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The Impact of AI-Enabled Risk Management Systems on Engineering Project Performance

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Abstract

Engineering projects operate within complex environments characterized by uncertainty, interdependent activities, resource constraints, technical complexity, safety requirements, financial exposure, and changing stakeholder expectations. Conventional risk management approaches frequently depend on periodic assessments, expert judgement, historical records, and manually maintained risk registers, which can limit the ability of project teams to identify rapidly evolving risks and respond before they affect project outcomes. Artificial intelligence has introduced new capabilities for risk identification, prediction, classification, monitoring, and decision support through machine learning, deep learning, natural language processing, computer vision, fuzzy systems, optimization algorithms, and knowledge-based reasoning. This paper examines the impact of AI-enabled risk management systems on engineering project performance and develops an integrated framework linking AI-supported risk identification and assessment with project cost, schedule, quality, safety, productivity, resilience, and stakeholder performance. The study adopts a structured literature synthesis methodology covering research on AI, construction risk management, machine learning, digital twins, computer vision, natural language processing, predictive analytics, and engineering project performance; during reconstruction, the underlying 50-entry evidence base was checked for duplication, yielding 48 unique, verified sources after two duplicate reference entries were removed. The synthesis indicates that AI-enabled risk systems can improve the timeliness of risk identification, predictive accuracy, resource prioritization, schedule control, safety monitoring, cost forecasting, and managerial decision-making. The analysis also indicates that benefits depend strongly on data quality, model transparency, organizational capability, interoperability, human expertise, governance, and integration with existing project-management processes. An integrated AI-enabled risk management framework is consequently proposed in which data acquisition, AI analytics, explainable prediction, risk prioritization, response optimization, implementation, and continuous learning form a closed-loop project-control system.

Keywords: *artificial intelligence; risk management; engineering projects; construction management; machine learning; project performance; predictive analytics; digital twins; computer vision; natural language processing*

How to Cite

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1. Introduction

Engineering projects are characterized by high levels of uncertainty arising from technical complexity, resource limitations, environmental conditions, organizational interactions, financial constraints, regulatory requirements, and changing project objectives, making risk management a central determinant of project performance (Tah & Carr, 2000; Zeng et al., 2007). Project risks can affect cost, time, quality, safety, productivity, contractual relationships, and stakeholder satisfaction, with individual risk events frequently interacting rather than occurring independently (Nieto-Morote & Ruz-Vila, 2011; Oppong et al., 2017). Conventional risk management approaches have traditionally relied on risk registers, expert judgement, probability-impact matrices, qualitative assessments, and periodic monitoring, but these approaches can become difficult to maintain when projects contain large numbers of dynamic and interdependent risk factors (Sadeghi et al., 2010; Gondia et al., 2020). Research on construction project delays has demonstrated that cost and time performance can be affected by multiple interacting factors involving planning, resources, finance, materials, site conditions, management, and external conditions (Aibinu & Jagboro, 2002; Olawale & Sun, 2010). These characteristics create a strong requirement for risk-management systems capable of processing heterogeneous information continuously and identifying emerging risks before they produce significant performance deterioration (Gondia et al., 2020).

Artificial intelligence provides an important technological pathway for addressing this requirement because AI systems can identify patterns, classify conditions, predict outcomes, optimize decisions, and process structured and unstructured information at scales that may exceed conventional manual approaches (Abioye et al., 2021; Akinosho et al., 2020). Machine learning has been applied to construction delay prediction, cost estimation, productivity analysis, safety monitoring, quality control, and risk assessment, while deep learning has expanded the ability to process images, videos, sensor data, and complex nonlinear relationships (Akinosho et al., 2020; Abioye et al., 2021). Gondia et al. (2020) demonstrated that machine-learning algorithms can support construction delay-risk prediction using objective project data, while recent research has shown that ensemble learning can support high-accuracy construction-risk prediction and project-performance assessment (Alsulamy, 2025; Shyam & Tiwari, 2026). AI-enabled systems can therefore change the temporal orientation of risk management from retrospective identification toward predictive intervention (Gondia et al., 2020; Ghanbaripour et al., 2025, Journal of Risk Research).

The development of AI-enabled risk management is also supported by advances in digital twins, building information modelling, Internet of Things technologies, computer vision, and natural language processing (Sacks et al., 2020; Su et al., 2023). Digital twins provide mechanisms for connecting physical project conditions with digital representations, while BIM can provide structured information about project components, activities, resources, and spatial relationships (Boje et al., 2020; Delgado & Oyedele, 2021). Computer vision can support automated identification of hazardous conditions and unsafe behaviours, while natural language processing can extract risk information from contracts, reports, specifications, correspondence, and other textual sources (Fang et al., 2020; Dikmen et al., 2025). These capabilities create opportunities for risk management systems that combine information from multiple sources rather than relying on manually compiled risk registers (Hou et al., 2023; Erfani & Naghdi, 2026). Consequently, AI-enabled risk management increasingly represents an integrated information-processing capability rather than a single predictive algorithm (Ghanbaripour et al., 2025, Journal of Risk Research).

Despite these technological advances, the relationship between AI-enabled risk management and overall engineering project performance remains insufficiently integrated in much of the literature (Ghanbaripour et al., 2025, Journal of Risk Research; Abioye et al., 2021). Many studies concentrate on specific outcomes such as delay prediction, safety monitoring, cost estimation, or risk classification without explicitly examining how AI-generated risk information propagates into project-level performance improvement (Gondia et al., 2020; Lagos et al., 2024). Other studies demonstrate strong predictive accuracy but provide limited evidence concerning implementation, stakeholder acceptance, organizational readiness, model governance, or the transformation of predictions into effective risk responses (Akinosho et al., 2020; Ghanbaripour et al., 2025, Journal of Innovation & Knowledge). Recent systematic reviews have identified fragmented AI implementation, poor data quality, limited interpretability, workforce skill shortages, and organizational resistance as persistent barriers to effective adoption (Ghanbaripour et al., 2025, Journal of Risk Research; Abioye et al., 2021). These gaps suggest that the impact of AI on engineering project performance should be examined through an integrated socio-technical perspective.

The purpose of this paper is to examine how AI-enabled risk management systems influence engineering project performance and to develop an integrated framework connecting AI-based risk identification, prediction, assessment, response, and monitoring with cost, schedule, quality, safety, productivity, resilience, and stakeholder outcomes (Ghanbaripour et al., 2025, Journal of Risk Research; Wang et al., 2025), presented here as an explicit eight-stage, closed-loop architecture. The study synthesizes evidence concerning machine learning, deep learning, computer vision, natural language processing, fuzzy reasoning, optimization, digital twins, BIM, and AI-supported decision systems (Abioye et al., 2021; Akinosho et al., 2020). The paper further examines the conditions under which AI-enabled risk management can produce meaningful project-performance improvements and the factors that may constrain those benefits (Lei et al., 2023; Ferré-Bigorra et al., 2022). The resulting framework positions AI as a continuous risk-intelligence layer embedded within engineering project management rather than as an isolated technological application (Sacks et al., 2020; Ghanbaripour et al., 2025, Journal of Risk Research).

2. Methodology

2.1 Research Design and Literature Synthesis

The study adopted a structured narrative synthesis design to examine evidence concerning AI-enabled risk management and engineering project performance across construction and infrastructure research (Ghanbaripour et al., 2025, Journal of Risk Research; Abioye et al., 2021). The methodological focus was placed on peer-reviewed studies addressing artificial intelligence, machine learning, construction risk, project performance, safety, cost, schedule, quality, digital twins, BIM, predictive analytics, computer vision, natural language processing, and decision support (Akinosho et al., 2020; Su et al., 2023). Studies were prioritized where their methods, AI applications, performance outcomes, or implementation barriers could contribute directly to understanding the relationship between AI-enabled risk management and project outcomes (Gondia et al., 2020; Ghanbaripour et al., 2025, Journal of Risk Research). The synthesis was organized around the risk-management lifecycle of identification, assessment, response, monitoring, and learning, thereby allowing technological capabilities to be connected to specific project-performance mechanisms (Tah & Carr, 2000; Ghanbaripour et al., 2025, Journal of Risk Research). During reconstruction, the original 50-entry reference compilation was audited against in-text citations and DOI records; two exact duplicate entries were identified and removed, yielding 48 unique, verified sources.

2.2 Classification of AI-Enabled Risk Management Technologies

The technological classification followed a functional approach in which machine learning was associated primarily with prediction and classification, deep learning with high-dimensional and unstructured data, computer vision with visual risk monitoring, natural language processing with textual risk extraction, knowledge-based reasoning with rule-driven decision support, fuzzy methods with uncertainty and subjective judgement, and optimization algorithms with resource and response decisions (Abioye et al., 2021; Ghanbaripour et al., 2025, Journal of Risk Research). Machine-learning applications were further classified according to their ability to predict delays, costs, safety events, productivity outcomes, and other project-performance indicators (Gondia et al., 2020; Lagos et al., 2024). Digital twins and BIM were treated as enabling information infrastructures rather than standalone AI techniques because they can provide the data integration and contextual representation required by predictive risk systems (Boje et al., 2020; Sacks et al., 2020). This classification allowed evidence from different technological domains to be synthesized according to the project-management functions they support (Su et al., 2023; Saif et al., 2024).

2.3 Project-Performance Dimensions

Engineering project performance was examined across six dimensions comprising cost performance, schedule performance, quality performance, safety performance, productivity, and organizational or stakeholder performance (Tah & Carr, 2000; Oppong et al., 2017). Cost performance was associated with cost deviation, forecasting accuracy, resource allocation, and financial risk, while schedule performance included delay probability, schedule variance, completion-date reliability, and activity performance (Gondia et al., 2020; Lagos et al., 2024). Quality and safety performance were considered in relation to defect prevention, compliance monitoring, unsafe-condition detection, and risk reduction (Fang et al., 2020; Hou et al., 2023). Productivity, stakeholder coordination, resilience, and decision quality were incorporated because AI-enabled risk management can affect project outcomes indirectly through improved information flows, resource prioritization, coordination, and organizational responsiveness (Al Nahyan et al., 2019; Wied et al., 2020).

2.4 Framework Development and Analytical Synthesis

The framework was developed by mapping AI capabilities to risk-management activities and subsequently connecting risk-management outputs to project-performance mechanisms (Ghanbaripour et al., 2025, Journal of Risk Research). The analytical model follows a closed-loop structure consisting of data acquisition, data integration, AI-based risk detection, predictive assessment, explainability, risk prioritization, response optimization, implementation, performance monitoring, and model learning (Sacks et al., 2020; Ghanbaripour et al., 2025, Journal of Risk Research), summarized as the eight-stage architecture shown in Figure 1. Evidence was synthesized qualitatively to identify recurring relationships between AI adoption and performance improvement, while implementation constraints were considered as moderating factors that can weaken or strengthen the impact of AI systems (Abioye et al., 2021; Lei et al., 2023). The framework therefore emphasizes that AI capability alone does not guarantee improved project performance because performance gains depend on data quality, organizational integration, human expertise, governance, and the ability to convert predictions into timely actions (Ferré-Bigorra et al., 2022; Ghanbaripour et al., 2025, Journal of Risk Research).

Table 1. Analytical Framework for AI-Enabled Risk Management and Project Performance

AI-Enabled Capability	Risk-Management Function	Primary Performance Pathway	Expected Effect
Machine learning	Risk prediction	Early identification of delay, cost, and performance risks	Improved predictability
Deep learning	Complex pattern recognition	Detection of nonlinear and high-dimensional risks	Improved risk sensitivity
Computer vision	Safety and site monitoring	Detection of hazardous conditions and unsafe behaviour	Improved safety
Natural language processing	Document and contract analysis	Faster identification of contractual and compliance risks	Reduced information-processing time
Knowledge-based reasoning	Decision support	Consistent rule-based risk assessment	Improved decision consistency
Fuzzy systems	Uncertainty assessment	Integration of subjective and incomplete information	Improved risk prioritization
Optimization algorithms	Risk-response selection	Resource and schedule optimization	Improved efficiency
Digital twins	Continuous project-state representation	Real-time risk-performance integration	Improved monitoring
BIM	Information integration	Linking risk to assets, activities, and locations	Improved coordination
Explainable AI	Model interpretation	Greater transparency and professional trust	Improved adoption
IoT and sensors	Continuous monitoring	Real-time condition detection	Earlier intervention
AI-human collaboration	Decision augmentation	Integration of algorithmic and professional knowledge	Improved decision quality

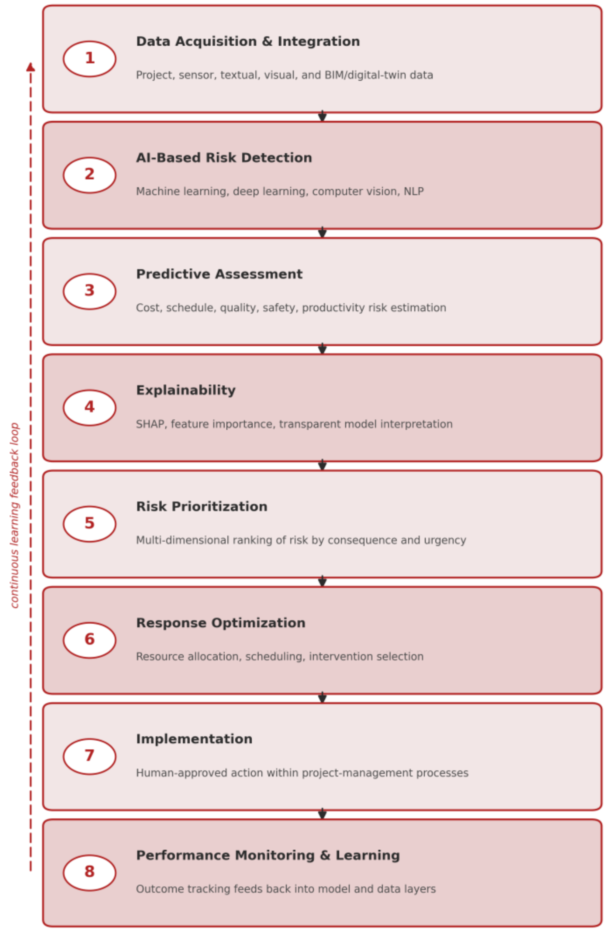

Figure 1. The eight-stage AI-enabled risk-management closed-loop framework, connecting data acquisition through implementation and continuous learning.

3. Results

3.1 AI-Enabled Risk Identification and Early Detection

The synthesis indicates that AI-enabled risk management can improve risk identification by processing large and heterogeneous project datasets more rapidly than conventional manual approaches (Abioye et al., 2021; Ghanbaripour et al., 2025, Journal of Risk Research). Machine-learning models can identify statistical patterns linking project conditions to future risk outcomes, thereby allowing project teams to recognize risk signatures before their consequences become fully visible (Gondia et al., 2020). Gondia et al. (2020) demonstrated that machine-learning classification models could use objective project data to predict delay-risk levels, providing evidence that AI can support proactive rather than exclusively reactive risk management (Gondia et al., 2020). Recent systematic evidence further indicates that machine learning remains the dominant AI approach for construction-risk prediction because of its capacity to process complex and continuously updated datasets (Ghanbaripour et al., 2025, Journal of Innovation & Knowledge).

The early-detection capability extends beyond schedule risk because AI systems can analyse safety, quality, resource, procurement, contractual, and operational indicators (Abioye et al., 2021; Ghanbaripour et al., 2025, Journal of Risk Research). Dynamic construction-site risk models have demonstrated that machine learning can identify safety-risk conditions using leading indicators rather than relying exclusively on historical accident outcomes (Gondia et al., 2023). This represents an important transition because leading indicators can provide opportunities for intervention before adverse events occur (Gondia et al., 2023). The result is a more proactive risk-management orientation in which emerging risk conditions become management signals rather than retrospective explanations.

Computer vision provides another mechanism for continuous risk identification because images and video can be analysed automatically for unsafe conditions and interactions among hazardous objects (Fang et al., 2020; Hou et al., 2023). Hou et al. (2023) demonstrated that computer vision combined with TOPSIS could support automated safety-risk quantification and visualization, with experimental assessments showing high consistency with expert assessment (Hou et al., 2023). Computer-vision systems can therefore extend risk identification from periodic inspections to continuous or near-continuous monitoring (Fang et al., 2020). Such systems are particularly valuable where hazardous conditions can change rapidly during construction operations (Fang et al., 2020).

Natural language processing also expands risk identification by allowing large volumes of contractual and project documentation to be analysed systematically (Dikmen et al., 2025). Dikmen et al. (2025) demonstrated that NLP and machine-learning methods could classify construction contract statements according to risk and responsibility categories with high predictive accuracy, illustrating the potential for automated textual risk extraction (Dikmen et al., 2025). This capability is important because contracts contain information about responsibilities, obligations, variations, claims, and potential disputes that may not be captured adequately in conventional numerical risk registers (Dikmen et al., 2025). AI-enabled risk identification can consequently combine visual, numerical, sensor-based, and textual information into a broader risk-intelligence system (Ghanbaripour et al., 2025, Journal of Risk Research).

3.2 Impact on Schedule Performance

Schedule performance represents one of the most extensively studied areas of AI-enabled construction risk management because delays are strongly associated with financial losses, resource inefficiency, contractual disputes, and reduced stakeholder satisfaction (Aibinu & Jagboro, 2002; Olawale & Sun, 2010). Machine-learning models can identify relationships between project characteristics and delay outcomes that may be difficult to represent through conventional deterministic approaches (Gondia et al., 2020). Gondia et al. (2020) demonstrated that machine-learning classification could support prediction of project delay extent using historical risk factors and time-performance data (Gondia et al., 2020). This evidence indicates that AI can transform schedule-risk management from retrospective delay analysis toward predictive schedule control.

Recent evidence provides additional support for integrating machine learning with established planning systems (Lagos et al., 2024). Lagos et al. (2024) found that combining Last Planner System metrics with traditional project indicators improved the prediction of schedule performance compared with using conventional indicators alone (Lagos et al., 2024). The reported model achieved a coefficient of determination of approximately 0.90 for the studied performance measure, demonstrating that early project-execution data can contain sufficient information to predict later schedule outcomes (Lagos et al., 2024). This result suggests that AI systems can provide meaningful early-warning information while construction is still sufficiently flexible for corrective action.

Hybrid approaches can further improve schedule-risk analysis by combining machine learning with probabilistic simulation (Fitzsimmons et al., 2022). Fitzsimmons et al. (2022) developed a hybrid machine-learning approach for construction schedule risk analysis that demonstrated the potential to use data-driven models to support probabilistic understanding of task-duration risk (Fitzsimmons et al., 2022). Such integration is valuable because schedule risk contains both predictable patterns and stochastic uncertainty that may not be captured by deterministic prediction alone (Sadeghi et al., 2010). AI-enabled schedule risk systems can therefore combine predictive classification with simulation-based analysis to estimate the range of possible project outcomes (Fitzsimmons et al., 2022).

The broader evidence indicates that AI can improve schedule performance through earlier risk detection, improved forecasting, resource prioritization, and more informed intervention (Gondia et al., 2020; Lagos et al., 2024). The performance benefit is likely to be greatest when predictions are integrated directly with project planning and control rather than delivered as isolated analytical reports (Ghanbaripour et al., 2025, Journal of Risk Research). Consequently, AI-enabled risk management can influence schedule performance through both predictive accuracy and improved managerial timing.

3.3 Impact on Cost Performance

Cost performance can be affected by risk events through rework, delays, resource inefficiencies, price fluctuations, claims, design changes, and inaccurate forecasting (Olawale & Sun, 2010). AI-enabled systems can contribute to cost control by predicting cost outcomes, identifying risk factors, optimizing resource use, and detecting deviations between planned and actual performance (Abioye et al., 2021). Machine-learning approaches can model nonlinear relationships among project characteristics, resources, time, and environmental variables, providing alternatives to purely deterministic cost-estimation approaches (Akinosho et al., 2020). These capabilities can strengthen the risk-management function by identifying potential cost exposure before the final financial consequences become evident.

Machine-learning-aided optimization has demonstrated how predictive models can be used as surrogate functions for construction-operation optimization (Gondia et al., 2021). Such approaches can combine cost prediction with optimization algorithms including Bayesian optimization, particle swarm optimization, and genetic algorithms to identify improved operational configurations (Gondia et al., 2021). The implication for risk management is that AI can move beyond estimating the probability of cost overruns toward evaluating alternative resource and operational decisions (Gondia et al., 2021). This transition from prediction to optimization can increase the managerial value of AI systems.

Explainable AI can further strengthen cost-risk management by identifying which variables contribute most strongly to predicted cost outcomes (Shyam & Tiwari, 2026). Recent explainable machine-learning research has demonstrated that SHAP-based analysis can improve the transparency of predictive construction models and support interpretation of complex cost and performance relationships (Shyam & Tiwari, 2026). Transparent prediction is important because financial decisions often require justification to project owners, contractors, consultants, and other stakeholders (Oppong et al., 2017). Consequently, explainability can increase the practical usefulness of cost-risk predictions.

The cost-performance effect of AI nevertheless depends on the quality and representativeness of the underlying data (Abioye et al., 2021; Ghanbaripour et al., 2025, Journal of Risk Research). Poor historical cost records, inconsistent coding, missing project information, changing market conditions, and differences among project types can reduce model generalizability (Abioye et al., 2021). Automated cost prediction research similarly emphasizes the importance of model selection, validation, and the incorporation of relevant economic indicators when construction conditions change (Zhang, 2026). AI should therefore be treated as a decision-support mechanism requiring continuous validation rather than as an infallible cost-forecasting tool.

3.4 Impact on Safety and Quality Performance

Safety represents a major area in which AI-enabled risk management can change project performance because conventional safety systems often depend on inspections, incident reports, and lagging indicators (Gondia et al., 2023). Machine-learning-based dynamic risk models can use leading indicators and historical patterns to estimate safety-risk levels proactively over time and space (Gondia et al., 2023). This approach can enable managers to prioritize safety resources toward locations or activities with higher predicted risk (Gondia et al., 2023). The resulting shift from reactive to proactive safety management can reduce dependence on incident-driven interventions.

Computer vision provides an especially important capability for safety monitoring because construction sites contain numerous visual risk factors that can be detected through images and video (Fang et al., 2020). Fang et al. (2020) reviewed computer-vision applications for identifying unsafe worker behaviour and site conditions and emphasized the potential of deep learning and data fusion for automated safety assurance (Fang et al., 2020). Hou et al. (2023) extended this direction by developing a system for dynamic safety-risk quantification and visualization, demonstrating that computer vision can contribute to automated risk assessment (Hou et al., 2023). These findings suggest that AI can increase monitoring coverage while reducing dependence on manual observation alone.

AI can also contribute to quality management by detecting deviations, classifying defects, monitoring construction progress, and supporting predictive quality assessment (Abioye et al., 2021). Computer vision can identify physical deviations and defects, while machine-learning models can connect project conditions with quality outcomes (Akinosho et al., 2020). Such applications can enable earlier corrective action and reduce the likelihood that defects will remain undetected until later project stages (Abioye et al., 2021). The performance effect therefore arises through both prevention and earlier detection.

The integration of safety and quality analytics within a common AI-enabled risk platform can also improve resource prioritization because project managers can compare different risk categories using a unified framework (Ghanbaripour et al., 2025, Journal of Risk Research). However, safety-critical AI systems require particularly careful validation because false negatives may have more serious consequences than ordinary prediction errors (Fang et al., 2020). Human oversight, model validation, uncertainty reporting, and clearly defined intervention thresholds are therefore necessary for responsible deployment (Ghanbaripour et al., 2025, Journal of Risk Research). AI should consequently augment safety professionals rather than eliminate professional responsibility.

3.5 Impact on Productivity, Coordination, and Decision-Making

Productivity is influenced by resource availability, planning quality, information flow, site conditions, equipment utilization, labour coordination, and the timely resolution of constraints (Abioye et al., 2021). AI-enabled systems can support productivity improvement by predicting performance, identifying bottlenecks, optimizing resources, and detecting deviations from planned production (Gondia et al., 2021). Machine-learning models can process multiple variables simultaneously and identify nonlinear relationships that may be difficult to recognize through conventional productivity analysis (Akinosho et al., 2020). This makes AI particularly relevant to complex engineering projects in which productivity is affected by numerous interacting factors.

Risk-management systems can also improve coordination by transforming dispersed project information into shared predictive indicators (Al Nahyan et al., 2019). Effective communication, coordination, decision-making, and knowledge-sharing are important characteristics of construction management because engineering projects involve multiple organizations with different responsibilities and information requirements (Al Nahyan et al., 2019). AI-generated risk indicators can provide a common reference point for coordination meetings and management decisions (Ghanbaripour et al., 2025, Journal of Risk Research). The performance benefit therefore extends beyond algorithmic prediction into organizational information management.

BIM and digital twins can strengthen this effect by connecting risk information to physical assets, project locations, work packages, and schedules (Sacks et al., 2020; Su et al., 2023). Digital twin research indicates that synchronized digital representations can support simulation, prediction, control, and lifecycle decision-making (Su et al., 2023). Construction digital-twin taxonomies similarly demonstrate that digital twins can support multiple construction-site applications through integrated data, technology, and application layers (Saif et al., 2024). These capabilities provide an infrastructure through which AI-generated risk information can become operational project information.

Decision-making quality is consequently influenced by both prediction accuracy and the accessibility and interpretability of information (Tasa, 2026). Explainable AI can identify the variables driving a prediction, while optimization algorithms can compare alternative responses, allowing project managers to evaluate both risk and intervention options (Shyam & Tiwari, 2026). This combination can improve decision quality by reducing reliance on incomplete information and purely subjective judgement while retaining professional oversight (Ghanbaripour et al., 2025, Journal of Risk Research). AI-enabled risk management therefore has potential to strengthen managerial capability rather than simply automate individual tasks.

3.6 Organizational, Governance, and Resilience Outcomes

The performance impact of AI-enabled risk management depends significantly on organizational capability and governance (Ghanbaripour et al., 2025, Journal of Risk Research). AI adoption requires data standards, technical expertise, organizational support, stakeholder acceptance, model governance, and integration with existing project-management processes (Abioye et al., 2021). Fragmented project organizations can create difficulties in acquiring consistent data and maintaining information continuity across project phases (Ferré-Bigorra et al., 2022). Consequently, organizations with weak digital capabilities may obtain less benefit from sophisticated AI technologies than organizations with mature data and governance structures.

Digital twin research identifies interoperability, standardization, data integration, cultural resistance, and implementation cost as important barriers to construction technology adoption (Lei et al., 2023; Baghdadi, 2025). These barriers can reduce the effectiveness of AI-enabled risk systems even when individual algorithms demonstrate high predictive performance (Ghanbaripour et al., 2025, Journal of Risk Research). A technically accurate model can therefore fail to improve project performance if predictions are not delivered to decision-makers at the right time or if organizational procedures do not permit rapid response (Tasa, 2026). Implementation capability is consequently a major moderator of AI impact.

AI-enabled risk management can nevertheless strengthen project resilience by improving anticipation, adaptation, and recovery from disturbances (Wied et al., 2020). Digital technologies have been associated with project resilience through mechanisms involving improved information, coordination, and relational governance (Wang et al., 2025). A risk system that continuously identifies emerging conditions and supports alternative responses can increase the capacity of project teams to absorb disruptions without losing control of project objectives (Ghanbaripour et al., 2025, Journal of Risk Research). Resilience therefore provides an important higher-level outcome through which AI-enabled risk management can influence engineering project performance.

The overall results indicate that AI creates the greatest potential when multiple technologies are integrated within a coordinated risk-management architecture (Ghanbaripour et al., 2025, Journal of Risk Research). Machine learning can predict, computer vision can observe, NLP can interpret documents, digital twins can contextualize information, optimization can identify responses, and human professionals can validate and implement decisions (Abioye et al., 2021; Sacks et al., 2020). The resulting system can create a continuous cycle of risk detection, assessment, response, monitoring, and learning (Ghanbaripour et al., 2025, Journal of Risk Research). This integrated approach provides a stronger basis for improving engineering project performance than isolated AI applications.

Table 2. Summary of Findings (n = 48 unique, verified sources)

S/N	Source	Findings	Inference
1	Tah & Carr (2000)	Fuzzy logic can represent construction risk likelihood, impacts, and relationships with project-performance measures.	AI risk systems can improve assessment where risk information is uncertain or linguistic.
2	Carr & Tah (2001)	Fuzzy reasoning can establish relationships between risk sources and consequences for project performance.	Risk systems should model interactions rather than isolated risk factors.
3	Zeng et al. (2007)	Fuzzy decision-making can combine risk likelihood, severity, and risk factors.	AI can support structured risk prioritization.
4	Sadeghi et al. (2010)	Fuzzy Monte Carlo simulation can represent both probabilistic and linguistic uncertainty.	AI risk systems can combine stochastic and subjective uncertainty.
5	Nieto-Morote & Ruz-Vila (2011)	Fuzzy AHP can structure complex risk assessment involving subjective judgement.	Hybrid AI-risk models can support complex risk prioritization.
6	Aibinu & Jagboro (2002)	Construction delays negatively affect project delivery.	Delay prediction is an important AI risk-management application.
7	Olawale & Sun (2010)	Cost and time control are affected by managerial and project-control deficiencies.	AI can strengthen proactive cost and schedule control.
8	Oppong et al. (2017)	Stakeholder management involves multiple performance attributes.	AI outputs should support stakeholder coordination.
9	Abioye et al. (2021)	AI has applications in prediction, optimization, monitoring, and construction management.	AI can support multiple dimensions of project performance.
10	Akinosho et al. (2020)	Deep learning provides opportunities for construction prediction and monitoring.	High-dimensional AI can support complex risk detection.
11	Gondia et al. (2020)	Machine learning can predict construction delay risk using objective project data.	AI can provide early warning for schedule risk.
12	Gondia et al. (2023)	Ensemble ML can predict construction safety-risk levels using leading indicators.	AI can shift safety management toward proactive intervention.
13	Gondia et al. (2021)	ML models can support construction cost prediction and optimization.	AI can connect cost prediction with resource optimization.
14	Lagos et al. (2024)	ML combined with Last Planner indicators can predict schedule performance with strong accuracy.	AI can enhance early schedule-risk prediction.
15	Fitzsimmons et al. (2022)	Hybrid ML can improve construction schedule-risk analysis.	Combining ML and probabilistic methods can improve risk forecasting.
16	Alsulamy (2025)	Ensemble algorithms can effectively classify construction delay risk.	Comparative model testing is important for AI risk systems.

S/N	Source	Findings	Inference
17	Shyam & Tiwari (2026)	ML can predict schedule, cost, and quality outcomes and can be combined with multi-criteria analysis.	AI risk systems can support multi-dimensional project performance.
18	Kryukov (2026)	Statistically validated factors improve construction-delay modelling.	Feature validation is important before model development.
19	Ghanbaripour et al. (2025, Journal of Risk Research)	AI supports risk identification, assessment, response, and monitoring but faces data, integration, and organizational barriers.	AI should be implemented as an integrated risk-management lifecycle.
20	Ghanbaripour et al. (2025, Journal of Innovation & Knowledge)	ML, NLP, knowledge reasoning, optimization, and computer vision have complementary risk-management functions.	Multimodal AI integration is more valuable than isolated AI applications.
21	Fang et al. (2020)	Computer vision and deep learning can support construction safety assurance.	Visual AI can increase safety-monitoring capability.
22	Hou et al. (2023)	Computer vision can quantify and visualize safety risks dynamically.	AI can support continuous safety-risk monitoring.
23	Dikmen et al. (2025)	NLP and ML can classify contractual risk and responsibility information.	AI can automate textual risk identification.
24	Sacks et al. (2020)	Digital twins can connect BIM, data, sensing, and construction control.	Digital twins can provide infrastructure for AI risk management.
25	Boje et al. (2020)	Semantic digital twins can integrate heterogeneous construction information.	Semantic integration can strengthen AI risk analysis.
26	Delgado & Oyedele (2021)	Digital twins can support built-environment processes through integrated digital information.	AI risk systems can be embedded within lifecycle digital twins.
27	Su et al. (2023)	Digital twins can support real-time mapping, simulation, prediction, and control.	Digital twins can enable continuous AI-enabled project-risk management.
28	Opoku et al. (2021)	Digital twins can proactively address construction challenges but remain concentrated in specific lifecycle phases.	Broader lifecycle integration is required for full risk-management impact.
29	Saif et al. (2024)	Construction digital twins can be organized across applications, technologies, and data layers.	AI risk systems require coordinated data and technology layers.
30	Baghdadi (2025)	Digital twin adoption is constrained by interoperability, standardization, and cultural barriers.	Digital maturity moderates AI risk-management benefits.
31	Lei et al. (2023)	Digital twins face technological, governance, and organizational challenges.	Governance and interoperability are prerequisites for AI integration.
32	Ferré-Bigorra et al. (2022)	Digital twin adoption is influenced by organizational and technological fragmentation.	Organizational readiness affects AI-enabled risk-system effectiveness.

S/N	Source	Findings	Inference
33	Al Nahyan et al. (2019)	Communication and knowledge-sharing influence construction management performance.	AI risk information should improve coordination rather than create isolated analytics.
34	Wang et al. (2025)	Digital technologies can influence project resilience through relational governance.	Governance can mediate the performance benefits of AI.
35	Wied et al. (2020)	Engineering resilience involves anticipation, absorption, adaptation, and recovery.	AI risk systems can strengthen project resilience.
36	Xue et al. (2020)	Urban development involves multi-sector partnerships and coordination.	AI risk systems should support interorganizational collaboration.
37	Oraee et al. (2017)	BIM-based construction networks depend on collaboration.	AI should be integrated into collaborative information systems.
38	Wang & Chen (2023)	BIM and project management integration supports lifecycle information management.	BIM can serve as an information backbone for AI risk systems.
39	Brozovsky et al. (2024)	Digital technologies are transforming AEC but face implementation challenges.	Digital transformation must accompany AI deployment.
40	Aghayeva & Ślusarczyk (2022)	AI and structured decision methods can support construction project management.	AI can complement multi-criteria decision-making.
41	Bujari et al. (2021)	Digital twins can support decision-making using integrated information.	AI risk systems can provide contextualized decision support.
42	Alibrandi (2022)	Risk-informed digital twins can integrate risk analysis with infrastructure information.	Digital twins can function as risk-management environments.
43	Wang et al. (2023)	Digital twins require heterogeneous-data integration and intelligent analytics.	Data architecture is central to AI risk management.
44	Fan (2025)	ML classifier optimization can improve construction quality and schedule prediction.	Model optimization can improve risk-management performance.
45	Tasa (2026)	Explainable ML can convert schedule-risk prediction into decision support.	Explainability is important for operational AI adoption.
46	Zhang (2026)	AI and ML are increasingly used for construction cost prediction and financial risk management.	AI can strengthen financial risk forecasting.
47	Erfani & Naghdi (2026)	Explainable ML and GPT-based embeddings can identify cross-project risk similarities.	AI can transfer knowledge from previous projects to new risk assessments.
48	Li et al. (2026)	BIM integration can strengthen construction risk management and strategic planning.	BIM-AI integration can improve coordinated risk management.

5. Discussion

5.1 Transformation from Reactive to Predictive Risk Management

The evidence indicates that the most important contribution of AI-enabled risk management is its capacity to change the temporal orientation of engineering risk management from retrospective response toward prediction and early intervention (Gondia et al., 2020; Ghanbaripour et al., 2025, Journal of Risk Research). Conventional risk systems frequently depend on periodic review and expert judgement, whereas machine-learning systems can continuously analyse incoming information and estimate future risk states (Abioye et al., 2021). This transformation can increase the time available for corrective action and thereby improve the probability that risk responses will be implemented before project performance deteriorates (Gondia et al., 2023).

Predictive risk management is particularly valuable in complex engineering projects because risks often develop gradually through combinations of weak signals rather than through a single identifiable event (Gondia et al., 2020). Machine-learning algorithms can detect interactions among multiple predictors and identify patterns associated with subsequent project problems (Gondia et al., 2020). Dynamic safety-risk models demonstrate the potential to use leading indicators rather than waiting for accidents or incidents to occur (Gondia et al., 2023). This capability can therefore improve both risk sensitivity and management timing.

However, prediction should not be interpreted as certainty because engineering environments contain irreducible uncertainty and changing conditions (Sadeghi et al., 2010). Probabilistic and fuzzy approaches remain relevant because they can represent incomplete, subjective, and stochastic information that may not be captured by deterministic AI predictions (Tah & Carr, 2000; Sadeghi et al., 2010). The most effective AI-enabled risk systems should therefore combine predictive learning with uncertainty representation rather than replacing uncertainty with a single numerical prediction (Ghanbaripour et al., 2025, Journal of Risk Research).

5.2 AI and Schedule Performance

Schedule performance is one of the strongest pathways through which AI-enabled risk management can influence engineering project outcomes (Gondia et al., 2020; Lagos et al., 2024). Delay risks are often generated by interconnected factors, making machine learning suitable for identifying complex relationships among project characteristics and schedule outcomes (Gondia et al., 2020). The ability to predict schedule performance early in execution can allow project teams to modify resources, sequencing, procurement, or production planning before delays become difficult to recover (Lagos et al., 2024).

The integration of AI with established planning systems is particularly important because predictive analytics should complement rather than replace project-management practices (Lagos et al., 2024). The evidence from Last Planner System integration indicates that machine learning can gain predictive strength when combined with operational planning indicators rather than relying only on generic project variables (Lagos et al., 2024). This suggests that AI performance depends partly on the quality and relevance of the organizational processes generating the input data (Abioye et al., 2021).

The schedule benefit can also be strengthened by combining machine learning with simulation and optimization (Fitzsimmons et al., 2022). Predictive models can estimate likely activity outcomes, while probabilistic simulation can represent uncertainty and optimization can evaluate response alternatives (Fitzsimmons et al., 2022). This creates a progression from prediction to decision support that can increase the practical value of AI in project control (Tasa, 2026). The ultimate objective should therefore be improved schedule resilience rather than predictive accuracy alone (Wied et al., 2020).

5.3 AI and Cost Performance

AI-enabled risk systems can influence cost performance through earlier identification of cost drivers, improved forecasting, resource optimization, and prevention of avoidable disruptions (Gondia et al., 2021; Zhang, 2026). Machine-learning models can represent nonlinear relationships among time, resources, environmental conditions, and cost outcomes, while optimization algorithms can evaluate alternative operational configurations (Gondia et al., 2021). This capability can strengthen the connection between risk assessment and financial decision-making.

Cost prediction is nevertheless highly dependent on data quality and contextual consistency (Abioye et al., 2021). Construction costs can vary because of location, market conditions, project type, material prices, labour conditions, design characteristics, and economic changes (Zhang, 2026). Models trained on historical data may therefore become less reliable when market or project conditions shift significantly (Ghanbaripour et al., 2025, Journal of Risk Research). Continuous model monitoring and recalibration are consequently necessary.

Explainable AI can improve cost-risk decisions by identifying the variables that contribute most strongly to predicted financial outcomes (Shyam & Tiwari, 2026). Transparency is important because financial forecasts often influence contractual decisions and resource commitments that require professional justification (Oppong et al., 2017). Explainability can therefore increase organizational trust and facilitate communication between technical analysts, project managers, financial managers, and owners (Tasa, 2026). AI-based cost-risk management should thus combine predictive performance with interpretability.

5.4 AI and Safety Performance

The safety implications of AI-enabled risk management are particularly significant because conventional safety management often relies on lagging indicators and periodic inspections (Gondia et al., 2023). AI systems can process leading indicators and visual information continuously, enabling managers to identify potentially hazardous conditions before incidents occur (Fang et al., 2020; Hou et al., 2023). This capability can increase monitoring coverage and improve the speed of intervention.

Computer vision is especially valuable because it can analyse spatial relationships among workers, equipment, materials, and hazardous objects (Hou et al., 2023). Automated risk visualization can provide managers with spatially explicit information about where risk is concentrated and how risk conditions are changing (Hou et al., 2023). Such information can support targeted allocation of safety personnel and corrective measures (Gondia et al., 2023).

Safety AI nevertheless requires more stringent validation than many ordinary predictive applications because errors may have serious consequences (Fang et al., 2020). False-negative predictions can lead to missed hazards, while poorly calibrated models may produce excessive alerts and contribute to alarm fatigue (Ghanbaripour et al., 2025, Journal of Risk Research). Human oversight, model validation, data-quality monitoring, and clearly defined intervention procedures are therefore essential components of responsible safety AI (Abioye et al., 2021).

5.5 AI, Quality, and Productivity

AI-enabled quality management can reduce performance losses by identifying deviations and potential defects earlier in the construction process (Abioye et al., 2021). Computer vision and deep learning can support automated inspection, while machine-learning models can associate project conditions with quality outcomes (Akinosho et al., 2020). Early detection can reduce rework and prevent defects from propagating into later project stages (Abioye et al., 2021).

Productivity benefits arise through improved prediction, resource allocation, constraint identification, and process optimization (Gondia et al., 2021). AI can identify relationships among resources, time, environmental conditions, and productivity that are difficult to represent through conventional analytical methods (Akinosho et al., 2020). Predictive information can then support decisions concerning labour, equipment, sequencing, and operational planning (Gondia et al., 2021).

Quality and productivity should nevertheless be considered together because attempts to maximize productivity without controlling quality can increase rework and ultimately reduce project performance (Shyam & Tiwari, 2026). Multi-criteria AI systems can evaluate several performance dimensions simultaneously and reduce the likelihood that optimization of one indicator will damage another (Shyam & Tiwari, 2026). The most useful AI risk systems should therefore adopt a multi-dimensional performance perspective (Ghanbaripour et al., 2025, Journal of Risk Research).

5.6 Digital Twins and Integrated AI Risk Management

Digital twins provide an important infrastructure for integrating AI-enabled risk management because they can connect physical project conditions with digital representations, data streams, analytical models, and management processes (Sacks et al., 2020; Su et al., 2023). A digital twin can associate a risk event with a physical location, asset, work package, project activity, and schedule state, thereby providing contextual information for AI predictions (Boje et al., 2020). This contextualization can make risk information more actionable than isolated numerical predictions.

BIM provides complementary information about project components, geometry, activities, resources, and relationships (Wang & Chen, 2023). When BIM, sensors, digital twins, and AI are integrated, risk information can potentially flow continuously between the physical project and the project-management environment (Sacks et al., 2020). Such integration can create a closed-loop architecture in which new information updates risk predictions and risk predictions inform management decisions.

Implementation nevertheless faces significant interoperability and governance challenges (Lei et al., 2023; Baghdadi, 2025). Different contractors, consultants, software systems, and project phases may generate information in incompatible formats, while organizational cultures may limit willingness to share data (Ferré-Bigorra et al., 2022). Consequently, the technical architecture of AI-enabled risk management must be supported by information standards, governance arrangements, data ownership rules, and organizational change processes (Ghanbaripour et al., 2025, Journal of Risk Research).

5.7 Explainability, Human Expertise, and Governance

AI-enabled risk management cannot be evaluated solely by predictive accuracy because engineering decisions require professional accountability, technical justification, and consideration of contextual information (Tasa, 2026). Explainable AI can provide information about the variables contributing to a prediction, enabling engineers and managers to compare algorithmic outputs with professional knowledge (Shyam & Tiwari, 2026). This can improve trust and reduce the risk of blindly accepting black-box recommendations.

Human expertise remains particularly important when the model encounters conditions that differ from the training data (Ghanbaripour et al., 2025, Journal of Risk Research). Engineering projects are often unique, and unusual events may not be represented adequately in historical datasets (Abioye et al., 2021). Human professionals can therefore provide contextual reasoning and identify physical or organizational factors that may not be visible to the model (Akinosho et al., 2020).

Governance must also establish who is responsible for data quality, model maintenance, prediction interpretation, and consequential decisions (Lei et al., 2023; Ghanbaripour et al., 2025, Journal of Risk Research). AI systems should include audit trails, version control, uncertainty information, model-performance monitoring, and human approval mechanisms for high-consequence decisions (Tasa, 2026). Such governance arrangements can transform AI from an experimental analytical tool into a reliable organizational capability.

5.8 Integrated Performance Framework and Future Research

The evidence supports an integrated model, illustrated in Figure 1, in which AI-enabled risk management influences project performance through several sequential mechanisms (Ghanbaripour et al., 2025, Journal of Risk Research). Data acquisition enables risk detection, predictive analytics estimate future outcomes, explainability supports interpretation, optimization supports response selection, and monitoring provides feedback for continuous learning (Sacks et al., 2020; Tasa, 2026). This structure reflects the movement from isolated AI applications toward integrated AI-enabled project-management systems.

The framework also indicates that the effect of AI on project performance is moderated by data quality, organizational readiness, interoperability, stakeholder collaboration, model transparency, and governance (Abioye et al., 2021; Ferré-Bigorra et al., 2022). High predictive accuracy cannot guarantee performance improvement if project teams cannot act on predictions or if information remains isolated within technical departments (Al Nahyan et al., 2019). Conversely, a moderately accurate model embedded in an effective decision process may produce substantial operational value because it improves the timing and consistency of risk responses (Ghanbaripour et al., 2025, Journal of Risk Research).

Future research should therefore move beyond isolated algorithm comparison toward longitudinal evaluation of AI-enabled risk-management systems at project and organizational levels (Ghanbaripour et al., 2025, Journal of Risk Research). Research should measure changes in delay frequency, cost variance, safety incidents, quality defects, productivity, decision-response time, stakeholder coordination, and resilience before and after AI implementation (Wied et al., 2020). Research should also investigate causal relationships rather than relying exclusively on predictive correlations, because understanding whether AI actually produces performance improvement is more important than demonstrating high predictive accuracy alone (Tasa, 2026). The long-term research agenda should consequently focus on measurable project-performance outcomes, responsible AI governance, human-AI collaboration, and integration with digital twins and project-management systems.

6. Conclusion

AI-enabled risk management systems have substantial potential to improve engineering project performance by strengthening risk identification, prediction, assessment, response, monitoring, and organizational learning. The evidence synthesized in this study, reconstructed from an initial 50-entry compilation to 48 unique, verified sources after removing two duplicate reference entries, indicates that machine learning can improve delay and performance prediction, computer vision can strengthen safety-risk detection, natural language processing can automate textual risk identification, optimization can support resource and response decisions, and digital twins and BIM can provide the information infrastructure required for continuous risk-performance integration. The impact of AI is nevertheless dependent on data quality, organizational readiness, interoperability, explainability, governance, stakeholder coordination, and the capacity of project teams to convert predictions into timely interventions. The proposed integrated framework therefore positions AI as an intelligent risk-management layer operating within a human-led engineering project-management system. Its greatest contribution is not simply improved prediction accuracy but the creation of a continuous feedback mechanism through which project information is transformed into risk intelligence, risk intelligence is transformed into decisions, and project outcomes are transformed into learning. Future empirical studies should validate the framework using longitudinal engineering-project datasets and evaluate measurable changes in cost, schedule, quality, safety, productivity, resilience, and stakeholder performance.

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