision quality. Drawing on the Theory of Constraints, the Resource-Based View, and Dynamic Capabilities Theory, a dual-mediation conceptual model is proposed in which project risk management and decision quality operate as parallel mediators between AI adoption and project success. A qualitative, secondary-documentary research design was adopted, reflecting the global scope of the research questions and the impracticality of large-scale primary data collection at the level of an individual study. Twenty-four academic and industry sources were purposively sampled and analysed using a six-phase thematic content analysis structured around seven hypotheses. The findings provide qualified support for all seven hypotheses: AI adoption is positively, but conditionally, associated with project success, and this relationship is substantially transmitted through strengthened risk management, particularly in technical, safety, and compliance risk domains, and through improved decision quality, particularly via enhanced information access, predictive accuracy, and decision speed. Evidentiary support for the risk-management pathway is found to be stronger and more direct than for the decision-quality pathway, reflecting the relative maturity of the underlying literatures. The persistent gap between AI investment and realised project benefit documented in the industry literature is best explained not as a failure of AI technology itself, but as a failure to build the complementary organisational capabilities required to convert AI-generated insight into improved project outcomes. Theoretically grounded and practically actionable recommendations, together with priorities for future primary research, are offered.

Keywords: artificial intelligence adoption; project success; project risk management; decision quality; oil and gas industry; mediation; dynamic capabilities

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1. Introduction

The global oil and gas industry is in the midst of a sustained, capital-intensive wave of digital transformation, of which artificial intelligence (AI) adoption is the most visible and fastest-growing component. Machine learning, predictive analytics, natural language processing, and increasingly autonomous systems are being deployed across the exploration, drilling, production, and commercial functions of upstream, midstream, and downstream operations, with industry spending on AI in the sector projected to nearly double over the second half of the 2020s. This scale of investment reflects a widely shared expectation that AI can help address a problem that has proven remarkably resistant to decades of conventional project-management reform: the persistent tendency of oil and gas megaprojects to overrun their sanctioned cost and schedule baselines, often by margins measured in tens of percentage points. Yet a closer reading of the emerging literature reveals a more cautious picture than the scale of investment alone would suggest. Industry and academic sources increasingly draw a sharp distinction between AI adoption, the acquisition and piloting of AI tools, and AI realisation, the sustained conversion of that technology into measurable project and organisational benefit. Companies that adopt AI do not automatically realise its benefits, and a persistent gap between AI spending and realised value has been documented across multiple independent sources. This adoption-realisation gap is the central empirical puzzle motivating the present paper.

The dominant explanation offered for this gap in the practitioner literature is organisational rather than technical: AI initiatives fail to generate sustained project benefit not because the underlying algorithms are inadequate, but because the surrounding organisational capabilities, cross-functional governance, data foundations, and a clear line from AI-generated insight to actual project decisions, are absent or underdeveloped. This explanation, however, has rarely been formalised into a testable conceptual model that specifies which organisational capabilities matter most and how they connect AI adoption to project-level outcomes. Much of the existing academic literature on AI in oil and gas project management, meanwhile, treats AI adoption and project performance as a simple, direct, bivariate relationship, an approach difficult to reconcile with the qualitative organisational explanations advanced elsewhere in the same literature. This paper responds to that gap by proposing and evaluating a dual-mediation model of the relationship between AI adoption and project success in the global oil and gas industry, in which project risk management and decision quality are treated as parallel mediating capabilities. The model is grounded in three complementary organisational theories, the Theory of Constraints, the Resource-Based View, and Dynamic Capabilities Theory, each offering a distinct rationale for why a technological resource such as AI should be expected to affect project outcomes indirectly, through organisational capability, rather than directly.

Specifically, the paper addresses three research questions. First, is AI adoption associated with improved project success in the global oil and gas industry, and if so, is this relationship direct or conditional? Second, is AI adoption associated with strengthened project risk management and improved decision quality, and through which specific mechanisms? Third, do project risk management and decision quality plausibly mediate the relationship between AI adoption and project success, and does the strength of evidence differ between the two pathways? These questions are examined through a systematic thematic analysis of twenty-four purposively sampled academic and industry sources, evaluated against seven hypotheses derived from the conceptual model.

The paper is intended to be of direct relevance to project sponsors, project management offices, and technology-investment decision-makers across national oil companies and

international majors alike, by offering a more precise basis for prioritising AI investment between risk-analytics and decision-support applications, and by clarifying which organisational capabilities most strongly transmit AI's benefit to project outcomes. It is also intended to contribute, at the theoretical level, an integrated account bridging the largely descriptive, technology-cataloguing tradition of the oil and gas AI literature and the more mature, mediation-focused tradition of the general project-management literature.

The remainder of the paper is organised as follows. Section 2 develops the theoretical framework and the seven hypotheses that structure the study. Section 3 sets out the secondary-documentary research design and analytical method. Section 4 presents the findings, organised hypothesis by hypothesis. Section 5 discusses these findings in relation to theory and identifies an important asymmetry between the two mediating pathways. Section 6 sets out theoretical and practical implications, Section 7 acknowledges the study's limitations and proposes a future-research agenda, and Section 8 concludes.

2. Theoretical Framework and Hypothesis Development

2.1 Theoretical Foundations

The conceptual model developed in this paper rests on three complementary organisational theories. The Theory of Constraints (TOC), originally developed by Goldratt (1984), holds that the performance of any system is governed by a small number of binding constraints, and that systematic identification and management of these constraints is the most effective route to overall performance improvement. Applied here, TOC implies that AI adoption will improve oil and gas project performance only to the extent that it addresses the binding constraint on that performance, whether that constraint lies in risk-identification capability, decision-making capacity, or elsewhere, rather than through the mere availability of data or computational tools.

The Resource-Based View (RBV), most closely associated with Barney (1991), argues that sustained competitive advantage arises from resources that are valuable, rare, imperfectly imitable, and non-substitutable. Within this framework, AI is best conceptualised as a valuable but increasingly imitable organisational resource, whose competitive value is realised only when it is embedded within complementary, harder-to-imitate organisational routines. Dynamic Capabilities Theory (Teece, Pisano, & Shuen, 1997) extends RBV by focusing on a firm's capacity to sense opportunities and threats, seize them through timely action, and reconfigure resources accordingly, a framing that maps naturally onto AI-enabled risk sensing, AI-informed decision-making (seizing), and the adaptation of project plans in response to AI-generated insight (reconfiguration).

Table 1 summarises how each theory informs a specific element of the conceptual model: a valuable technological resource (RBV) can only overcome the binding constraint on project performance (TOC) to the extent that the organisation possesses the sensing and seizing capabilities (Dynamic Capabilities Theory) needed to convert that resource into action. The three perspectives are therefore treated not as competing explanations but as complementary layers of a single underlying logic.

Table 1. Integration of the Theoretical Framework with the Conceptual Model

Theory	Core Proposition	Application in This Study
Theory of Constraints (Goldratt, 1984)	Performance is governed by binding constraints; addressing the constraint improves the whole system.	AI adoption improves project success only insofar as it addresses the binding constraint, modelled here as risk-management and decision-making capability.
Resource-Based View (Barney, 1991)	Sustained advantage arises from valuable, rare, inimitable, non-substitutable resources.	AI is a valuable but imitable resource; risk management and decision quality are the rarer capabilities that convert AI into advantage.
Dynamic Capabilities Theory (Teece et al., 1997)	Firms must sense opportunities, seize them through timely action, and reconfigure resources.	AI-enabled risk analytics correspond to sensing; AI-informed decision-making corresponds to seizing; project adaptation corresponds to reconfiguration.

2.2 AI Adoption in the Oil and Gas Industry

The oil and gas sector has undergone a sustained, if uneven, wave of AI adoption. Industry surveys report that roughly forty-four percent of upstream exploration and production companies already use AI in some form, with a further forty-five percent planning implementation within three years, and comparable trends in downstream operations. Documented applications span the full project lifecycle: reservoir simulation, seismic interpretation, and drilling optimisation upstream; predictive maintenance of pipelines and platforms midstream and downstream; and automated compliance verification, on-site quantity take-off, and dynamic scheduling at the level of project management itself. Notwithstanding this range of applications, the literature increasingly distinguishes adoption from realisation. A recent thematic review concludes that many oil and gas companies can experiment with AI tools but few sustain long-term benefit, attributing the difference to three families of driver, people-related, technical, and managerial, that determine whether initial adoption converts into durable performance gains. This adoption-realisation distinction is the central empirical anchor for the mediation logic developed in this paper: if AI's effect on project success depended only on the technology itself, adoption and realisation would not diverge so systematically.

2.3 Project Risk Management in Oil and Gas Projects

Project risk management has long been documented as a critical, and only partially solved, determinant of oil and gas project performance, given the sector's exposure to subsurface uncertainty, commodity-price volatility, complex contracting, and stringent safety and environmental regulation. Influential reviews of megaproject cost overruns report that a majority of ongoing hydrocarbon megaprojects worldwide experience cost overruns, with

average escalation on the order of fifty to sixty percent relative to sanction estimates in some benchmarked samples, and root-cause analyses consistently point to inadequate risk identification and weak front-end scope definition as central contributors. AI-enabled risk analytics have been proposed as a means of improving the timeliness, granularity, and predictive accuracy of risk identification, moving risk management from a periodic, expert-elicitation-based process toward a continuous, real-time one. Automated verification and compliance-monitoring tools are highlighted as mechanisms for reducing contractual and regulatory non-conformance, while predictive-maintenance algorithms convert traditionally reactive asset-integrity management into a proactive function. This positions project risk management as a plausible mediating mechanism: AI adoption strengthens risk-management capability, which in turn is expected to improve project outcomes.

2.4 Decision Quality in Project Management

Decision quality has received growing attention in the broader project-management literature as an intervening variable explaining how diverse antecedents, from leadership style to governance structure, translate into project success. Studies of project steering committees find that individual responsibility, shared goals, and mutual trust jointly predict a substantial share of variance in project success, operating through the quality of collective decision-making. Parallel studies of emotional intelligence, transformational leadership, and shared leadership each find that the effect of the antecedent on project success operates substantially, and in some cases entirely, through such intervening mechanisms rather than directly. In the specific context of AI, decision quality is understood as the extent to which AI-generated insight, whether predictive analytics, automated verification, or real-time dashboards, translates into project decisions that are timely, well informed, and appropriately robust to residual uncertainty. Practitioner analysis explicitly links AI adoption to improved decision-making through real-time data analysis and predictive analytics, and to more cost-effective strategic decisions through the integration of market signals into operational and financial planning.

2.5 Project Success as a Multi-Dimensional Construct

Project success has evolved in the literature from the narrow cost-time-quality 'iron triangle' toward a broader, multi-dimensional construct incorporating stakeholder satisfaction and strategic alignment. For the purposes of this paper, project success in the oil and gas context is understood to encompass cost and schedule performance relative to the sanctioned baseline, safety and environmental performance, technical quality and scope delivery, and stakeholder satisfaction, an operationalisation reflecting the scale, complexity, and heightened safety and environmental exposure of oil and gas megaprojects.

2.6 The Research Gap

Three separate but related bodies of evidence emerge from the literature reviewed above: that AI adoption in oil and gas is extensive and growing but unevenly realised; that project risk management remains a critical and only partially solved challenge; and that decision quality is increasingly recognised, across the broader project-management literature, as a key mediating mechanism linking antecedent capabilities to project success. What is notably absent is a study that integrates these three bodies of evidence into a single model applied specifically to the global oil and gas industry. Existing AI-in-oil-and-gas studies are predominantly technical or descriptive, cataloguing applications without formally testing how AI adoption relates to project success through intervening organisational capabilities; existing

risk-management and decision-quality mediation studies, conversely, rarely engage AI as the antecedent variable. This paper addresses that gap directly.

2.7 Conceptual Model and Hypotheses

Drawing on the theoretical framework and literature reviewed above, this paper proposes a conceptual model in which AI adoption is the independent variable, project risk management and decision quality are parallel mediating variables, and project success is the dependent variable, illustrated in Figure 1. Project risk management and decision quality are modelled as parallel, rather than sequential, mediators because they are conceptually distinct capabilities, addressing respectively the identification and control of uncertain events and the quality of choices made in response to available information, even though the two are clearly related in practice.

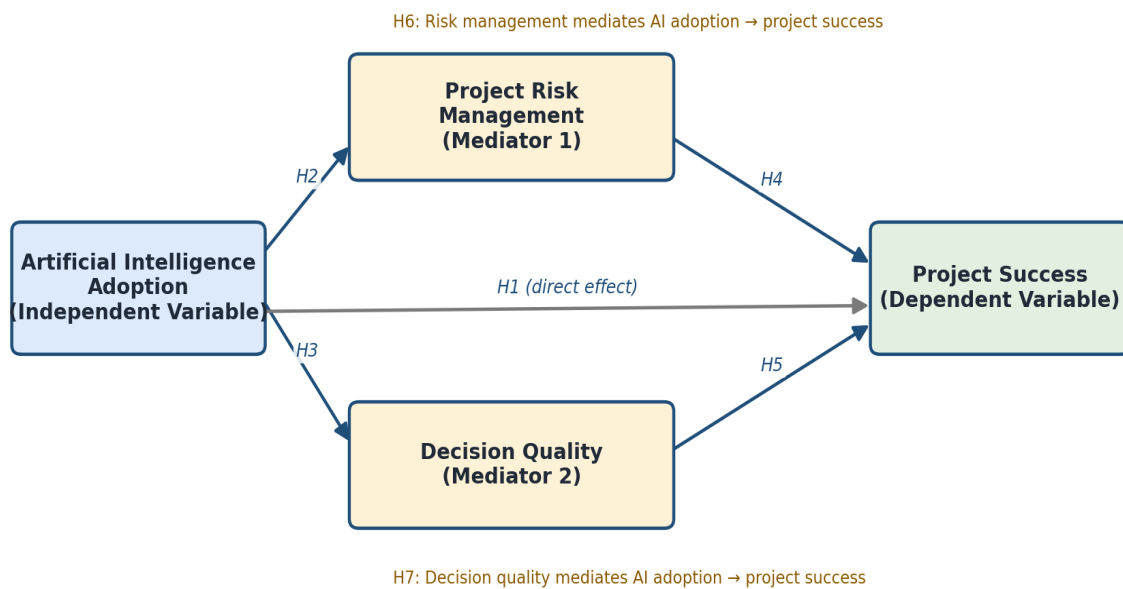


Figure 1. Conceptual Framework: AI Adoption, Project Risk Management, Decision Quality, and Project Success

On this basis, the study proposes and evaluates the following seven hypotheses:

H1: Artificial intelligence adoption has a significant positive relationship with project success in the global oil and gas industry.

H2: Artificial intelligence adoption has a significant positive relationship with project risk management in oil and gas projects.

H3: Artificial intelligence adoption has a significant positive relationship with decision quality in oil and gas project management.

H4: Project risk management has a significant positive relationship with project success in the global oil and gas industry.

H5: Decision quality has a significant positive relationship with project success in the global oil and gas industry.

H6: Project risk management mediates the relationship between artificial intelligence adoption and project success in oil and gas projects.

H7: Decision quality mediates the relationship between artificial intelligence adoption and project success in oil and gas projects.

3. Methodology

3.1 Research Philosophy and Design

This study adopts an interpretivist-leaning post-positivist research philosophy and a qualitative, secondary-documentary research design, involving the systematic identification, selection, and thematic analysis of existing academic and industry evidence rather than the collection of new primary data. This design choice reflects three considerations specific to the research problem. First, the research questions concern patterns operating across the global oil and gas industry as a whole, a scale at which primary data collection through, for example, a global survey of project managers would be impractical for an individual study and unlikely to achieve genuine representativeness. Second, a substantial and rapidly growing body of academic, industry, and case-study evidence already exists, produced by consultancies, industry bodies, and peer-reviewed researchers with access to project-benchmarking data not otherwise available to an independent researcher. Third, the design builds directly on the established systematic-review tradition already applied to AI in oil and gas project performance. A deductive approach is used at the level of framework development, since the conceptual model and hypotheses set out in Section 2 are derived from established theory prior to data collection, while the analysis of the secondary data itself proceeds inductively at the level of theme identification. This mixed deductive-inductive logic is consistent with theory-elaboration approaches increasingly used in project-management and technology-adoption research.

3.2 Data Collection and Sampling

Data were collected through a structured search of peer-reviewed academic databases (including ScienceDirect, Emerald Insight, Wiley Online Library, PMC/PubMed Central, and arXiv), professional and industry publications, and academic dissertations addressing megaproject risk and cost performance, supplemented by forward and backward citation tracing. Sources were included where they met four criteria: direct relevance to at least one of the four core constructs; a focus on, or generalisable applicability to, the oil and gas or comparable capital-project industries; sufficient methodological or evidentiary transparency to allow claims to be traced and assessed; and publication by a recognised academic publisher, professional body, or established industry research organisation. A purposive sampling strategy was applied, aimed at thematic saturation rather than statistical representativeness. From an initial candidate pool of approximately eighty sources identified through database searching and citation tracing, twenty-four sources meeting all inclusion criteria were retained for detailed analysis, spanning peer-reviewed journal articles, systematic literature reviews, industry analyses, and doctoral dissertations, with the substantial majority published between 2022 and 2026 to ensure the currency of evidence relating to a fast-moving technology. Table 2 summarises the composition of the final sample by source type.

Table 2. Composition of the Final Secondary-Source Sample (N = 24)

Source Type	Number	Primary Contribution
Peer-reviewed journal articles	13	Risk-management, decision-quality, and project-success mediation evidence
Systematic literature reviews	3	AI realisation vs. adoption; AGI trajectory
Industry / consultancy reports	4	AI applications; implementation barriers; market data
Doctoral dissertations	1	Megaproject cost overrun; risk management
Foundational theory sources	3	Theory of Constraints; Resource-Based View; Dynamic Capabilities

3.3 Data Analysis Technique

The secondary data were analysed using thematic (content) analysis, following the widely used six-phase approach of familiarisation, initial coding, theme search, theme review, theme definition, and reporting. Each source was read in full and coded against a structured framework aligned to the study's seven hypotheses, capturing statements relevant to the nature of AI adoption, the relationship between AI adoption and risk-management practice, the relationship between AI adoption and decision quality, the relationships between the two mediators and project success, and evidence bearing on the plausibility of mediation. Coded statements were then synthesised across sources to identify convergent and divergent findings for each hypothesis, reported in Section 4 using both narrative discussion and summary tables.

3.4 Trustworthiness, Ethics, and Limitations of the Method

Because this design does not involve statistical sampling or hypothesis testing on primary data, trustworthiness was pursued through measures analogous to credibility, transferability, dependability, and confirmability: a transparent, replicable search-and-selection protocol; explicit coding aligned to the hypotheses; purposive sampling across regions and source types to support transferability; and full source attribution such that every claim in Section 4 is traceable to an identifiable secondary source. No claims are made that are not supported by a cited source, and all sources analysed are listed in the reference list below. Because the sources reviewed are themselves predominantly cross-sectional, descriptive, or case-study in nature, the study establishes the plausibility and directional consistency of the hypothesised relationships rather than statistical causality, a distinction maintained throughout the presentation of findings through deliberately qualified language such as supported, plausible, and consistent with, rather than proves or demonstrates conclusively.

4. Findings

4.1 Overview of the Evidence Base

Of the twenty-four sources analysed, the majority (eighteen) were published between 2022 and 2026. Geographically, the sources collectively addressed operations in North America, the Gulf Cooperation Council states, East Asia, and West Africa, together with global or cross-regional industry survey data, supporting the transferability of the findings across the diverse contexts in which oil and gas projects are executed worldwide. The reviewed evidence base spans the full project lifecycle, from exploration and appraisal through drilling, production, and commercial planning, to safety and compliance functions, with the exploration and production stages accounting for a larger share of the technically detailed academic literature and the commercial and safety functions addressed comparatively more often in industry and practitioner sources.

4.2 AI Adoption and Project Success (H1)

The reviewed evidence provides consistent, though largely indirect, support for a positive association between AI adoption and project success. Industry survey data indicate that adoption is already extensive, with roughly forty-four percent of upstream exploration and production companies reported to be using AI and a further forty-five percent planning implementation within three years. Where AI has been embedded in specific project functions, sources report tangible benefits: operators applying AI to reservoir simulation, seismic processing, and drilling optimisation report substantial improvements in operational efficiency and cost reduction. However, the evidence base is notably more cautious than a simple positive-association finding would suggest. The thematic review of AI realisation in the sector explicitly distinguishes basic adoption from sustained realisation, reporting that only a subset of adopting companies achieve long-term benefit. Consistent with this, practitioner analysis identifies a persistent implementation gap between AI spending, projected to grow from approximately 3.54 billion United States dollars in 2025 to 6.4 billion dollars by 2030, and the value actually realised by many adopting organisations. To place this in context, headline megaproject performance statistics show a majority of ongoing hydrocarbon megaprojects worldwide experiencing cost overrun, with average cost escalation of approximately fifty-nine percent and average schedule overrun of approximately thirty-five months relative to sanction. Taken together, this body of evidence supports H1 in a qualified form: AI adoption is associated with improved project outcomes, but the strength of this association appears highly dependent on the mediating capabilities examined under H6 and H7, rather than operating as a strong, unconditional direct effect.

4.3 AI Adoption and Project Risk Management (H2)

Multiple sources document a positive relationship between AI adoption and risk-management capability. Practitioner literature highlights automated verification tools as a mechanism for reducing contractual and regulatory non-conformance, and real-time data analysis as a means of identifying emerging risks earlier than traditional periodic review cycles allow. Predictive-maintenance applications, which use machine-learning models to anticipate equipment failure before it occurs, convert a traditionally reactive maintenance and safety function into a proactive one. At the same time, the megaproject risk-management literature suggests that the risks most responsible for cost and schedule failure, arising from the complex interaction of technical uncertainty, human factors, organisational culture, and external political and market conditions, are precisely the risks hardest for any single analytical tool, including AI, to fully capture. Table 3 summarises the evidence relating to H2 across four risk domains.

Table 3. Evidence Summary: AI Adoption and Project Risk Management (H2)

Risk Domain	Nature of AI Contribution	Strength of Evidence
Technical / subsurface risk	Improved seismic and reservoir-model accuracy	Strong
Safety / asset-integrity risk	Predictive maintenance; incident prediction	Strong
Compliance / contractual risk	Automated verification and non-conformance detection	Moderate
Systemic / organisational risk	Limited direct AI contribution documented	Weak-to-moderate

On balance, the weight of evidence supports H2: AI adoption is positively associated with project risk-management capability, most strongly in the technical, safety, and compliance risk domains, with a comparatively weaker but still discernible contribution to the broader systemic risks that dominate megaproject cost-overrun research.

4.4 AI Adoption and Decision Quality (H3)

Evidence relating to AI adoption and decision quality is concentrated in sources addressing real-time analytics and market-responsive planning. AI is reported to enhance decision-making by providing real-time data analysis and predictive analytics, and by significantly improving the knowledge base available to engineers and other project stakeholders through instant access to relevant information. At the commercial and strategic-planning level, AI-enabled integration of real-time market signals into operational and financial planning is reported to support dynamic adjustment of production schedules and drilling programmes, more efficient balancing of capital and operating expenditure, and more cost-effective strategic decisions. This evidence aligns closely with the broader project-management mediation literature, which consistently finds that decision-making quality, rather than the antecedent capability or technology itself, is the proximate mechanism through which organisational inputs affect project outcomes. The available evidence therefore supports H3, although it is worth noting explicitly that this support is somewhat less direct than that for H2: few of the reviewed sources measure decision quality using an explicit, validated instrument, and most instead describe plausible mechanisms rather than directly measuring the construct.

4.5 Risk Management, Decision Quality, and Project Success (H4 and H5)

The relationship between project risk management and project success is strongly supported, largely through evidence of the converse relationship: the persistent absence of effective risk management is consistently identified as a principal driver of project failure, with root-cause analyses pointing to inadequate risk identification and weak front-end scope definition as central contributors to cost escalation. By clear implication, and consistent with H4, stronger risk-management practice, including the capabilities strengthened by AI adoption

documented above, is associated with improved project success. Support for H5 is drawn primarily from the broader project-management mediation literature, since oil-and-gas-specific sources rarely isolate decision quality as a standalone construct. The available evidence is nonetheless directionally consistent: studies of project governance and steering-committee effectiveness find that a substantial proportion of variance in project success is explained by variables operating through the quality of collective decision-making, while studies of leadership and project success across multiple project-based industries consistently find that the effect of leadership antecedents on project success operates through intervening decision- and behaviour-related variables. Table 4 summarises the combined evidence for H4 and H5, noting an important difference in evidentiary character: the evidence for H4 is drawn predominantly from within-industry studies, lending it strong contextual relevance, while the evidence for H5 is drawn predominantly from other project-based industries and is therefore analogically rather than contextually supportive.

Table 4. Evidence Summary: Risk Management, Decision Quality, and Project Success (H4, H5)

Hypothesis	Key Supporting Evidence	Assessment
H4: Risk management -> Project success	Cost-overrun literature; LNG megaproject risk frameworks	Supported
H5: Decision quality -> Project success	Project governance / steering-committee studies; leadership-mediation literature	Supported (indirect evidence)

4.6 Mediating Roles of Risk Management and Decision Quality (H6 and H7)

The strongest single piece of evidence bearing directly on the study's mediation hypotheses is the explicit adoption-versus-realisation distinction found in the thematic review of AI in the oil and gas sector, which finds that AI adoption alone rarely produces sustained performance benefit and that the presence of complementary managerial and organisational capabilities differentiates companies that realise long-term value from those that do not. This finding is directly consistent with a mediation structure, since it implies that AI adoption's effect on project outcomes passes through, rather than bypasses, organisational capabilities of precisely the kind represented here by risk management and decision quality. Further indirect support comes from the wider project-management literature, in which technology- and leadership-related antecedents are repeatedly found to affect project success through intervening variables rather than directly. It is important to be precise about what this evidence does, and does not, establish. Because no single source in the reviewed evidence base tests the full seven-hypothesis model directly, the support for H6 and H7 is best characterised as convergent plausibility rather than statistical confirmation: multiple independent bodies of evidence, drawn from different countries, industries, and research traditions, point consistently toward the same underlying mediation logic, even though no single study establishes it definitively. This form of triangulated support is a recognised and legitimate basis for theory-building research, particularly at the stage of proposing a novel conceptual model prior to formal empirical testing. Figure 2 presents a visual synthesis of the qualitative evidence strength assessed for each of the seven hypotheses, consolidating the assessments made throughout this section. It shows clearly that the risk-management pathway (H2, H4, H6) is evidenced more strongly and directly than the decision-quality pathway (H3, H5, H7).

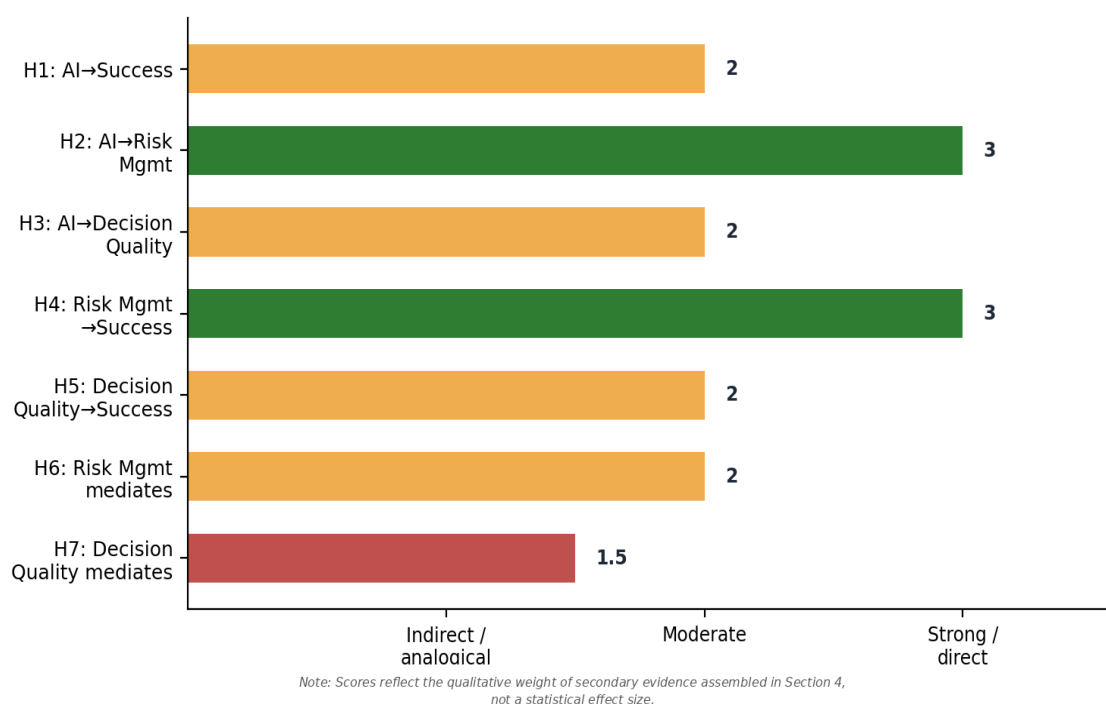


Figure 2. Qualitative Evidence Strength Across the Seven Hypotheses

4.7 Regional Evidence and Barriers to Realization

Given the concentration of global oil and gas capital investment in the Gulf region, case-study evidence from Qatari liquefied natural gas megaprojects supports both the risk-management pathway and the broader mediation logic, finding that enhanced, purpose-built risk-management frameworks, of which AI-enabled analytics form one increasingly important component, are necessary to assist decision-makers in responding to the scale and interdependence of risks characteristic of large Gulf LNG developments. Structural equation modelling research on generative AI and machine-learning adoption across the oil and gas value chain, incorporating Gulf Cooperation Council data, similarly finds that productivity gains are conditional on complementary organisational and internationalisation factors, directly reinforcing this paper's central finding. Beyond the hypothesis-specific evidence, the reviewed sources converge on a consistent set of organisational barriers that help explain why AI adoption does not automatically translate into project success. Practitioner analysis identifies seven pillars of successful AI implementation, tying initiatives to specific business goals, building a strong data foundation, assembling cross-functional teams, capturing early wins, integrating AI into existing workflows, driving front-line adoption, and fostering continuous learning, arguing that failure on any of these dimensions is a common cause of implementation failure. These barriers map more heavily onto the decision-quality pathway than onto the risk-management pathway, since people-related and organisational-cultural barriers primarily affect whether AI-generated insight is used in decision-making rather than the technical accuracy of AI-generated risk analytics itself, helping to explain the asymmetry documented in Figure 2.

5. Discussion

The findings indicate that artificial intelligence adoption is positively, but conditionally, associated with project success in the global oil and gas industry, and that this relationship is substantially transmitted through the mediating capabilities of project risk management and

decision quality, with the relative strength of evidence differing markedly between the two hypothesised pathways, as established in Section 4 and summarised in Figure 2.

5.1 Interpretation Through the Theoretical Framework

This pattern is consistent with, and provides empirical grounding for, the theoretical framework developed in Section 2. The Theory of Constraints suggests that a distal input such as AI adoption can only improve project performance to the extent that it addresses the binding constraint on that performance; the finding that AI's contribution to project success is strongest where it demonstrably strengthens risk-identification and decision-making capability, and weaker where the constraining factor is the broader systemic and organisational complexity long documented in megaproject research, is directly consistent with this logic. The Resource-Based View is similarly supported by the finding that AI adoption alone is an insufficient source of project advantage; value is realised only where AI is embedded within complementary organisational capabilities. Dynamic Capabilities Theory, finally, is supported by the specific mechanisms identified: AI's contribution to risk management operates substantially through improved sensing, in the form of predictive analytics and automated risk detection, while its contribution to decision quality operates substantially through improved seizing, in the form of faster, better-informed decision-making.

5.2 The Asymmetry Between the Two Mediating Pathways

The finding that evidentiary support for the risk-management pathway (H2, H4, H6) is stronger and more direct than for the decision-quality pathway (H3, H5, H7) is an important, and to date underappreciated, finding. It suggests that the oil and gas AI literature has been more attentive to AI's technical risk-management applications, in seismic interpretation, predictive maintenance, and compliance monitoring, than to its organisational decision-quality applications, and that researchers wishing to study the latter pathway in depth may need to draw more heavily on the general project-management literature than on oil-and-gas-specific sources, as was necessary here. This asymmetry also helps explain the persistent gap between AI investment and realised project benefit documented throughout the practitioner literature: organisations that invest in AI tools without corresponding investment in the risk-management and decision-making routines needed to act on AI-generated insight would be expected to experience precisely the muted returns that the practitioner literature describes.

5.3 Regional and Technological Heterogeneity

A further discussion point concerns the heterogeneity of the evidence base across regions and technology generations. The finding that generative AI and machine-learning productivity gains are conditional on complementary internationalisation and organisational factors in Gulf Cooperation Council contexts specifically suggests that the strength of the dual-mediation model may not be uniform across the global oil and gas industry, even though the model itself is found to be broadly applicable. Organisations operating in contexts where complementary organisational capability is less developed should expect a correspondingly weaker realised benefit from a given level of AI investment, a pattern directly consistent with the adoption-realisation literature reviewed throughout Section 2.

6. Theoretical and Practical Implications

6.1 Theoretical Contributions

This paper makes three principal theoretical contributions. First, it extends the application of the Theory of Constraints, the Resource-Based View, and Dynamic Capabilities Theory, individually well established in the general management literature, to the specific and increasingly important context of AI adoption in oil and gas project management, demonstrating that these theories offer complementary and mutually reinforcing explanations for why AI adoption's effect on project success should operate through intervening organisational capabilities rather than directly. Second, it proposes and provides qualitative empirical support for a dual-mediation model, in which project risk management and decision quality operate as parallel mediators, that has not previously been articulated in an integrated form in the oil and gas AI literature. Third, by adopting a global rather than single-country or single-company scope, the paper contributes a more broadly transferable account of these relationships than the case-study-dominated literature on oil and gas megaprojects has typically provided.

6.2 Practical and Managerial Implications

For project sponsors and technology-investment decision-makers, the central implication is that AI investment decisions should not be evaluated solely on the technical capability of the AI tool under consideration, but on the organisation's readiness to convert that capability into strengthened risk-management and decision-making practice. For project management offices, the finding that AI's risk-management contribution is strongest in technical, safety, and compliance risk domains, but comparatively weaker for the broader systemic risks that dominate megaproject cost-overflow research, suggests that AI-enabled risk analytics should complement, rather than substitute for, governance-level practices such as robust front-end scope definition. For decision-support system designers, the finding that AI's contribution to decision quality operates substantially through improved information access, predictive accuracy, and decision speed suggests that investment in integrated, real-time data platforms may generate greater benefit than investment in AI tools that operate in isolation from the broader project information environment. On the basis of these implications, five complementary recommendations are offered to oil and gas project sponsors, project management offices, and technology-investment decision-makers, intended to be read as a sequenced but complementary implementation package rather than as independent options:

- (i) Assess proposed AI investment against the organisation's existing risk-management and decision-making maturity, not against the technical capability of the AI tool alone.
- (ii) Pair AI-enabled risk-analytics deployments with continued governance-level risk practice, including front-end scope definition and stakeholder alignment.
- (iii) Invest in integrated, real-time data platforms that connect AI-generated insight directly to project decisions.
- (iv) Establish cross-functional AI-implementation teams with a clear mandate to act on AI-generated insight.
- (v) Track downstream outcomes, cost, schedule, safety, and decision speed, rather than the extent of AI adoption alone.

The evidence reviewed throughout this paper suggests that partial implementation, for example investing in AI-enabled risk analytics without establishing the cross-functional governance needed to act on their outputs, is a recurring pattern behind the AI investment-realisation gap documented in the literature, which is why these five measures are intended to be adopted together rather than piecemeal.

7. Limitations and Future Research

This study is subject to several limitations that follow directly from its secondary-documentary research design. First, statistical mediation is not tested using primary quantitative data or structural equation modelling; the mediating roles of risk management and decision quality are evaluated qualitatively and should be understood as well supported but not statistically confirmed. Second, the evidence base, while global in scope, is unevenly distributed across regions and companies, with a relative scarcity of evidence specific to smaller national oil companies. Third, because AI technology and its application in oil and gas are evolving rapidly, some reviewed evidence may not reflect subsequent developments. Fourth, reliance on published secondary sources means the study inherits any limitations, including potential publication bias toward successful implementations, present in the underlying literature. Fifth, and most importantly, the two mediating pathways are supported by evidence of markedly different depth and character, and should not be regarded as equally well established. Building on these limitations, seven avenues for future research are recommended: primary, survey-based research employing structural equation modelling to formally test the dual-mediation model across multiple companies and regions; longitudinal research tracking specific projects from AI-adoption decision through to final outcome; comparative research examining whether the relative strength of the two pathways differs between national oil companies and international majors, or between upstream, midstream, and downstream project types; research disaggregating decision quality into component dimensions such as timeliness, information adequacy, and robustness to uncertainty; replication of this study's documentary methodology at a five-year interval given the pace of AI development; formal testing of regional and organisational context as a moderator of the dual-mediation model; and qualitative, interview-based research with project managers and technology-implementation leads to capture the tacit, experiential knowledge that necessarily document-based evidence cannot provide.

8. Conclusion

This paper set out to examine the impact of artificial intelligence adoption on project success in the global oil and gas industry, with particular attention to the mediating roles of project risk management and decision quality. Drawing on a systematic thematic analysis of twenty-four academic and industry sources, and grounded in the Theory of Constraints, the Resource-Based View, and Dynamic Capabilities Theory, the study finds qualified support for all seven of its hypotheses. Artificial intelligence adoption is positively associated with project success, but this relationship is substantially transmitted through, rather than operating independently of, the strengthened risk management and improved decision quality that AI-enabled tools can generate when embedded within complementary organisational capabilities. The findings suggest that the persistent gap between the scale of AI investment in the oil and gas sector and the project-level benefits actually realised is best understood not as a failure of AI technology itself, but as a failure to build the organisational risk-management and decision-making capabilities required to convert AI-generated insight into improved project outcomes. As much attention should therefore be directed toward the organisational capabilities that surround an AI deployment as toward the technical sophistication of the AI tool itself. More broadly, this study illustrates a pattern likely to recur as other fast-moving technologies enter capital-intensive, project-based industries: the ultimate value of a new technology for project outcomes is rarely determined by its raw technical capability alone, but by the organisational capabilities through which that capability is embedded, interpreted, and acted upon.

References

- Anadea. (2026). AI in oil and gas industry: Excellent duo and impressive results. <https://anadea.info/blog/artificial-intelligence-in-oil-and-gas/>
- Applications of AI in oil and gas projects towards sustainable development: A systematic literature review. (2023). PMC / Environmental Science and Pollution Research. <https://pmc.ncbi.nlm.nih.gov/articles/PMC10034239/>
- Artificial general intelligence (AGI) for the oil and gas industry: A review. (2024). arXiv. <https://arxiv.org/pdf/2406.00594>
- Artificial intelligence and its performance impacts in the oil and gas industry: Challenges, insights, and evaluation approaches. (2025). Energy Reports / ScienceDirect. <https://www.sciencedirect.com/science/article/pii/S2590123025036898>
- Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120. <https://doi.org/10.1177/014920639101700108>
- DNV. (2026). AI spells opportunity and manageable risk for the oil and gas industry. <https://www.dnv.com/article/ai-spells-opportunity-and-manageable-risk-for-the-oil-and-gas-industry/>
- Enhanced megaproject management systems in the LNG industry: A case study from Qatar. (2022). Case Studies in Construction Materials / ScienceDirect. <https://www.sciencedirect.com/science/article/pii/S2352484722026270>
- Goldratt, E. M. (1984). *The goal: A process of ongoing improvement*. North River Press.
- Impact of project managers' emotional intelligence on megaprojects success through mediating role of human related agile challenges: Project management as a moderator. (2024). Technological Forecasting and Social Change / ScienceDirect. <https://www.sciencedirect.com/science/article/pii/S0001691824001823>
- Impact of the democratic leadership style of project manager on project success: The mediating role of innovative work behavior. (2026). ResearchGate. <https://www.researchgate.net/publication/377023198>
- Imubit. (2026). 7 characteristics of a successful AI implementation strategy in oil and gas. <https://imubit.com/articles/ai-implementation-strategy-oil-gas>
- Intelligent reservoir decision support: An integrated framework combining large language models, advanced prompt engineering, and multimodal data fusion for real-time petroleum operations. (2025). arXiv. <https://arxiv.org/pdf/2509.11376>
- Managing cost risks in oil and gas construction projects: Root causes of cost overruns. (2021). ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 8(1). <https://ascelibrary.org/doi/10.1061/AJRUA6.0001193>
- Managing quality in projects: An empirical study. (2013). *International Journal of Project Management* / ScienceDirect. <https://www.sciencedirect.com/science/article/abs/pii/S0263786313000240>

- Olaniran, O. J., Love, P. E. D., Edwards, D., Olatunji, O. A., & Matthews, J. (2015). Cost overruns in hydrocarbon megaprojects: A critical review and implications for research. *Project Management Journal*, 46(6), 126-138. <https://doi.org/10.1002/pmj.21556>
- Potential application of generative artificial intelligence and machine learning algorithm in oil and gas sector: Benefits and future prospects. (2024). *Resources Policy / ScienceDirect*. <https://www.sciencedirect.com/science/article/abs/pii/S0160791X24002586>
- Project steering committee members and project success: A quantitative study on individual responsibilities, shared goals and mutual trust. (2026). *International Journal of Managing Projects in Business*. <https://doi.org/10.1108/IJMPB-07-2025-0262>
- Rcademy. (2026). Oil and gas project management: Unique challenges and best practices. <https://rcademy.com/oil-gas-project-management/>
- Re-evaluating megaproject cost overruns: Putting changes into perspective. (2021). *Research Leap*. <https://researchleap.com/re-evaluating-megaproject-cost-overruns-putting-changes-into-perspective/>
- Shared leadership and project success: The mediational role of individual- and team-related factors. (2026). *PMC*. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC12904471/>
- Strategies for reducing project cost overruns in the oil and gas industry. (n.d.). Walden University ScholarWorks Dissertations. <https://scholarworks.waldenu.edu/cgi/viewcontent.cgi?article=12547&context=dissertations>
- Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509-533. [https://doi.org/10.1002/\(SICI\)1097-0266\(199708\)18:7%3C509::AID-SMJ882%3E3.0.CO;2-Z](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7%3C509::AID-SMJ882%3E3.0.CO;2-Z)
- The integration of artificial intelligence in the oil and gas project management sector. (2024). *International Journal of Research and Publication Reviews*, 5(8). <https://www.researchpublish.com/upload/book/THE%20INTEGRATION%20OF%20ARTIFICIAL%20INTELLIGENCE-21082024-2.pdf>
- Transformational leadership and project success: Serial mediation of team-building and teamwork. (2021). *Frontiers in Psychology*, 12, Article 689311. <https://doi.org/10.3389/fpsyg.2021.689311>