International Journal of Information Systems and Project Management (IJISPM)
2026, 14(2), e140204, DOI: 10.12821/ijispm140204

RESEARCH ARTICLE

Leveraging artificial intelligence for project risk management: insights from evidence-based analyses and case studies

Afef Saihi
Department of Management Science and Engineering
Khalifa University, Abu Dhabi, UAE,
afef.saihi@ku.ac.ae

Abstract
Artificial Intelligence (AI) has emerged as a transformative force in project risk management (PRM), transitioning traditional methods into dynamic, proactive frameworks capable of addressing modern project complexities. This evolution enables PRM to align more effectively with strategic goals while addressing uncertainties across diverse industries. Despite its promise, AI adoption in PRM varies significantly across sectors, presenting gaps in application and understanding. This study explores AI's role in enhancing PRM, focusing on its impact on risk management elements, emerging trends, and real-world applications. Using a qualitative and evidence-based methodology, the research integrates insights from academic literature, industry reports, and consulting publications, supplemented by case studies of leading organizations. Findings reveal substantial advancements in PRM through AI, highlighting improved decision-making, operational efficiency, and enhanced resilience. Case studies from Siemens, JPMorgan Chase, and Turner Construction demonstrate AI's effectiveness in tackling challenges, optimizing processes, and achieving objectives. This study expands academic discourse on AI adoption in PRM and provides actionable insights for organizations, offering guidance to overcome barriers and maximize technological investments.

Keywords
artificial intelligence; project risk management; risk mitigation; evidence-based analysis; case studies.

Received: 30 January 2025| Accepted: 16 July 2025

1. Introduction

Project management has always been a critical discipline, underpinning the successful execution of tasks across various industries. From construction to software development, effective project management ensures that objectives are met within the constraints of time, budget, and resources. One of the most fundamental components of project management is risk management, which is the process of identifying, assessing, and mitigating risks that could jeopardize project success (Muriana & Vizzini, 2017; Rahi et al., 2021). Projects are inherently uncertain and can be affected by various risks, including financial constraints, technical issues, resource shortages, and external factors such as market fluctuations and regulatory changes (Ulusoy & Hazır, 2021). As projects become increasingly complex, the ability to effectively manage risks is a critical determinant for their success. Traditional methods of risk management, often based on qualitative assessments and historical data, are proving insufficient and can be limited by human biases and the inability to process large volumes of data. This inadequacy is driving the search for more robust and dynamic approaches, with Artificial Intelligence (AI) emerging as a transformative technology offering the potential to reshape project risk management (PRM) practices through greater accuracy, efficiency, and proactivity (Li et al., 2024).

Artificial Intelligence has the potential to revolutionize PRM by providing advanced tools for data analysis and decision-making. AI's capabilities in data processing, pattern recognition, and predictive analytics offer promising solutions to the challenges of traditional risk management. Project managers can leverage these capabilities to analyze vast amounts of data from diverse sources, identify patterns that may indicate potential risks, and predict future risks with higher accuracy (Yazdi et al., 2024). AI-driven approaches enhance proactive risk identification and mitigation while also facilitating continuous monitoring and dynamic adjustments to address emerging uncertainties in projects. AI encompasses a range of technologies and techniques, each offering unique advantages for PRM. Machine learning algorithms, for instance, can learn from historical project data to make accurate predictions about future risks (Hamada, 2024). Natural Language Processing (NLP) can analyze textual data from project documents, emails, and reports to uncover hidden risks (Gao et al., 2024). Predictive analytics can forecast the likelihood of risks occurring and their potential impact on the project (Jahan, 2024). These AI-driven techniques can provide a more comprehensive and proactive approach to risk management compared to traditional methods, significantly improving overall project outcomes.

The integration of AI into project management is already yielding positive results in various industries. For example, in the construction industry, the use of AI has shown significant improvements in managing risks (Kelemu et al., 2023). One notable case is that of the construction firm Skanska, which has implemented AI tools to analyze project data and predict potential delays and cost overruns. These tools analyze factors such as project schedules, financial records, and weather forecasts, enabling project managers to take corrective actions before risks materialize. This proactive approach has resulted in more timely project completions and reduced costs (Sarahrudge, 2024). Similarly, the banking industry has embraced AI to enhance risk assessment, mitigation, and decision-making processes. AI has been applied in credit scoring models, fraud detection systems, stress testing tools, and cybersecurity risk management (Dewasiri et al., 2024). For instance, JPMorgan Chase has adopted AI to enhance its risk management processes. The company uses machine learning algorithms to detect and mitigate fraudulent activities by analyzing transaction patterns in real-time. This implementation has significantly improved overall risk management efficiency and led to a 50% reduction in false positives and a 30% increase in the detection rate of actual fraudulent activities (Wick, 2024). In the transportation sector, Erfani et al. (2023) demonstrated the use of AI in analyzing risks across 11 major U.S. transportation projects. Their framework revealed that 64% of initially identified risks were realized, while 50% of total risks emerged during project execution. Teams using proactive risk monitoring achieved better cost and schedule performance, showcasing the importance of AI in real-time risk tracking and adaptive management. Further case studies and industry examples demonstrate the broad applicability of AI in addressing the evolving challenges of PRM, making it a cornerstone of innovation in the field. Despite its potential, the integration of AI into PRM is not without challenges. Issues such as data quality, algorithm bias, and the need for skilled personnel to manage AI systems must be addressed to fully harness the benefits of AI (Wasike, 2024).

Developing a comprehensive framework for AI integration into PRM is essential to overcoming these challenges. This framework should provide guidelines for various aspects of this integration such as data collection and analysis, AI tool selection, and the implementation and monitoring of AI-driven risk management processes.

While existing literature acknowledges the general limitations of conventional PRM techniques, a more structured gap analysis reveals specific methodological and conceptual constraints that hinder their effectiveness in dynamic project environments. Widely used approaches such as Monte Carlo simulations, Delphi techniques, and statistical modeling suffer from critical weaknesses. Monte Carlo analysis depends heavily on predefined probability distributions, making it vulnerable to inaccurate or outdated input assumptions (Muriana & Vizzini, 2017). The Delphi method is time-intensive and reliant on expert consensus, which introduces subjectivity and inconsistency (Beaudrie et al., 2016). Traditional statistical models, while useful for forecasting, often assume linearity and lack the flexibility to handle unstructured, incomplete, or real-time data, characteristics increasingly present in complex projects (Seddik & Rachid, 2023). To better articulate the need for AI in this context, these limitations can be categorized into three dimensions. Theoretically, traditional methods lack the adaptive, learning-based capabilities necessary to reflect the evolving nature of project risks. Methodologically, they are constrained by rigid structures and limited in processing diverse data formats or dynamic feedback loops. Contextually, these tools often underperform when applied across varying industries or scaled to more complex project settings. AI techniques directly address these challenges: machine learning offers adaptive, data-driven risk forecasting; NLP enables the extraction of insights from unstructured textual sources; and reinforcement learning facilitates continuous, real-time decision-making in uncertain conditions.

Given the transformative potential of AI and the existing challenges in traditional risk management approaches, this study aims to explore and analyze how AI can be leveraged to enhance PRM. To guide this investigation, the following research question is posed: How can AI be leveraged to enhance PRM and what are its impacts on the key elements of risk management? Specifically, the research focuses on the trends shaping AI adoption in PRM, evidence of its effectiveness, and insights drawn from real-world case studies to inform best practices and future research directions. The specific objectives of this study are:

- Identify the trends in the adoption of AI technologies for PRM across various industries.
- Evaluate the current state of evidence regarding the effectiveness of AI in addressing challenges related to risk identification, assessment, mitigation, and monitoring in project management.
- Examine real-world case studies to extract key insights that inform best practices.
- Discuss implications and future research directions for AI-driven PRM.

This study offers both theoretical and practical contributions. Theoretically, it contributes to the growing literature by synthesizing how AI is being adopted in PRM across industries and categorizing its use across key risk functions. Practically, it provides actionable insights for project professionals by illustrating AI applications through real-world case studies, enabling informed adoption and implementation. These dual contributions aim to bridge the current gap between academic research and managerial practice in AI-driven PRM.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature. Section 3 outlines the methodology employed in this study. Section 4 presents the results, including findings from the case studies and evidence-based analysis of AI's effectiveness in PRM. Finally, Section 5 concludes the paper by summarizing the key insights and suggesting directions for future research.

2. Related literature

2.1. Traditional approaches to project risk management: key elements and limitations

PRM is a critical discipline aimed at identifying, assessing, mitigating, and monitoring risks that could negatively impact the success of a project. Traditional approaches to PRM have been the cornerstone of this process, providing structured methods to address uncertainties within projects. However, as project complexity has increased, the limitations of these methods have become apparent, highlighting the need for more advanced and dynamic approaches (Uzzafer, 2010).

Traditional risk management revolves around four core elements: risk identification, assessment, mitigation, and monitoring (Larson & Gray, 2014; Rahi, 2019). These elements provide a systematic framework to manage risks throughout a project's lifecycle. The literature emphasizes that PRM is not a linear process, as it might initially appear, but rather a cyclical one, with feedback loops interconnecting its various elements (Pym, 1987). These feedback loops facilitate the continuous refinement of risk strategies, allowing adjustments based on updated information and evolving project conditions.

- Risk identification involves systematically identifying uncertainties that could affect project objectives. Traditional techniques such as brainstorming sessions, checklists, and expert judgment are commonly used (Mojtahedi et al., 2010; Yim et al., 2015). However, critiques in the literature highlight their reliance on stakeholder input and experience to compile a list of potential risks. While effective for basic identification, they often miss hidden or emerging risks due to their dependence on subjective perspectives (Beaudrie et al., 2016).
- Risk assessment focuses on evaluating the likelihood and potential impact of the identified risks. Traditional risk assessment employs both qualitative and quantitative methods. Qualitative tools such as risk matrices and probability-impact charts categorize risks to help prioritize responses. Quantitative methods, such as Monte Carlo simulations and decision trees, use data to calculate probabilities and model potential outcomes (Beaudrie et al., 2016; Larson & Gray, 2014; Liu et al., 2017; Micán et al., 2020). Although these methods offer valuable insights, they can be constrained by the availability and quality of historical data, as well as the inherent uncertainty in predictions. Monte Carlo analysis, in particular, relies heavily on predefined probability distributions, making it less effective in fast-changing or poorly understood risk environments.
- Risk mitigation focuses on strategies to reduce the likelihood or impact of risks. Common approaches include risk avoidance, transfer (e.g., through insurance), reduction, or acceptance. Mitigation planning often involves creating contingency plans or adjusting project schedules and budgets (Bhoola et al., 2014). However, scholars often critique these methods for being reactive rather than proactive, addressing risks only after they materialize. They also tend to lack real-time adaptability, which can reduce their usefulness in dynamic or high-velocity projects.
- Risk monitoring is an ongoing process that tracks identified risks, evaluates the effectiveness of mitigation strategies, and identifies new risks. Traditional approaches rely on regular updates to risk registers, progress reports, and periodic review meetings (Kaur & Singh, 2018). These methods, while essential, are often static and may fail to adapt to dynamic changes in project environments.

While traditional approaches provide a robust foundation for managing risks, they face significant limitations that reduce their effectiveness in modern, complex projects. Recent literature critiques their static nature, noting that they capture risks at a specific point in time but fail to adapt to evolving project conditions (Fridgeirsson et al., 2021). Qualitative techniques, despite their utility, are prone to human biases, which can compromise the accuracy and reliability of risk evaluations (Shang, 2017). Similarly, quantitative approaches are heavily dependent on historical data, which may not always be relevant or available, particularly for innovative or unprecedented projects (Seddik & Rachid, 2023). Furthermore, as project complexity increases, traditional methods struggle with scalability, often proving inadequate for processing large volumes of data and addressing interconnected risks (Fridgeirsson et al., 2021).

In addition to these widely recognized limitations, specific methodological tools such as the Delphi technique have been critiqued for being time-consuming and subject to participant bias. Statistical models often presume linear relationships and fail to accommodate uncertainty inherent in unstructured or incomplete datasets. These constraints become especially problematic in complex projects that generate high-frequency or high-volume data, where adaptability and responsiveness are essential. To synthesize these challenges, limitations in traditional PRM methods can be categorized into three dimensions:

- Theoretical gaps refer to the inability of traditional methods to adapt or learn over time. For instance, methods like Monte Carlo simulation are built on predefined assumptions and do not evolve as new risk data emerges. In contrast, machine learning algorithms continuously update their risk models based on ongoing data streams.
- Methodological gaps arise from traditional methods' reliance on structured inputs, often numerical or expert-driven, and their limited ability to handle unstructured data or automate updates. Delphi, for example, is highly qualitative and labor-intensive. By contrast, NLP allows the automated extraction of risk signals from large volumes of textual data (e.g., reports, emails).
- Contextual gaps relate to how well a method generalizes across industries or scales. A risk matrix used in construction may not suit agile software projects or supply chain disruptions. However, AI models, particularly those using transfer learning, can be fine-tuned for different domains, enhancing cross-context applicability.

These gaps reveal the need for a new generation of risk management solutions that can accommodate complexity, uncertainty, and speed. Emerging technologies, such as AI, offer transformative potential by enabling real-time analysis, predictive insights, and proactive risk mitigation, which will be explored in subsequent sections.

2.2. Key trends of AI in project risk management

AI has emerged as a transformative force in PRM, offering advanced capabilities that extend beyond the limitations of traditional approaches. The growing complexity and dynamic nature of modern projects have necessitated innovative solutions to enhance the identification, assessment, mitigation, and monitoring of risks (Uzzafer, 2010). The literature increasingly highlights the integration of AI technologies, such as machine learning (ML), natural language processing (NLP), and predictive analytics, as pivotal in reshaping risk management practices. These technologies provide real-time insights, automate processes, and enable proactive decision-making (Yadav et al., 2024). This section explores the key trends driving the adoption and integration of AI into PRM. These trends collectively highlight the transformative potential of AI in overcoming traditional PRM limitations, paving the way for a more adaptive, data-driven, and proactive approach to managing risks.

2.2.1. Widespread adoption of predictive analytics

One of the most significant trends in AI-driven PRM is the adoption of predictive analytics to anticipate potential risks and outcomes. Predictive analytics leverages historical and real-time data to forecast the likelihood of risks occurring and their potential impacts. For example, AI algorithms can analyze past project performance data to identify patterns and correlations, enabling project managers to predict delays, cost overruns, or resource shortages with greater accuracy (Moussa et al., 2024). This trend is particularly prominent in industries such as construction and manufacturing, where large datasets are readily available, and predictive insights can drive strategic decision-making (Khodabakhshian et al., 2024; Sahli et al., 2023). Recent comparative analyses, such as the work of Yazdi et al. (2024), further reinforce this trend by emphasizing that machine learning-based models significantly enhance the accuracy and reliability of risk identification and prediction compared to traditional qualitative and probabilistic methods. Their findings highlight AI's capacity to improve early risk detection, manage uncertainty, and support more proactive risk mitigation strategies across complex projects.

2.2.2. Integration with Big Data and IoT

The convergence of AI with big data analytics and the Internet of Things (IoT) is another notable trend. Modern projects often generate vast amounts of data from diverse sources, including sensors, devices, and systems. AI-powered tools are increasingly being integrated with IoT platforms to process and analyze this data in real-time (Jahan Karamthulla et al., 2024). For instance, in infrastructure projects, AI systems can monitor equipment performance and environmental conditions through IoT sensors, providing early warnings of potential failures or risks (Villegas-Ch et al., 2024). This integration enhances the ability to monitor complex projects dynamically and make data-driven decisions.

2.2.3. Enhanced text and document analysis with NLP

NLP is revolutionizing the way textual data is analyzed in PRM. NLP algorithms can extract meaningful insights from unstructured data, such as project reports, meeting minutes, and contractual documents (Turner, 2023). Through identifying keywords, phrases, and sentiment patterns, NLP tools can uncover hidden risks and provide project managers with actionable insights (Gao et al., 2024). For example, an NLP system can analyze communication logs to detect early signs of conflict or misalignment among stakeholders, enabling timely interventions (Goncharenko, 2024).

2.2.4. Automation of risk management processes

AI is driving the automation of routine and labor-intensive risk management tasks, allowing project managers to focus on strategic activities. Tasks such as updating risk registers, generating risk reports, and monitoring compliance with mitigation plans are increasingly being automated through AI-driven platforms (Yazdi et al., 2024). Automation improves efficiency while reducing the likelihood of human error in repetitive processes, ensuring a more consistent and reliable approach to risk management (Jahan Karamthulla et al., 2024; Soares et al., 2020).

2.2.5. AI-augmented decision-making

The role of AI in supporting and augmenting human decision-making is a growing trend. AI systems are not intended to replace human expertise but to complement it by providing data-driven recommendations and simulations (Mariani & Mancini, 2024). Decision support systems powered by AI can present project managers with multiple scenarios, along with the associated risks and opportunities, enabling informed choices. These tools also enhance collaboration by providing a shared platform for stakeholders to visualize risks and agree on mitigation strategies (Taheri Khosroshahi, 2024).

2.2.6. Industry-specific applications and customization

AI applications in PRM are becoming increasingly tailored to industry-specific needs. For instance, in the finance sector, AI is widely used for fraud detection and cybersecurity risk assessment (Gautam, 2023), while in healthcare, AI-driven tools help manage clinical trial risks by predicting patient outcomes and resource requirements (Mohammed et al., 2024). Customization of AI tools to address the unique risk profiles of different industries is a growing focus, enhancing their effectiveness and adoption (Csiszar et al., 2020).

2.3. Emerging research streams in AI for project risk management

The integration of AI into PRM is redefining traditional approaches, transforming how risks are identified, assessed, and mitigated, particularly in increasingly complex and dynamic project environments (Li et al., 2024). Through a detailed analysis of the literature, several interconnected research streams have emerged, showcasing how AI is being leveraged to address critical challenges and enhance decision-making processes in PRM. These streams collectively reflect a shift towards more intelligent, adaptive, and domain-specific risk management strategies, facilitated by cutting-edge technologies.

Several review studies have laid foundational insights into the evolution of AI in PRM. Tian et al. (2024) conducted a comprehensive bibliometric and systematic literature review on AI in construction risk management, identifying dominant themes, research clusters, and collaboration networks that shape the field's intellectual structure. Afzal et al. (2021) provided a comprehensive classification of AI techniques used for risk assessment in construction, emphasizing complexity-risk interdependencies. Khatib et al. (2021) highlighted the trajectory of AI applications in both project and risk management, mapping key developments and research gaps. Sousa et al. (2021) and Secundo et al. (2024) reviewed how machine learning has enabled new strategic capabilities in PRM and shifted it toward predictive and autonomous models. These reviews informed the current research landscape by highlighting methodological advances, implementation barriers and the potential of AI to enhance risk responsiveness.

One of the most transformative advancements in this field is the application of machine learning (ML) to analyze vast datasets, uncover hidden patterns, and predict risks with high accuracy. For instance, Gondia et al. (2020) demonstrated the efficacy of ML models such as Decision Trees and Naive Bayes in forecasting project delays within the construction industry, while Haghighi & Ashrafi (2024) proposed an ML-integrated framework for software projects that ranks risks and predicts project success or failure based on risk profiles. The Engineering Machine-learning Automation Platform (EMAP) developed by Choi et al. (2021) further exemplifies how ML enhances contractor decision-making in engineering projects, predicting risks at various project stages. These findings are echoed by Sousa et al. (2021), who claimed that ML-enabled tools provide superior risk detection and response rates compared to traditional methods. These applications highlight the central role of ML in enabling proactive risk management and fostering resilience in project execution.

In parallel, AI-driven decision support systems (DSS) are proving instrumental in elevating risk mitigation strategies. These systems leverage advanced modeling techniques to provide real-time, actionable insights for project managers. Bayesian networks, as presented by Xiaocong & Ling (2010), have proven effective in capturing the interdependencies among risks, facilitating real-time assessments and informed decision-making. Similarly, Zaouga & Rabai (2021) developed an ontology-based DSS that employs NLP to generate tailored recommendations, addressing specific risk scenarios. Furthermore, simulation-based models, such as those introduced by Fang & Marle (2012), integrate network-based risk evaluations, enabling dynamic prioritization and mitigation of interconnected risks. The synthesis by Al-Saffar et al. (2024) further supports the integration of DSS tools, especially within high-uncertainty domains like construction, where traditional assessment models underperform. These advancements indicate the growing sophistication of DSS tools, which are increasingly designed to tackle the intricacies of modern project ecosystems.

Beyond generic applications, AI has found significant traction in domain-specific contexts, where tailored approaches address unique challenges. For example, in the construction industry, AI supports planning, simulation, and material sourcing, as highlighted by Makaula et al. (2021), while Gondia et al. (2020) focused on predictive analytics for construction project delay risks. In software development, Haghighi & Ashrafi (2024) combined ML with decision-making frameworks to handle uncertainty. Afzal et al. (2021) also noted that industry-focused models are necessary to capture sector-specific risk interactions, especially in high-stakes environments. These domain-focused innovations reflect the adaptability of AI in addressing sector-specific nuances and optimizing project outcomes.

A key strength of AI lies in its cognitive capabilities and real-time adaptability, which have revolutionized how risks are managed during project execution. By leveraging predictive analytics and big data, Elkhatib et al. (2023) demonstrated AI's ability to proactively identify risks even in highly complex environments, enabling timely interventions. Similarly, Nyqvist et al. (2024) showcased GPT-4's ability to generate comprehensive risk management plans, significantly outperforming human experts in certain aspects. Fridgeirsson et al. (2023) contribute to this view by contextualizing PRM within volatile, uncertain, complex, and ambiguous environments, advocating for real-time intelligent systems to dynamically adapt to project complexity. These advancements emphasize AI's potential to enhance agility and responsiveness in project management.

As AI becomes a mainstay in PRM, it brings ethical and societal considerations to the forefront. Transparency and accountability in AI-driven decision-making, as emphasized by Li et al. (2024), are critical to ensuring stakeholder trust and adoption. Additionally, Makaula et al. (2021) addressed societal concerns such as job displacement, advocating for collaborative frameworks where AI augments rather than replaces human expertise. Secundo et al. (2024) similarly suggested that organizations must not only adopt AI tactically but align it with ethical governance and cross-functional learning practices to ensure sustainable transformation. Such considerations are pivotal in balancing technological advancement with societal well-being.

Lastly, the integration of emerging technologies, such as drones, robotics, and IoT, in conjunction with AI solutions, is significantly enhancing PRM practices. During the COVID-19 pandemic, El khatib et al. (2023) illustrated how drones, powered by AI-driven analytics, effectively mitigated unknown-unknown risks by reducing infection risks with high accuracy. Similarly, Qasim et al. (2022) emphasized the utility of drones for safety and risk assessments in construction projects, particularly during restricted site access. These technologies, when combined with AI capabilities such as real-time data processing and predictive analytics, serve as valuable extensions of AI's functionality, bridging gaps in physical accessibility, operational efficiency, and decision-making precision. This synergy between AI and emerging technologies emphasizes the holistic potential of integrated systems to effectively address complex risk management challenges.

3. Research methodology

This study adopts a qualitative and evidence-based research methodology (Robinson et al., 2021) supported by a triangulated approach (Mishra & Rasundram, 2017) to explore the transformative role of AI in PRM. The choice of methodology is driven by the exploratory nature of the research objectives, which aim to understand both the conceptual contributions and the practical applications of AI across PRM functions. This section outlines the philosophical foundation, design rationale, and implementation of the research methods employed in this study.

3.1. Research philosophy and design

This study adopts an inductive reasoning approach that allows patterns, themes and insights to emerge through the integration of multiple data sources (Jebreen, 2012). The exploratory nature of this research, together with its objective to draw generalizable insights from qualitative data and understand emerging phenomena such as AI-driven PRM, makes the inductive approach highly suitable. Furthermore, the study's philosophical stance is aligned with constructivism (Guba & Lincoln, 1994), which posits that knowledge is co-constructed through interaction, experience and interpretation. This paradigm supports the integration of academic theory, industry expertise, and practical case experiences to capture the multidimensional nature of AI's role in PRM.

Given this orientation, a qualitative design was adopted to capture the complexity, diversity and dynamic characteristics of AI applications in PRM. Triangulation was employed to enhance the validity and richness of findings through the integration of three complementary streams of evidence: (1) academic literature, (2) industry and consulting firm reports, and (3) real-world case studies. This approach enables a comprehensive and multi-perspective understanding of the research problem, allowing for convergence of evidence and cross-validation of insights (Patton, 1999). The overall research methodology framework is summarized in Figure 1.

3.2. Mapping study of AI's role in PRM

The initial phase of the research involves a mapping study to systematically analyze the influence of AI technologies on key elements of PRM. This mapping exercise is structured to identify the ways AI enhances risk identification, assessment, mitigation, and monitoring, as well as its ability to overcome the limitations of traditional methods.

The mapping study commenced with the design of comprehensive search keywords related to AI technologies and PRM functions. A structured search was conducted using major academic databases such as Scopus and Web of Science, covering publications from 2010 to 2024. The following Boolean search string was applied: ("Project" AND ("Risk management" OR "Risk identification" OR "Risk assessment" OR "Risk mitigation" OR "Risk monitoring" OR "Contingency plan") AND ("Artificial intelligence" OR "Machine learning" OR "Predictive analytics" OR "Natural language processing" OR "AI" OR "ML" OR "NLP")). Articles were included if they were peer-reviewed, focused on the application or impact of AI in PRM, and provided empirical or conceptual insights. The filtration process involved three stages: (1) an initial screening of titles and abstracts to exclude irrelevant or duplicate records; (2) a full-text review to assess alignment with the research objectives; and (3) classification of eligible articles based on the PRM components they address (e.g., identification, assessment, mitigation, or monitoring). Inclusion criteria required studies to demonstrate a clear link between AI applications and project risk functions, while exclusion criteria eliminated articles that were not in English, lacked peer-review, or addressed AI in non-project contexts. Identified sources were then categorized based on the PRM components they address, and synthesized to reveal trends, technological enablers, and use cases.

3.3. Evidence-based analysis

The second phase involves evidence-based analysis using insights derived from industry and consulting firm reports. This phase bridges the gap between academic theories and real-world applications of AI in PRM by leveraging data and insights from authoritative industry sources. To ensure the relevance and reliability of the findings, sources were selected based on the following criteria:

- Publications by reputable consulting firms and organizations, such as Gartner, KPMG, Project Management Institute, among others.
- Provision of quantitative or qualitative evidence of AI’s impact on PRM outcomes.
- Coverage of various project management sectors.

Reports were retrieved through targeted searches on official websites, practitioner databases, and public business intelligence platforms. The extracted data included metrics, success factors, challenges, and best practices associated with AI adoption in PRM. These findings complemented the academic mapping study by validating observed patterns and contributing practical insights regarding the implementation and value realization of AI technologies.

3.4. Case study selection and analysis

The third phase of the research involves in-depth analysis of selected real-world case studies to illustrate the practical and tangible application of AI in PRM. These case studies provide concrete examples that connect theoretical understanding with industry practices. They serve to contextualize the insights from the mapping study and evidence-based analysis, demonstrating the practical benefits and limitations of AI in diverse project environments. Case study selection was based on the following predefined criteria:

- Alignment with PRM components: The case studies must address one or more core PRM elements (e.g., risk identification, assessment, mitigation).
- Integration of AI technologies: Selected cases should showcase the application of AI techniques, such as predictive analytics or NLP, in risk management.
- Industry diversity: To capture AI's cross-sectoral relevance, cases represent industries such as construction, finance, and supply chain management.
- Documented outcomes: Each case study includes measurable outcomes or qualitative insights regarding the challenges faced, strategies implemented, and results achieved.
- Innovative practices: The studies highlight unique approaches and actionable lessons.

Following these criteria, Siemens, JPMorgan Chase, and Turner Construction were selected as representative cases due to their industry leadership, documented application of AI in PRM, and publicly available information regarding their AI-driven risk management initiatives. Each case study was analyzed through thematic analysis, focusing on how AI technologies were integrated, what challenges were encountered, what benefits were realized, and what lessons could be generalized for broader organizational contexts.

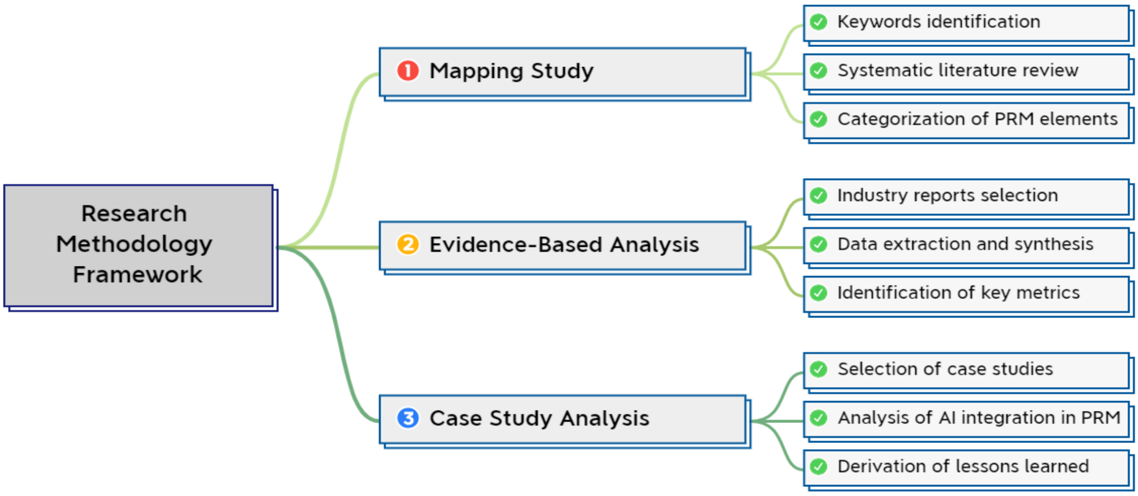

Fig.1. Research methodology framework

4. Results and Discussion

This section outlines the results obtained through the three methodological approaches: the systematic mapping study, analysis of industry-based evidence, and the assessment of case studies.

4.1. Key insights from the mapping phase

The mapping study serves as the foundational phase of this research, systematically analyzing the transformative impacts of AI on key elements of PRM. Synthesizing insights from academic literature and industry applications, the study identifies how advanced AI technologies are reshaping risk management practices and the specific benefits each area can derive from these trends. Each component was examined to highlight the specific AI technologies leveraged, their resulting impacts, and the practical implications. This detailed examination provides a structured framework that outlines the relationship between AI and PRM, highlighting opportunities for optimization and innovation.

AI has enabled significant advancements across all elements of PRM, including risk identification, assessment, mitigation, and monitoring. For instance, in the domain of risk identification, AI technologies such as ML, NLP, and RPA have automated the early detection of potential risks by analyzing historical project data and extracting risk-related information from project documents. Similarly, in risk assessment, tools like predictive analytics and Bayesian networks provide nuanced insights into the likelihood and impact of risks, while automating the evaluation process to reduce manual effort. The integration of simulation models, decision support systems, and workflow automation has further optimized risk mitigation, enabling real-time scenario modeling and effective execution of mitigation plans. Finally, in risk monitoring, the use of real-time data analytics and anomaly detection algorithms ensures continuous surveillance of project progress, with automated reporting tools streamlining stakeholder communication. Table 1 presents a structured summary of several impacts, detailing the AI solutions employed, their contributions to enhancing PRM practices, and practical examples of use cases. These advancements emphasize the ability of AI to enhance accuracy, efficiency, and responsiveness in risk management, aligning with recent trends in data-driven decision-making and proactive risk mitigation.

Table 1. Key AI technologies and their impacts across PRM elements with use cases

PRM component	AI technologies leveraged	Key impacts of AI on PRM	Use cases	Supporting references
Risk Identification	- Machine Learning - Natural Language Processing - Robotic Process Automation (RPA)	- Automated risk detection: AI models analyze historical project data to identify potential risks early in the project lifecycle. - Document analysis automation: NLP techniques extract risk-related information from project documents, while RPA automates the data extraction process.	- AI-generated risk logs provide project managers with a list of potential risks based on project context. - Automated systems review contracts and communications to flag potential risk factors.	(Al Zarooni & El Khatib, 2023; Erfani, 2023; Fujii et al., 2022; Kestenholz, 2023; Odejide & Edunjobi, 2024; Parekh & Olivia, 2024; Takyar, 2024)
Risk Assessment	- Predictive Analytics - Bayesian Networks - Process Automation Tools	- Enhanced risk evaluation: AI assesses the probability and impact of identified risks by analyzing large datasets. - Causal relationship modeling: Bayesian Networks identify relationships between risk factors. - Automated data collection: Automation tools gather and process data for risk assessment, reducing manual effort.	- AI models predict project delays by evaluating factors like resource availability and task dependencies. - AI systems determine how specific risks influence project outcomes. - Automated systems compile real-time data from various sources to continuously update risk profiles.	(Afzal et al., 2021; Atif & Qureshi, 2024; Baryannis et al., 2019; Basrai & Ben Ali, 2024; Iacono et al., 2024; Li et al., 2024; Pal et al., 2023; Wiesweg et al., 2020)
Risk Mitigation	- Simulation Models - Decision Support Systems - Workflow Automation	- Optimized mitigation strategies: AI suggests effective risk response strategies by simulating various scenarios. - Automated decision-making: AI systems provide actionable insights for risk response planning. - Streamlined risk response execution: Workflow automation implements mitigation actions promptly.	- AI recommends resource reallocation to address potential bottlenecks, ensuring project continuity. - AI evaluates the effectiveness of different mitigation plans. - Automated systems trigger predefined responses to emerging risks, minimizing delays.	(Kestenholz, 2023; Li et al., 2024; Odejide & Edunjobi, 2024; O'Neill, 2024; Yaseen, 2021; Yazdi et al., 2024; Öztemel & Tuncer, 2024)
Risk Monitoring	- Real-Time Data Analytics - Anomaly Detection Algorithms - Automated Reporting Tools	- Continuous risk surveillance: AI monitors ongoing project activities to detect deviations from the plan. - Proactive Issue Resolution: AI anticipates potential problems before they escalate. - Automated Risk Reporting: Tools generate and distribute risk reports without manual intervention.	- AI identifies schedule slippages by analyzing real-time progress data, enabling prompt corrective actions. - AI alerts project managers to emerging risks based on data trends. - Automated systems compile and send daily risk summaries to stakeholders.	(Algheetany et al., 2024; Chenya et al., 2022; Harish & Mansurali, 2024; Li et al., 2024; Loftus, 2003; O'Neill, 2024; Prasanth, 2024; Soravito, 2023)

4.2. Evidence-based analysis of AI role in PRM

Building upon the insights from the mapping study, this section examines the tangible impacts of AI integration into PRM by analyzing data from industry reports and consulting firm publications. These sources provide empirical evidence of how AI technologies enhance risk management practices, leading to measurable improvements in project outcomes. The market for AI in trust, risk, and security management was valued at $1.7 billion in 2022 and is expected to grow to $7.4 billion by 2032, with a compound annual growth rate of 16.2% (Allied Market Research, 2023). This exponential growth highlights the increasing adoption of AI in PRM, as organizations recognize its potential to deliver cost savings, efficiency gains, and more proactive risk management strategies. Key evidence-based metrics demonstrating the benefits of AI integration into PRM are summarized in Figure 2.

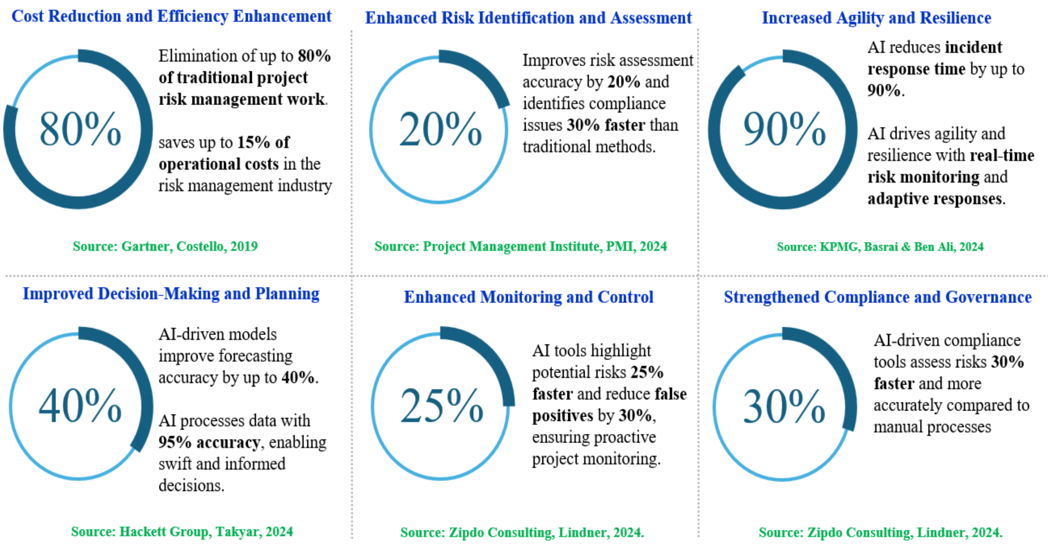

Fig. 2. Evidence-based metrics from industry leaders

4.2.1. Cost Reduction and Efficiency Enhancement

The adoption of AI in PRM has been shown to significantly reduce costs and improve efficiency. According to a report by Gartner (Costello, 2019), AI can automate routine tasks in project management including risk management processes, potentially eliminating up to 80% of traditional project management work, thereby allowing project managers to focus on strategic activities. Additionally, AI-driven predictive analytics enable more accurate forecasting of project risks, which can lead to a reduction in contingency costs and more efficient resource allocation. Furthermore, the adoption of AI in PRM has led to significant cost reductions and efficiency improvements across various industries. For instance, according to a report by Zipdo Consulting (Lindner, 2024), AI can save up to 15% of operational costs in the risk management industry, improve the efficiency of claims processing by up to 60% in the insurance industry, and reduce the time needed for credit risk analysis by up to 70% for banks.

4.2.2. Enhanced Risk Identification and Assessment

AI technologies, such as ML and NLP, enhance the ability to identify and assess risks by analyzing large volumes of data to detect patterns and anomalies. The Project Management Institute (PMI) notes that AI can assist in risk identification, analysis, and provide general recommendations for risk mitigation, thereby improving the comprehensiveness of risk assessments (PMI, 2024). This leads to earlier detection of potential issues and more effective mitigation strategies. Notably, 61% of risk professionals report that AI adoption has increased their ability to forecast risk scenarios (Lindner, 2024). AI-powered risk models can process data from multiple sources simultaneously, improving risk assessment accuracy by 20%. Moreover, AI-driven risk assessments can identify compliance issues 30% faster than traditional methods, with an overall improvement in predictive analytics accuracy by 25%. Furthermore, Takyar (2024) indicates that predictive analytics models driven by AI can reduce project delays by as much as 30% and ensure timeline adherence, especially in sectors such as IT and software development.

4.2.3. Improved Decision-Making and Strategic Planning

AI significantly enhances decision-making and strategic planning by providing data-driven insights derived from complex datasets. Leveraging AI for PRM allows organizations to identify trends, optimize resource allocation, and prioritize risk mitigation efforts effectively. According to a report by Hackett Group (Takyar, 2024), organizations implementing AI-enhanced risk models report an increase in forecasting accuracy by up to 40%. Additionally, AI's ability to process structured and unstructured data sources with 95% accuracy has enhanced decision-making capabilities. This capability reduces decision-making cycles by synthesizing large volumes of data in real time, ensuring swift and informed risk responses (Lindner, 2024).

4.2.4. Increased Agility and Resilience

AI enables organizations to build more agile and resilient project management practices by providing real-time risk monitoring and adaptive response mechanisms. According to a KPMG report, AI and machine learning techniques are transforming risk management in the financial services sector by enabling real-time risk identification and response, which can be extrapolated to project management contexts (Basrai & Ben Ali, 2024). This agility allows for quicker adaptation to changing project conditions and external factors, thereby enhancing overall project resilience. For instance, according to Zipdo Consulting report (Lindner, 2024), AI can reduce incident response times by up to 90%, enabling swift containment and resolution of issues.

4.2.5. Enhanced Monitoring and Control

AI facilitates continuous project monitoring through real-time data analytics and anomaly detection, enabling prompt corrective actions. Automated reporting tools provide stakeholders with up-to-date information, improving transparency and communication. For example, according to a Zipdo Consulting report (Lindner, 2024), AI can reduce cyber incident response times by up to 90%, highlight potential risk cases 25% faster than traditional methods, and reduce false positives by 30%. These capabilities ensure that risk monitoring and control remain proactive and precise.

4.2.6. Strengthened Compliance and Governance

AI enhances compliance management by automating the identification and monitoring of regulatory risks. According to Lindner (2024), AI-driven tools can assess compliance-related risks 30% faster and with greater accuracy compared to manual processes, ensuring adherence to standards and mitigating regulatory penalties. Moreover, AI systems equipped with NLP can continuously scan regulatory updates, flagging potential impacts on ongoing projects and ensuring proactive adjustments. Integrating ML algorithms allows organizations to predict areas of non-compliance before they occur, allowing for preventive action and improved governance frameworks.

4.3. Case studies of AI-enabled risk management breakthroughs

This section showcases real-world applications of AI in PRM, focusing on notable organizations and their transformative journeys. Each case study delves into the specific challenges faced by the company in risk management, the AI-driven solutions deployed, the tangible outcomes achieved, and the key lessons that can inform broader adoption and innovation in managing project risks.

4.3.1. Siemens - mitigating supply chain risk with AI-powered intelligence

In today's volatile global landscape, supply chain disruptions pose a significant challenge to businesses across industries. Siemens, a global technology powerhouse, recognized the need for proactive risk management and turned to AI to enhance supply chain resilience and optimize operations. This case is developed based on insights from AI Expert Network (2023), Acain (2023), Perry (2024), and Siemens Press (2023).

Siemens manages an intricate supply chain that spans multiple industries and regions. This complexity presents significant challenges in risk management, particularly in predicting and mitigating disruptions. Traditional methods often fall short in processing the vast and diverse data impacting supply chains, such as geopolitical events, natural disasters, and fluctuating market demands. Maintaining real-time visibility into component availability, potential bottlenecks, and emerging risks is crucial for informed decision-making but remains a persistent challenge (Perry, 2024). Ensuring business continuity by minimizing downtime and production delays due to supply chain disruptions is essential to meet customer demands and maintain profitability.

To address these issues, Siemens acquired “Supplyframe” in 2021, integrating its AI-powered Design-to-Source Intelligence platform with Siemens “Xcelerator”. This integration enabled real-time insights into global component availability, demand, cost, and compliance during the design phase (Siemens Press, 2023). Advanced AI algorithms analyze extensive data from supplier databases, logistics networks, and market trends to identify potential disruptions and predict their impacts. This proactive approach allows Siemens to implement mitigation strategies, such as securing alternative suppliers or adjusting production schedules, thereby enhancing supply chain resilience and ensuring business continuity (Acain, 2023).

This AI-driven approach to supply chain risk management has yielded significant benefits, including enhanced resilience through improved anticipation and response to disruptions, which minimizes operational impacts. While specific figures are not publicly available, Siemens reports significant reductions in downtime due to proactive risk mitigation (AI Expert Network, 2023). Additionally, the company has achieved increased efficiency by optimizing processes, reducing costs, and improving on-time delivery. Real-time data and AI-powered insights have empowered teams to make informed decisions and proactively manage risks. This case exemplifies the trend highlighted in the literature (e.g., Yazdi et al., 2024; Khodabakhshian et al., 2024) where predictive analytics and AI-powered monitoring substantially enhance early risk detection, resilience, and proactive decision-making in complex project environments. Siemens’ experience demonstrates the practical realization of these AI-driven benefits, as emphasized in recent academic studies.

The company’s integration of AI into its supply chain risk management offers valuable lessons for organizations aiming to enhance resilience in complex, global operations. A key takeaway is the importance of proactive risk identification and mitigation to foresee potential disruptions and implement appropriate strategies. Another critical lesson is the value of integrating AI solutions within existing digital infrastructures. The incorporation of Supplyframe's platform into its Xcelerator ecosystem exemplifies how such integration can provide a cohesive digital framework that unifies various operational facets.

4.3.2. JPMorgan Chase – enhancing risk management with AI-driven strategies

JPMorgan Chase & Co., a leading global financial services firm, operates across investment banking, financial services, and asset management sectors, serving millions of clients worldwide. The firm manages a vast array of financial products and services, necessitating robust risk management practices to safeguard assets and maintain regulatory compliance. This case is developed based on insights from Palakurti (2024), Nimmagadda (2022), Moses (2024), DigitalDefynd (2024), and JPMorgan (2023).

The company faces multifaceted risk management challenges due to the dynamic nature of financial markets. Traditional fraud detection methods often struggle to keep pace with sophisticated fraudulent activities, leading to potential financial losses and reputational damage (Nimmagadda, 2022). Navigating complex and evolving regulatory landscapes requires meticulous monitoring and reporting to avoid legal penalties. Additionally, manual processes in risk assessment and compliance are time-consuming and prone to human error which impacts the overall operational efficiency (Palakurti, 2024).

To address these challenges, JPMorgan Chase has implemented advanced AI-driven solutions across various operational areas. In fraud detection, the bank utilizes machine learning algorithms to analyze vast datasets, enabling real-time transaction monitoring and the identification of anomalous patterns indicative of fraudulent activity. This proactive approach enhances the bank's ability to prevent financial crimes and minimize associated losses (DigitalDefynd, 2024). For regulatory compliance, AI systems automate the monitoring and reporting processes, ensuring adherence to complex and evolving legal requirements (JPMorgan, 2023). By systematically analyzing legal documents and transactions, these systems reduce the risk of non-compliance and the potential for legal penalties. Additionally, the integration of AI into operational workflows streamlines risk assessment and compliance tasks, significantly reducing manual effort and the likelihood of human error, thereby improving overall efficiency (Palakurti, 2024).

JPMorgan Chase's integration of AI into its risk management framework has yielded significant benefits. The deployment of AI-driven fraud detection systems has enhanced the bank's ability to identify and prevent fraudulent activities, thereby reducing financial losses and bolstering customer trust (Nimmagadda, 2022). In regulatory compliance, AI has streamlined monitoring and reporting processes, ensuring adherence to complex legal requirements and minimizing the risk of penalties (JPMorgan, 2023). Operational efficiency has improved through the automation of manual tasks, leading to faster and more accurate risk assessments (Moses, 2024). Notably, the bank's AI-driven Contract Intelligence (COiN) platform has automated the review of complex legal documents, reportedly saving over 360,000 hours of manual work annually (DigitalDefynd, 2024). These advancements have collectively strengthened JPMorgan's resilience against financial crimes and operational risks. This practical deployment aligns with the observations of Mariani and Mancini (2024), who highlight that AI-driven decision support systems play a pivotal role in enhancing project performance by enabling faster, data-informed responses to emerging risks and fostering resilience in complex and dynamic environments. Moreover, JPMorgan's use of machine learning to monitor and detect fraud aligns with Yazdi et al. (2024)'s findings on the superiority of AI models in handling predictive risk identification compared to traditional qualitative methods.

The bank's experience offers valuable lessons for organizations aiming to enhance risk management through AI. A proactive approach to AI adoption is crucial, involving significant investment in technology and talent to effectively develop and implement AI solutions. Ensuring robust AI and model risk governance is essential to maintain the integrity and reliability of AI systems. Additionally, fostering a culture of continuous learning and adaptation enables organizations to keep pace with technological advancements and evolving risk landscapes.

4.3.3. AI-driven risk management in Turner Construction projects

Turner Construction Company, a leading North American builder, operates across diverse market segments, including healthcare, education, commercial, and sports facilities. With a vast portfolio of large-scale projects, Turner faces significant challenges in identifying and mitigating risks that could lead to project delays, cost overruns, and safety incidents. Traditional risk management approaches often fall short in proactively addressing potential issues, necessitating more advanced solutions. This case is developed based on insights from Subramanian & Singh (2024), Ghodsian (2024), Hyscaler (2024), and Psico-smart Editorial Team (2024).

Turner Construction Company faces multifaceted challenges in PRM. Ensuring worker safety amidst heavy machinery, heights, and electrical hazards is paramount, as traditional safety measures are often reactive, addressing issues only after they occur. Unforeseen factors such as weather conditions, labor shortages, and supply chain disruptions can lead to project delays and increased costs, impacting timelines and profitability. Additionally, handling vast amounts of project data manually is time-consuming and prone to errors, affecting decision-making processes. These challenges necessitate a proactive and integrated approach to effectively mitigate risks and ensure successful project delivery.

To address these challenges, Turner Construction integrated AI-driven strategies into its PRM processes. Implementing AI systems that analyze real-time data from construction sites enables the identification of potential safety hazards before they escalate, allowing for timely interventions and reducing the likelihood of accidents (Hyscaler, 2024). Additionally, employing AI algorithms to analyze historical project data allows Turner to predict high-risk areas, facilitating early detection of issues and timely mitigation strategies (Ghodsian, 2024). Furthermore, AI facilitates efficient handling of large datasets, streamlining processes such as document classification, archiving, and retrieval, thereby enhancing regulatory compliance and reducing manual effort (Psico-smart Editorial Team, 2024). These applications reflect the trends identified in recent literature (e.g., Gao et al., 2024; Erfani et al., 2023), where AI-driven text analysis and predictive modeling significantly improve real-time risk monitoring, compliance management, and proactive issue detection in complex project environments. Turner’s experience highlights the operational benefits of adopting these advanced AI-enabled techniques, including safer and more efficient project delivery.

The implementation of AI in Turner Construction's risk management processes has led to notable advancements in project delivery. AI-powered safety management systems have achieved a remarkable 22% reduction in accident rates, as reported in industry case analyses (Hyscaler, 2024). Furthermore, AI-enabled proactive risk assessment and mitigation strategies have driven a 12% decrease in project overruns, resulting in more predictable schedules and budgets (Ghodsian, 2024). Lastly, the automation of data management processes has streamlined workflows, reducing document search time by 30%, enabling project teams to concentrate on critical tasks and optimize resource allocation (Psico-smart Editorial Team, 2024).

Turner Construction's experience offers valuable lessons for the construction industry. It highlights the importance of proactive risk identification; utilizing AI for early detection of potential issues allows for timely interventions, preventing minor problems from escalating into major setbacks. Furthermore, seamless integration of AI solutions within existing project management frameworks ensures a cohesive and effective risk management strategy, making AI-driven insights readily available and actionable for project teams.

4.3.4. Comparison of AI-driven PRM practices with traditional frameworks

The findings from the case studies presented in this research reveal a notable evolution in PRM practices compared to traditional frameworks such as PMBOK. While PMBOK emphasizes structured, linear processes for risk identification, assessment, mitigation planning, and monitoring, AI-driven approaches introduce dynamic, real-time capabilities that enhance adaptability and predictive foresight. In particular, the Siemens and Turner Construction cases illustrate how AI-powered predictive analytics and monitoring go beyond static risk registers, enabling continuous reassessment based on live data streams. Similarly, JPMorgan Chase's use of machine learning algorithms exemplifies how AI facilitates proactive risk mitigation compared to the more reactive nature of traditional qualitative assessments. These AI-enabled advancements complement and extend the foundational risk management principles of PMBOK by promoting more data-driven, adaptive, and anticipatory risk practices, thereby addressing some of the limitations of traditional frameworks in complex and rapidly evolving project environments.

5. Conclusion and future research directions

The integration of AI into PRM has proven transformative across diverse industries, addressing the complexities of modern projects while enhancing risk identification, assessment, mitigation, and monitoring. This study aimed to investigate the role of AI in PRM through three core objectives: (1) identifying trends in AI adoption for PRM, (2) evaluating its effectiveness through evidence-based insights, and (3) analyzing real-world case studies to derive practical insights. Leveraging a qualitative and evidence-based approach, this research synthesized insights from academic literature, industry and consulting firm reports, and case studies of leading organizations including Siemens, JPMorgan Chase, and Turner Construction. The findings revealed significant advancements driven by AI, highlighting its capacity to improve decision-making, operational efficiency, and resilience in PRM. Case studies demonstrated AI's ability to proactively address risks, streamline processes, and deliver measurable outcomes such as reduced safety incidents, cost overruns, and enhanced compliance.

This study contributes to the academic literature by providing a structured synthesis of how AI is applied across key PRM functions, thereby addressing a critical gap in understanding its role. From a practical perspective, it offers actionable and evidence-based insights to support project professionals in informed decision-making regarding the adoption and implementation of AI technologies. Together, these contributions help bridge the gap between scholarly discourse and real-world application, advancing both theoretical understanding and managerial practice in AI-enabled PRM.

Despite its contributions, this study is not without limitations. It primarily focused on successful applications of AI, potentially overlooking instances where adoption faced barriers or did not meet expectations. Furthermore, the case studies predominantly examined large organizations, leaving gaps in understanding the challenges and opportunities for small and medium-sized enterprises (SMEs). Finally, much of the analysis emphasized immediate benefits, with limited exploration of AI's long-term impacts on project outcomes, adaptability, and sustainability. In addition to these considerations, several methodological limitations associated with AI-driven PRM practices must be acknowledged. Algorithm bias remains a significant concern, as AI systems trained on historical project data may inadvertently reinforce outdated patterns or overlook novel risks. Data quality issues also pose challenges, as the effectiveness of AI-based predictions depends heavily on the accuracy, completeness, and timeliness of input data. Furthermore, governance concerns related to AI transparency, accountability, and ethical oversight continue to evolve, posing risks for organizations seeking to deploy AI-based risk management solutions at scale. Addressing these challenges through robust governance frameworks, continuous validation, and ethical design will be essential to fully realizing the potential of AI-driven PRM systems.

To build on these insights, several future research directions are proposed. First, exploring cases of AI adoption challenges or failures could offer valuable lessons for navigating barriers and setting realistic expectations. Second, developing tailored AI frameworks for SMEs could promote wider adoption and inclusivity across organizational contexts. Third, investigating the ethical and societal implications of AI in PRM will ensure its responsible use. Fourth, longitudinal studies examining AI's sustained impact on PRM practices could provide a deeper understanding of its role in fostering innovation and resilience in the face of evolving project complexities. Finally, investigating strategies to mitigate algorithm bias, enhance data quality, and develop comprehensive governance frameworks for AI-driven PRM systems would be valuable to ensure ethical, transparent and sustainable deployment of AI technologies in project environments.

References

Acain, S. (2023). Enhancing supply chain prediction with AI. Siemens Thought Leadership. https://blogs.sw.siemens.com/thought-leadership/2023/07/13/enhancing-supply-chain-prediction-with-ai/

Afzal, F., Yunfei, S., Nazir, M., & Bhatti, S. M. (2021). A review of artificial intelligence based risk assessment methods for capturing complexity-risk interdependencies: Cost overrun in construction projects. *International Journal of Managing Projects in Business*, *14*(2), 300-328. https://doi.org/10.1108/IJMPB-02-2019-0047

AI Expert Network. (2023). Case Study: How Siemens Is Transforming Supply Chain with AI. AI Expert Network. https://aiexpert.network/case-study-how-siemens-is-transforming-supply-chain-with-ai/

Al Zarooni, L., & El Khatib, M. (2023). Robotics Process Automation (RPA) and Project Risk Management. *International Journal of Business Analytics and Security (IJBAS)*, *3*(1), 75-91. https://doi.org/10.54489/ijbas.v3i1.198

Algheetany, N., Othman, A. A. E., & Alamoudy, F. O. (2024). Artificial Intelligence Towards Enhancing the Risk Management Practices During the Design Process. In IOP Conference Series: Earth and Environmental Science. 1396(1), 012036. https://doi.org/10.1088/1755-1315/1396/1/012036

Allied Market Research. (2023). AI Trust, Risk and Security Management Market Size, Share, Competitive Landscape and Trend Analysis Report. https://www.alliedmarketresearch.com/ai-trust-risk-and-security-management-ai-trism-market-A97526.

Al-Saffar, M. A., Darwish, A. S., Farrell, P. E. T. E. R., & Saffar, N. E. H. A. L. (2024). A Critical Analysis of Traditional and Ai-Based Risk Assessment Frameworks for Sustainable Construction Projects. *Journal of engineering science & technology*, *19(1)*, 35-54.

Atif, A., & Qureshi, M. A. (2024, August). Enhancing Digital Resilience through AI in Industry 5.0: A Technology Management Perspective. In 2024 Portland International Conference on Management of Engineering and Technology (PICMET) (pp. 1-9). IEEE.

Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: state of the art and future research directions. *International journal of production research*, *57*(7), 2179-2202. https://doi.org/10.1080/00207543.2018.1530476

Basrai, A., & Ben Ali, S. (2024). Artificial Intelligence in Risk Management. KPMG. https://kpmg.com/ae/en/home/insights/2021/09/artificial-intelligence-in-risk-management.html

Beaudrie, C. E., Kandlikar, M., & Ramachandran, G. (2016). Using expert judgment for risk assessment. In *Assessing nanoparticle risks to human health* (pp. 91-119). Elsevier.

Bhoola, V., Hiremath, S., & Mallik, D. (2014). An Assessment of risk response strategies practiced in software projects. *Australasian Journal of Information Systems*, *18*(3).

Chenya, L., Aminudin, E., Mohd, S., & Yap, L. S. (2022). Intelligent risk management in construction projects: Systematic Literature Review. *IEEE Access*, *10*, 72936-72954. https://doi.org/10.1109/ACCESS.2022.3189157

Choi, S. W., Lee, E. B., & Kim, J. H. (2021). The engineering machine-learning automation platform (Emap): A big-data-driven ai tool for contractors' sustainable management solutions for plant projects. *Sustainability (Switzerland)*, *13*(18), Article 10384. https://doi.org/10.3390/su131810384

Costello, K. (2019). Gartner says 80 percent of today's project management tasks will be eliminated by 2030 as Artificial Intelligence takes over. In: From Gartner: https://www.gartner.com/en/newsroom/press-releases/2019-03-20-gartner-says-80-percent-of-todays-project-management

Csiszar, A., Hein, P., Wächter, M., Verl, A., & Bullinger, A. C. (2020, September). Towards a user-centered development process of machine learning applications for manufacturing domain experts. In 2020 Third International Conference on Artificial Intelligence for Industries (AI4I) (pp. 36-39). IEEE. https://doi.org/10.1109/AI4I49448.2020.00015

Dewasiri, N. J., Dharmarathna, D. G., & Choudhary, M. (2024). Leveraging artificial intelligence for enhanced risk management in banking: A systematic literature review. Artificial intelligence enabled management: An emerging economy perspective, 197-213.

DigitalDefynd. (2024). 5 ways JP Morgan is using AI – Case Study. DigitalDefynd. https://digitaldefynd.com/IQ/jp-morgan-using-ai-case-study.

El khatib, M., Al-Shalabi, A., Alamim, A., Alblooshi, H., Alhosani, S., Al-Kaabi, Alshurideh, M. (2023). How Drones Can Mitigate Unknown-Unknown Risks Case of Covid-19. In *Studies in Computational Intelligence,* 1056, 717-732. https://doi.org/10.1007/978-3-031-12382-5_38

Elkhatib, M., Zitar, R. A., Alnaqbi, K. A., Alnaqbi, W., Alharmoodi, S., & Baydoun, A. (2023). Effect of Big Data and Analytics on Managing Projects. *International Journal of Computer Applications, 30(2).*

Erfani, A. (2023). Data-driven risk modeling for infrastructure projects using artificial intelligence techniques (Doctoral dissertation, University of Maryland, College Park).

Erfani, A., Ma, Z., Cui, Q., & Baecher, G. B. (2023). Ex post project risk assessment: Method and empirical study. *Journal of Construction Engineering and Management*, *149*(2), 04022174. https://doi.org/10.1061/JCEMD4.COENG-12588

Fang, C., & Marle, F. (2012). A simulation-based risk network model for decision support in project risk management. *Decision Support Systems*, *52*(3), 635-644. https://doi.org/10.1016/j.dss.2011.10.021

Fridgeirsson, T. V., Ingason, H. T., Jonasson, H. I., & Kristjansdottir, B. H. (2021). The VUCAlity of projects: A new approach to assess a project risk in a complex world. *Sustainability*, *13*(7), 3808. https://doi.org/10.3390/su13073808

Fridgeirsson, T. V., Ingason, H. T., Jonasson, H. I., & Gunnarsdottir, H. (2023). A qualitative study on artificial intelligence and its impact on the project schedule, cost and risk management knowledge areas as presented in PMBOK®. *Applied Sciences*, *13*(19), 11081. https://doi.org/10.3390/app131911081

Fujii, M., Sakaji, H., Masuyama, S., & Sasaki, H. (2022). Extraction and classification of risk-related sentences from securities reports. *International Journal of Information Management Data Insights*, *2*(2), 100096. https://doi.org/10.1016/j.jjimei.2022.100096

Gao, N., Touran, A., Wang, Q., & Beauchamp, N. (2024). Construction risk identification using a multi-sentence context-aware method. *Automation in Construction*, *164*, 105466. https://doi.org/10.1016/j.autcon.2024.105466

Gautam, A. (2023). The evaluating the impact of artificial intelligence on risk management and fraud detection in the banking sector. *AI, IoT and the Fourth Industrial Revolution Review*, *13*(11), 9-18.

Ghodsian, N. (2024). Top 8 AI in Project Management Case Studies. Neuroject. https://neuroject.com/ai-in-project-management-case-studies

Goncharenko, P. (2024). The potential of using artificial intelligence in communications within project management (Master's thesis, School of Technology, University of Applied Sciences).

Gondia, A., Siam, A., El-Dakhakhni, W., & Nassar, A. H. (2020). Machine learning algorithms for construction projects delay risk prediction. *Journal of Construction Engineering and Management*, *146*(1), 04019085. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001736

Guba, E. G., & Lincoln, Y. S. (1994). Competing paradigms in qualitative research. Handbook of qualitative research, 2(163-194), 105.

Haghighi, M. H., & Ashrafi, M. (2024). A novel framework for risk management of software projects by integrating a new COPRAS method under cloud model and machine learning algorithms. *Annals of Operations Research*, *338*(1), 675-708. https://doi.org/10.1007/s10479-023-05653-3

Hamada, M. A. (2024, August). Machine Learning Model to Enhance the Quality of Software Development Risk Management. In 2024 IEEE 14th International Conference on Control System, Computing and Engineering (ICCSCE) (pp. 265-270). IEEE.

Harish, V., & Mansurali, A. (2024). Data-Driven Excellence: Unravelling the Potential of Analytics in Project Management. In *Using Strategy Analytics for Business Value Creation and Competitive Advantage* (pp. 388-428). IGI Global.

Hyscaler. (2024). Transformational Impact of AI on Construction Safety. https://hyscaler.com/insights/impact-of-ai-on-construction-safety.

Iacono, M., Mastroianni, M., Palmieri, F., & Saporito, A. (2024, July). A Tool to Support Automation of Risk Assessment. In International Conference on Computational Science and Its Applications (pp. 126-143). Cham: Springer Nature Switzerland.

Jahan Karamthulla, M., Muthusubramanian, M., Tadimarri, A., & Tillu, R. (2024). Navigating the Future: AI-Driven Project Management in the Digital Era. *International Journal for Multidisciplinary Research*, *6*(2), 1-11.

Jahan, S. A. (2024). Utilizing Predictive Analytics and Machine Learning for Enhanced Project Risk Management and Resource Optimization. *IPHO-Journal of Advance Research in Business Management and Accounting*, *2*(11), 24-31. https://doi.org/10.5281/zenodo.14249361

Jebreen, I. (2012). Using inductive approach as research strategy in requirements engineering. International Journal of Computer and Information Technology, 1(2), 162-173.

JPMorgan. (2023). AI and Model Risk Governance. https://www.jpmorgan.com/technology/news/ai-and-model-risk-governance

Kaur, Y., & Singh, S. (2018). Risk Mitigation Planning, Implementation, and Progress Monitoring: Risk Mitigation. In *Analyzing the Role of Risk Mitigation and Monitoring in Software Development* (pp. 1-20). IGI Global.

Kelemu, M. T., Rotimi, J. O. B., & Samarasinghe, D. A. S. (2023, November). Exploring the Potentials of Artificial Intelligence in Managing Project Deliverables and Risk in Construction Projects: A Bibliometric Analysis. In International Conference on Engineering, Project, and Production Management (pp. 287-303). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-56878-7_17

Kestenholz, P. (2023). How AI Is Revolutionizing Project Management: Three Use Cases. Forbes Technology Council. https://www.forbes.com/councils/forbestechcouncil/2023/03/30/how-ai-is-revolutionizing-project-management-three-use-cases/

Khatib, E., ZM, R., & Al-Nakeeb, A. (2021). The effect of AI on project and risk management in health care industry projects in the United Arab Emirates (UAE). *International Journal of Applied Engineering Research*, 6(1).

Khodabakhshian, A., Malsagov, U., & Re Cecconi, F. (2024, March). Machine Learning Application in Construction Delay and Cost Overrun Risks Assessment. In Future of Information and Communication Conference (pp. 222-240). Cham: Springer Nature Switzerland.

Larson, E., & Gray, C. (2014). *Project Management: The Managerial Process 6e*. McGraw Hill.

Li, H., Yazdi, M., Nedjati, A., Moradi, R., Adumene, S., Dao, U.,...Garg, H. (2024). Harnessing AI for Project Risk Management: A Paradigm Shift. In *Studies in Systems, Decision and Control*, 518, 253-272. https://doi.org/10.1007/978-3-031-51719-8_16

Lindner, J. (2024). AI In The Risk Management Industry: Surprising Statistics Revealed. Zipdo Consulting. https://zipdo.co/research/ai-in-the-risk-management-industry-statistics

Liu, J., Jin, F., Xie, Q., & Skitmore, M. (2017). Improving risk assessment in financial feasibility of international engineering projects: A risk driver perspective. *International Journal of Project Management*, 35(2), 204-211. https://doi.org/10.1016/j.ijproman.2016.11.004

Loftus, K. (2003). Intelligent risk profiling for project management (Master's thesis, Stellenbosch University, South Africa).

Makaula, S., Munsamy, M., & Telukdarie, A. (2021, April). Impact of artificial intelligence in South African construction project management industry. In Proceedings of the International Conference on Industrial Engineering and Operations Management, Sao Paulo, Brazil (pp. 5-8).

Mariani, C., & Mancini, M. (2024). AI's Role in Project Management: An Overview of the Literature and a Research Agenda. In International Workshop "A Multidisciplinary Approach to Embrace Complexity and Sustainability in Megaprojects (pp. 142-157). Springer, Cham.

Micán, C., Fernandes, G., & Araújo, M. (2020). Project portfolio risk management: A structured literature review with future directions for research. International Journal of Information Systems and Project Management, 8(3), 67-84. https://doi.org/10.12821/ijispm080304

Mishra, R. D., & Rasundram, J. (2017). Triangulation an essential tool to enhance the validity of a case study. *Scholarly Research Journal for interdisciplinary studies*, *4*(31), 69-74.

Mohammed, M. A., Mohammed, V. A., Ganesh, A., & Kiruthiga, T. (2024). Investigating the Advantages of AI-driven Predictive Analysis in Healthcare. In 2024 IEEE 3rd World Conference on Applied Intelligence and Computing (AIC) (pp. 167-172). IEEE.

Mojtahedi, S. M. H., Mousavi, S. M., & Makui, A. (2010). Project risk identification and assessment simultaneously using multi-attribute group decision making technique. *Safety science*, *48*(4), 499-507.

Moses. (2024). JPMorgan Chase's Approach to Risk Assessment and Mitigation. Bakelf. https://bakelf.com/jpmorgan-chases-approach-to-risk-assessment-and-mitigation

Moussa, A., Ezzeldin, M., & El-Dakhakhni, W. (2024). Predicting and managing risk interactions and systemic risks in infrastructure projects using machine learning. *Automation in Construction*, *168*, 105836. https://doi.org/10.1016/j.autcon.2024.105836

Muriana, C., & Vizzini, G. (2017). Project risk management: A deterministic quantitative technique for assessment and mitigation. *International Journal of Project Management*, 35(3), 320-340. https://doi.org/10.1016/j.ijproman.2017.01.010

Nimmagadda, V. S. P. (2022). AI-Powered Risk Management Systems in Banking: A Comprehensive Analysis of Implementation and Performance Metrics. *Australian Journal of Machine Learning Research & Applications*, *2*(1), 280-323.

Nyqvist, R., Peltokorpi, A., & Seppänen, O. (2024). Can ChatGPT exceed humans in construction project risk management?. *Engineering, Construction and Architectural Management*, *31*(13), 223-243. https://doi.org/10.1108/ECAM-08-2023-0819

Odejide, O. A., & Edunjobi, T. E. (2024). AI in project management: exploring theoretical models for decision-making and risk management. *Engineering Science & Technology Journal*, *5*(3), 1072-1085.

O'Neill, P. (2024). Part II: 8 Use Cases for AI in Risk Management. Redhand Advisors. https://redhandadvisors.com/part-ii-8-use-cases-for-ai-in-risk-management

Pal, D. K. D., Chitta, S., Bonam, V. S. M., Katari, P., & Thota, S. (2023). AI-Assisted Project Management: Enhancing Decision-Making and Forecasting. *Journal of Artificial Intelligence Research*, *3*(2), 146-171.

Palakurti, N. R. (2024). The Intersection of Information Technology, Financial Services, and Risk Management, Including AI and ML Innovations. *International Journal of Computer Engineering and Technology (IJCET)*, *15*(4), 665-682. https://doi.org/10.5281/zenodo.13361616

Parekh, R., & Olivia, M. (2024). Utilization of artificial intelligence in project management. *International Journal of Science and Research Archive*, *13*(1), 1093-1102. https://doi.org/10.30574/ijsra.2024.13.1.1779

Patton, M. Q. (1999). Enhancing the quality and credibility of qualitative analysis. Health services research, 34(5 Pt 2), 1189.

Perry, N. (2024). Siemens: Embracing Technology to Manage the Unexpected. Procurement Magazine. https://procurementmag.com/articles/siemens-embracing-technology-to-manage-the-unexpected

PMI. (2024). Shaping the Future of Project Management With AI. Project Management Institute, Inc. https://www.pmi.org/learning/thought-leadership/ai-impact/shaping-the-future-of-project-management-with-ai

Prasanth, S. M. K. (2024). Top 10 AI Use Cases Transforming Project Management Across Various Industries. NimbleWork. https://www.nimblework.com/blog/ai-use-cases-project-management/

Psico-smart Editorial Team. (2024). Future Trends in Workplace Safety: Predictive Analytics and AI Applications. https://psico-smart.com/en/blogs/blog-future-trends-in-workplace-safety-predictive-analytics-and-ai-applications-162719

Pym, D. V. (1987). Risk Management. *PM Network*, *1 (3)*, 33–36.

Qasim, A., El Refae, G., Eletter, S., & Issa, H. (2022, May). The application of drone technology in construction projects: risk management approach. In 2022 Cesare Conference Publications.

Rahi, K. (2019). Project resilience: A conceptual framework. International Journal of Information Systems and Project Management, 7(1), 69-83. https://doi.org/10.12821/ijispm070104

Rahi, K., Bourgault, M., & Preece, C. (2021). Risk and vulnerability management, project agility and resilience: a comparative analysis. International Journal of Information Systems and Project Management, 9(4), 5-21. https://doi.org/10.12821/ijispm090401

Robinson, K. A., Brunnhuber, K., Ciliska, D., Juhl, C. B., Christensen, R., & Lund, H. (2021). Evidence-based research series-paper 1: what evidence-based research is and why is it important? *Journal of Clinical Epidemiology*, *129*, 151-157. https://doi.org/10.1016/j.jclinepi.2020.07.020

Sahli, A., Pei, E., & Evans, R. (2023). A Conceptual Framework for Applying Artificial Intelligence to Manufacturing Projects. In IFIP International Conference on Advances in Production Management Systems (pp. 650-661). Cham: Springer Nature Switzerland.

Sarahrudge. (2024). AI is Coming, Are You Ready? https://construction-today.com/news/ai-is-coming-are-you-ready/

Secundo, G., Mele, G., Passiante, G., & Ligorio, A. (2024). How machine learning changes Project Risk Management: a structured literature review and insights for organizational innovation. *European Journal of Innovation Management*, 27(8), 2597-2622. https://doi.org/10.1108/EJIM-11-2022-0656

Seddik, H. M., & Rachid, C. (2023). Fuzzy approach and possibility to solve uncertainty weaknesses in conventional quantitative risk assessment. *Soft Computing*, 27(10), 6109-6133.

Shang, K. (2017). Improving Objectivity in Project Risk Management. In *Handbook of Research on Leveraging Risk and Uncertainties for Effective Project Management* (pp. 248-265). IGI Global.

Siemens Press. (2023). Siemens brings real-time supply chain intelligence to Siemens Xcelerator and the digital twin. Siemens Press Release. https://press.siemens.com/global/en/pressrelease/siemens-brings-real-time-supply-chain-intelligence-siemens-xcelerator-and-digital-twin

Soares, R. A., Chaves, M. S., & Pedron, C. D. (2020). W4RM: A prescriptive framework based on a wiki to support collaborative risk management in information technology projects. International Journal of Information Systems and Project Management, 8(1), 67-83. https://doi.org/10.12821/ijispm080104

Soravito, G. (2023). Artificial Intelligence for Risk Management: a Systematic Review (Doctoral dissertation, Politecnico di Torino).

Sousa, A., Faria, J. P., & Mendes-Moreira, J. (2021, July). An Analysis of the State of the Art of Machine Learning for Risk Assessment in Software Projects (S). In *SEKE* (pp. 217-222). https://doi.org/10.18293/SEKE2021-097

Subramanian, P., & Singh, R. (2024). Artificial Intelligence in International and National Project Management: Strategic Innovations for Success in the US and Beyond. *Baltic Multidisciplinary Research Letters Journal*, *1*(2), 42-48.

Taheri Khosroshahi, F. (2024). The future of project management: Embracing artificial intelligence for enhanced efficiency, data-driven decision-making, and collaborative teamwork (Master's thesis, University of Gothenburg, Sweden).

Takyar, A. (2024). AI in Project Management: Use cases, benefits, techniques, solution and implementation. LeewayHertz. https://www.leewayhertz.com/ai-in-project-management/

Tian, K., Zhu, Z., Mbachu, J., Ghanbaripour, A., & Moorhead, M. (2024). Artificial intelligence in risk management within the realm of construction projects: A bibliometric analysis and systematic literature review. Journal of Innovation & Knowledge, 10(3), 100711. https://doi.org/10.1016/j.jik.2025.100711

Turner, E. (2023). Integrating Natural Language Processing (NLP) for Real-Time Communication and Collaboration in Project Management. *Hong Kong Journal of AI and Medicine*, *3*(2), 39-44.

Ulusoy, G., & Hazır, Ö. (2021). *Introduction to Project Modeling and Planning*. Springer.

Uzzafer, M. (2010). A New Dimension in Software Risk Managment. *World Academy of Science, Engineering & Technology*, 340-344.

Villegas-Ch, W., García-Ortiz, J., & Sánchez-Viteri, S. (2024). Towards Intelligent Monitoring in IoT: AI Applications for Real-Time Analysis and Prediction. *IEEE Access*. https://doi.org/10.1109/ACCESS.2024.3376707

Wasike, J. (2024). The Impact of AI-Driven Decision Support Systems on Project Risk Management. https://dev.to/joshuawasike/the-impact-of-ai-driven-decision-support-systems-on-project-risk-management-knl

Wick, J. (2024). AI-powered GRC in Banking and Financial Services https://hitachids.com/insight/ai-powered-grc-in-banking-and-financial-services/

Wiesweg, F., Vogelsang, A., & Mendez, D. (2020, August). Data-driven risk management for requirements engineering: An automated approach based on Bayesian networks. In 2020 IEEE 28th International Requirements Engineering Conference (RE) (pp. 125-135). IEEE.

Xiaocong, H., & Ling, K. (2010, April). A risk management decision support system for project management based on bayesian network. In 2010 2nd IEEE International Conference on Information Management and Engineering (pp. 308-312). IEEE.

2026, 14(2), e140204, DOI: 10.12821/ijispm140204

Yadav, P., Gupta, P., Sijariya, R., & Sharma, Y. (2024). Artificial Intelligence in Risk Management. *Artificial Intelligence for Risk Mitigation in the Financial Industry*, 1-25.

Yaseen, A. (2021). Reducing industrial risk with AI and automation. *International Journal of Intelligent Automation and Computing*, 4(1), 60-80.

Yazdi, M., Zarei, E., Adumene, S., & Beheshti, A. (2024). Navigating the Power of Artificial Intelligence in Risk Management: A Comparative Analysis. *Safety*, 10(2), 42. https://doi.org/10.3390/safety10020042

Yim, R., Castaneda, J., Doolen, T., Tumer, I., & Malak, R. (2015). A study of the impact of project classification on project risk indicators. *International Journal of Project Management*, 33(4), 863-876. https://doi.org/10.1016/j.ijproman.2014.10.005

Zaouga, W., & Rabai, L. B. A. (2021). A decision support system for project risk management based on ontology learning. *International Journal of Computer Information Systems and Industrial Management Applications*, 13, 11-11.

Öztemel, E., & Tuncer, Y. (2024). Review of AI in Project Management and Conceptual Analysis on Risk Management. In *Engineering and Technology Management in Challenging Times* (pp. 221-237). Springer.

Biographical notes

Afef Saihi is a faculty member in the Department of Management Science and Engineering at Khalifa University, United Arab Emirates. She holds a Ph.D. in Engineering Systems Management from the American University of Sharjah. Her research spans digital transformation, sustainable performance evaluation, supply chain management, artificial intelligence applications across various industrial domains, and maintenance engineering, among others. With a strong record of publications in top-tier journals and prior experience in both academia and industry, she brings a multidisciplinary perspective to her work at the intersection of engineering and management science.

ORCID: 0000-0002-3664-8664