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# Artificial intelligence in construction project management: Trends, challenges and future directions

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## Abstract

Contemporary construction projects are characterized by escalating complexity, voluminous data flows, and stringent sustainability requirements, rendering conventional project management methods increasingly inadequate. In response, artificial intelligence (AI) has emerged as a transformative enabler in construction project management, offering advanced capabilities in predictive analytics, process automation, and intelligent decision support. This paper explores the role of AI in the identified principal functions of construction project management, including time management, cost estimation, quality assurance, occupational health and safety, risk mitigation, resource optimization, and design management through a narrative literature review. Analysis demonstrates that AI-driven approaches significantly enhance operational efficiency and system resilience by enabling proactive identification of schedule delays, cost overruns, and safety hazards. For example, image-recognition systems integrated with Internet-of-Things sensors facilitate real-time monitoring of site conditions and adaptive response to disruptions, while neural-network models trained on historical project data yield more accurate cost forecasts than traditional estimation techniques. In the design management domain, generative design algorithms and AI-enhanced BIM integration have the potential to automate clash detection, optimize form and function, and generate innovative design alternatives that align with cost, energy, and sustainability objectives. Beyond efficiency gains, AI fosters a paradigm shift toward predictive, data-driven, and adaptive management practices that strengthen project resilience, enabling teams to anticipate, absorb, and recover from unforeseen challenges while improving project performance and sustainability. Critical barriers to widespread AI adoption are also identified in this study. Fragmented and non-standardized data ecosystems impede model training and interoperability with legacy systems, while organizational resistance and a shortage of professionals skilled in both AI and construction hinder implementation. Ethical and legal concerns—stemming from the “black-box” nature of many AI algorithms—further complicate accountability in safety-critical decisions. By synthesizing these challenges, the strategic role of AI is highlighted not only as a technological innovation but also as a catalyst for cultural and organizational transformation toward more resilient project delivery. Targeted future research directions include empirical validation of AI tools in live project environments, development of sector-specific AI frameworks tailored to the peculiarities of the construction industry, interdisciplinary collaboration among engineers, data scientists, and managers, and educational initiatives to upskill the workforce. Collectively, these steps will help bridge the gap between theoretical potential and real-world impact, positioning AI as a cornerstone of intelligent, resilient, sustainable, and high-performing construction project management.

*Keywords:* artificial intelligence, construction project management, digital transformation in construction, smart construction technologies

## 1. Introduction

Construction projects are inherently complex, involving multiple stakeholders, dynamic environmental conditions, and significant uncertainty across design, execution, and handover phases. Traditional project management approaches—largely heuristic and siloed—struggle to process the growing volumes of data generated by modern Building Information Models (BIM), IoT sensors, and digital records. In response, artificial intelligence (AI) offers transformative capabilities in predictive analytics, process automation, and intelligent decision support. While prior studies

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highlight isolated technical applications—such as computer vision for safety monitoring or neural networks for cost estimation—there is a lack of holistic, function-oriented reviews that map AI across core construction project management domains.

This study fills that gap by conducting a structured narrative literature review to: (1) identify current and emerging AI applications in core domains such as planning, cost control, quality assurance, safety, risk mitigation, resource optimization, organizational learning, information management, design, and sustainability; (2) evaluate the technical and organizational challenges hindering adoption; and (3) propose strategic implications and future research directions. By aligning findings with the PMBOK (Project Management Body of Knowledge) framework, it provides both academic insight and a practical roadmap for integrating AI solutions into real-world construction project management and elucidates the strategic role of AI in advancing the efficiency, resilience, and sustainability of construction project management.



## 2. Background

### *2.1. Artificial Intelligence (AI)*

Artificial intelligence (AI) refers to machines performing tasks that require human-like cognitive functions—perception, learning, reasoning, and decision-making (Russell & Norvig, 2009). Early AI research in the mid-20th century explored symbolic reasoning, search algorithms, and knowledge representation, but high expectations led to an “AI winter” of reduced funding until advances in algorithms and hardware reignited interest (Russell & Norvig, 2009; Clark, 2015). The advent of big data—massive, high-velocity, high-variety datasets—proved a catalyst for modern AI, as machine learning (ML) and deep learning (DL) algorithms outperformed traditional statistics in pattern detection and prediction (Schneeweiss, 2014; Allam & Dhunny, 2019).

AI is typically categorized by scope and capability. Today’s deployed systems are Artificial Narrow Intelligence (ANI)—domain-specific tools that outperform humans on narrowly defined tasks such as image recognition or NLP. Artificial General Intelligence (AGI) remains theoretical, promising human-level cognitive adaptability and reasoning across tasks, while Artificial Superintelligence (ASI) is a speculative future stage exceeding human creativity and wisdom (Microsoft, n.d.). Beyond scope, AI spans a competency spectrum: Analytical AI handles data interpretation and inference, Human-inspired AI adds emotional intelligence, and Humanized AI aspires toward self-awareness (Kaplan & Haenlein, 2019).

Core AI research addresses reasoning under uncertainty, planning, perception, and learning from data (Luger, 2004). These advances have produced daily life tools like virtual assistants, recommendation engines, autonomous vehicles, and diagnostic tools. In industry—particularly logistics, energy, finance, and construction—AI promises efficiency gains, cost savings, and enhanced decision support by transforming raw data into actionable insights (Kowalski et al., 2012). In this study, AI methods—such as neural networks, computer vision, NLP, generative design—that directly impact key construction project management domains were focused.

### *2.2. Construction Project Management*

Construction projects are inherently complex socio-technical systems, requiring the coordination of design, planning, execution, monitoring, and handover under uncertainty. Traditional methods—often siloed, heuristic, and reactive—struggle with today’s scale, data volume, and sustainability demands (PMI, 2017; Walker, 2015). AI offers a transformative alternative by converting large, heterogeneous datasets (e.g., BIM models, IoT sensor streams, historical project records) into predictive insights and automated processes.

Key AI benefits in construction project management include proactive risk identification, optimized scheduling, dynamic resource allocation, and real-time quality and safety monitoring. For example, machine-learning models trained on past project data can predict cost overruns and delay risks before they materialize, while computer-vision systems analyze site images to detect safety hazards and quality defects instantaneously (Ekanayake et al., 2024; Lee & Lee, 2023). By integrating AI with legacy BIM and ERP platforms, teams can automate clash detection, perform generative design explorations, and simulate environmental impacts—thereby enhancing both efficiency and resilience.



Despite this promise, the sector's digital maturity remains low and AI in construction remains an underexplored area. Fragmented data architectures, interoperability issues, limited AI expertise, and organizational inertia continue to slow adoption (Toor & Ogunlana, 2010; Bang & Olsson, 2022). Addressing these barriers through standardized data protocols, interdisciplinary training, and executive buy-in is critical to realizing AI's full potential in construction project management.

## 3. Methodology

The study employs a structured narrative literature review approach with thematic analysis. Unlike a full systematic review protocol (e.g., PRISMA), this method balances rigor and flexibility, allowing thematic depth while ensuring transparency in selection and coding. Although it is particularly effective in emerging fields such as AI in construction project management to synthesize broad and multidisciplinary insights; the study is subject to certain limitations: reliance on secondary sources may exclude recent innovations not yet reflected in published literature, and the rapidly evolving nature of AI technologies may render some findings outdated over time.

A structured yet flexible review process was implemented to identify, evaluate, and interpret relevant studies, with the goal of answering the following research questions: (1) What are the emerging and current applications of AI in core construction project management domains, (2) What technical and organizational challenges hinder AI adoption, and (3) What are the future research and practice directions to maximize AI's impact.

A comprehensive search was conducted across major academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar, covering peer-reviewed journal articles, conference proceedings, and industry reports published between 2000 and 2025. Search queries included combinations of keywords as artificial intelligence, construction project management, project management, construction, digital transformation, smart construction, and AI in construction.

Inclusion criteria were: (1) Publications written in English, (2) Studies that explicitly address AI applications in construction project management, and (3) Articles providing empirical evidence, conceptual frameworks, case studies, or reviews. Exclusion criteria included: (1) Studies unrelated to the construction industry, (2) Articles focusing solely on generic AI applications without contextual relevance, and (3) Publications lacking methodological transparency or peer review.

A thematic analysis was conducted using inductive open coding. Eligible studies were manually coded, and codes were iteratively clustered into themes corresponding to project management functions based on their frequency and conceptual relevance. The thematic framework was guided by the PMBOK to ensure alignment with established domains of construction project management. Multiple readings and comparative analysis were employed to ensure consistency and to refine emergent categories. The synthesis of trends, recurring challenges, and practical use cases aimed to evaluate both the maturity and practical relevance of AI applications in the field. The flow diagram of the study can be briefly seen in Figure 1.

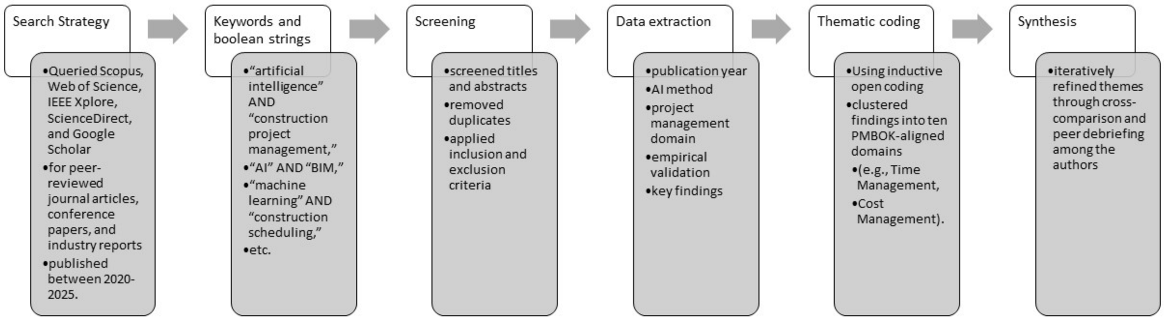


**Figure 1** The flow diagram of the study

## 4. Findings

### *4.1. Artificial Intelligence in Construction Project Management*

The construction sector's complexity, voluminous data flows, and uncertainty make it ripe for AI's pattern recognition, predictive analytics, and automation capabilities. Across planning, monitoring, and control, AI methods—machine learning, computer vision, and NLP—have the potential to contribute to decision-making, proactive delay forecasting, cost and quality alerts, and safety hazard detection, shifting the field from reactive heuristics to data-driven decision support and increasing efficiency across all phases of the project life cycle (Eadie et al., 2013; Bang & Olsson, 2022; Aladağ et al., 2024; Adebayo et al., 2025).

The potential application areas of AI in construction projects are extensive. In particular, AI-supported systems are being applied in critical areas such as scheduling and planning, resource management, cost estimation, quality control, and occupational health and safety. These systems accelerate decision-making processes and reduce the margin of error. For example, Lee and Lee (2023) developed deep learning-based models that detect unsafe behavior and PPE non-compliance in real time using computer vision. Such applications illustrate how AI not only augments on-site monitoring but also enhances overall project control. Moreover, machine learning algorithms trained on historical project data can predict project delays or cost overruns in advance, enabling project managers to take proactive measures. Furthermore, AI technologies such as image recognition, natural language processing, and autonomous equipment can be effectively utilized to enhance safety on construction sites, analyze real-time on-site conditions, and monitor workforce performance.

AI is often confused with automation in project management, but they are distinct. Automation executes predefined, structured tasks based on human-set rules. It has served many project management needs until recently. However, as workflows grow in complexity and data volume expands, automation alone is no longer sufficient. AI systems differ by learning from data, adapting over time, and making decisions without explicit programming (Riter, 2019). In project management, AI evolves from simple task automation to integrated systems that can coordinate teams, suggest process improvements, and make autonomous decisions (Burger, 2017). This shift positions AI as a transformative force—not just a tool—capable of advancing sustainability, safety, planning, risk analysis, cost control, and strategic oversight in construction project management (Bang & Olsson, 2022).

Originally conceptualized in the mid-20th century, AI long failed to meet expectations until recent advances in technology, big data, and machine learning significantly accelerated its development. AI is now seen as a potentially transformative tool for solving persistent problems in the construction industry, such as design errors, delays, inefficiencies, and occupational risks. Its ability to process large volumes of project data, support decision-making, improve cost and quality control, automate repetitive tasks, and enable real-time monitoring highlights its potential. By offering predictive analytics that help project managers optimize resources, manage risks, and enhance project performance, AI is expected to significantly improve productivity, safety, and sustainability in construction. As data volumes in the sector continue to grow, the use of AI will become more widespread, and this technology is poised to become an indispensable tool for successful project management in the future (Aladağ et al., 2024). Tian et al. (2025) further confirm this potential through a bibliometric review, highlighting that AI supports proactive risk mitigation across cost, schedule, safety, and quality domains.



Nonetheless, the integration of AI applications into project management is not merely a technical transformation but also entails a managerial and cultural shift. For successful integration, it is crucial to raise industry professionals' awareness of AI technologies and enhance their digital competencies. Hence, fully benefiting from AI is directly related not only to technological infrastructure but also to the human factor.

Despite its growing promise, the adoption of artificial intelligence (AI) in construction project management faces several critical challenges that hinder its widespread implementation. The adoption of AI applications continues to face challenges such as high implementation costs, a shortage of skilled personnel, data security concerns, and resistance stemming from the industry's traditionally conservative structure (Sacks et al., 2020). One of the foremost barriers is the lack of high-quality, structured, and standardized data, which is essential for training effective AI models but is often fragmented and inconsistent across platforms in construction projects (Khosrowshahi & Arayici, 2012). Moreover, the inherently complex and project-based nature of construction—with its site-specific variables, dynamic workflows, and non-repetitive processes—makes it difficult to generalize or transfer AI models across different projects or contexts. Technological fragmentation and interoperability issues between AI tools and legacy systems, such as Building Information Modeling (BIM) or Enterprise Resource Planning (ERP), also complicate integration efforts (Bilal et al., 2016). Compounding these issues is the shortage of professionals with dual expertise in both AI and construction, which limits practical deployment and innovation.

Furthermore, organizational resistance to change, particularly in firms rooted in traditional project management practices, poses a cultural barrier to adoption, often exacerbated by concerns over automation-induced job displacement (Perera et al., 2020). AI's “black-box” nature, especially in complex decision-making processes, introduces ethical and legal uncertainties surrounding accountability and liability—challenges that are particularly significant in a risk-averse industry like construction (Bai et al., 2020). The absence of standardized benchmarks and publicly available datasets also makes it difficult to validate AI models, limiting transparency and slowing industry trust. Additionally, real-time data collection, essential for many AI applications, raises cybersecurity and data privacy concerns, especially when sensitive project information is shared across cloud-based platforms.

A further challenge lies in the trust dynamic between human decision-makers and AI systems. Even when AI generates accurate recommendations, construction professionals may hesitate to act on them without clear interpretability or user-friendly interfaces. Lastly, the gap between academic innovation and real-world implementation persists, as many AI tools are developed under controlled conditions and lack robust testing in complex, real-world environments. These multifaceted challenges underline the need for industry-wide collaboration, regulatory clarity, improved data infrastructure, and a cultural shift toward embracing data-driven innovation in construction project management and addressing them is essential for realizing the full potential of AI in enhancing efficiency, sustainability, and decision-making in construction project management.

### *4.2. Key Application Areas of Artificial Intelligence in Construction Project Management*

Similar to the construction industry's traditionally slow adaptation to technological advancements, project management as a discipline has also been relatively slow in adopting machine learning and artificial intelligence (AI) technologies (Burger, 2017). However, as the use of AI expands across other industries, its application in construction project management continues to gain traction. In particular, advancements in technology, the emergence of the big data paradigm, and the increasing complexity and scale of contemporary construction projects underscore the necessity of AI implementation in project management. Critical reviews in projects underscore not only the potential of AI for monitoring and control but also the pressing requirement for ethical use, standardized datasets, and explainable systems (Chen et al., 2025).



AI technologies have the potential to transform not only technical processes but also decision-making mechanisms, project management strategies, and on-site operations. Artificial intelligence can be employed throughout the entire project life cycle, contributing to areas ranging from design optimization and resource planning to risk analysis, quality control, and even building life cycle assessments (Akinosho et al., 2020). At a broader level, recent reviews emphasize that AI adoption in project management is contingent on explainable, trustworthy AI systems, clear data governance, and alignment with human decision-making norms (Salimimoghadam et al., 2025).

Although AI-based project management tools remain relatively limited compared to other industries, several experimental applications are emerging. These include: analyzing team productivity to estimate task durations, ranking enterprise-level communication databases, automatically scheduling tasks based on workload and task duration, issuing alerts when budget or schedule overruns are anticipated, predicting the most suitable team member for specific tasks and assigning responsibilities accordingly, automatically distributing information to users based on relevance, visualizing notifications and updates, forecasting unattainable deadlines, and refining task time estimates. There are notable AI implementation attempts across various project management knowledge areas and processes. Among all, the most prominent potential application areas are: time management, cost management, quality management, occupational health and safety management, risk management, resource management, organizational learning, information management, design management and environmental sustainability. A brief summary can be seen in Table 1.

**Table 1** Brief Summary of Application Areas of AI in Construction Project Management

| Domain | AI Methods & Tools | Key Theme Example |
|---|---|---|
| Time Management | Deep learning, Computer vision | Delay forecasting |
| Cost Management | ANN, SVM, Regression trees | Real-time budget alerts |
| Quality Management | UAV imagery + CNN detection | Automated defect detection |
| Occupational Health & Safety | NLP, Sensor fusion | PPE compliance monitoring |
| Risk Management | Bayesian networks, NLP | ISO 31000 automated assessment |
| Resource Management | Predictive analytics | Labor/equipment forecasting |
| Organizational Learning | NLP, Knowledge graphs | Lessons-learned indexing |
| Information Management | Ontologies, Semantic indexing | Automated BIM clash detection |
| Design Management | Generative design, Digital twins | Parametric form finding |
| Environmental Sustainability | LCA modeling, Optimization algos | Carbon footprint scenario analysis |

#### *4.2.1. Time Management*

Time management in construction projects is a critical factor in ensuring that the project is completed within the planned timeframe. Project delays can lead to increased costs and contractual disputes (Love et al., 2016). Therefore, planning processes must be managed dynamically and in a predictive manner. Artificial intelligence provides solutions to this need through algorithms trained on historical project data. In particular, methods such as machine learning (ML) and deep learning (DL) can be used to predict potential causes of delay during the project lifecycle and to develop alternative planning scenarios. AI-based systems can analyze project schedules to identify dependencies between work packages, optimize critical path methods, and balance resource utilization in relation to time. For example, a hybrid deep learning model combining neural network demonstrate >93 % accuracy in time estimation for construction projects

(Cheng et al., 2025). Moreover, IoT sensors and on-site observations that provide real-time data streams can be integrated with AI algorithms, enabling continuous monitoring of on-site progress. This allows project managers to make decisions not only based on historical data but also with a forward-looking perspective.



AI's contribution in this area is not limited to the planning stage; it also enhances the accuracy of schedule updates during project execution and enables the creation of early warning systems against potential risks. As a result, more realistic and flexible project schedules can be created, increasing the likelihood of project success. For instance, one of the technologies developed to enhance construction productivity is the Doxel AI system, which utilizes autonomous recorders to capture images and conduct laser scans. It employs AI-based measurements to monitor progress and quality, providing real-time tracking of site status and improving team efficiency. This enables continuous tracking of potential discrepancies between planned and actual project schedules, allowing for more accurate forecasting (Doxel AI, n.d.). In addition, a variety of AI-assisted project management software tools serve professionals in the scheduling and planning domains of construction projects, contributing to the overall value created by the project. These tools help reduce the time and human resources allocated to project planning processes, thereby enhancing overall project efficiency. While tools like Doxel AI exemplify emerging commercial solutions in this domain, peer-reviewed works provides scientific validation of the approach. For example, Ekanayake et al. (2024) developed a deep-learning model for computer-vision based construction progress monitoring, automatically recognizing as-built conditions and reporting real-time status via a web-based platform. Recent advances also include AI-enhanced scheduling tools trained on BIM data and expert planning records, which can automatically sequence activities and predict resource requirements—eliminating the need for manual constraints and significantly streamlining planning workflows (Al-Sinan et al., 2024).

#### *4.2.2. Cost Management*

Cost management is one of the most critical processes in ensuring the economic sustainability of construction projects. Deviations in project costs can arise due to various factors such as fluctuations in material prices, labor inefficiencies, planning errors, and unforeseen site conditions (Flyvbjerg et al., 2003). While traditional cost estimation methods often fall short in reflecting this complexity, AI-based solutions have the potential to offer a more dynamic and data-driven approach to the process. As in all profit-oriented industries, the construction sector seeks to maximize the benefits of digital innovations in cost reduction, budget optimization, preliminary cost estimation, and financial planning. In this regard, AI-based project management softwares are increasingly employed to enhance efficiency in construction. For example, a hybrid deep learning model combining neural network demonstrate >97 % accuracy in cost estimation for construction projects (Cheng et al., 2025).

Artificial intelligence can learn from large datasets derived from previous projects to generate more accurate cost forecasts for future undertakings. Machine learning models—particularly artificial neural networks (ANN), support vector machines (SVM), and regression trees—can analyze a wide range of variables, including project size, location, contract type, work items, and procurement processes, to deliver precise cost estimates. Recent comparative reviews show that deep learning and hybrid models outperform traditional ML methods in terms of cost estimation accuracy, achieving up to 90% accuracy in construction project forecasts (Shamim et al., 2025). Moreover, AI can analyze real-time cost data generated during project execution, thus enabling continuous budget monitoring. As a result, deviations can be detected early, and decision-makers can take timely corrective actions. AI-assisted decision support systems can continuously monitor expenditures against the allocated budget and provide cost alerts to project managers. Additionally, proactive scenario analyses can be conducted to anticipate potential price fluctuations in the construction materials and equipment supply chain. Overall, AI applications can contribute to making cost management in construction projects more transparent, data-driven, and predictable, thereby providing a significant advantage in ensuring the financial success of projects.

### *4.2.3. Quality Management*

Quality management in the construction industry is important to ensure that projects are completed within the desired standards, on time, and within budget. Encompassing factors such as material quality, workmanship, structural compliance, and occupational health and safety, quality management is one of the primary determinants of project success. However, traditional quality control methods are often time-consuming, prone to human error, and largely reactive in nature. In this context, artificial intelligence (AI) holds the potential to make quality management processes in construction more efficient, rapid, and proactive.

AI-supported quality management systems can perform real-time inspections and evaluations on construction sites, particularly through the integration of computer vision, machine learning, and big data analytics. For instance, visual data captured by drones and cameras can be analyzed using AI algorithms to automatically detect quality deviations such as surface defects, cracks, or misalignments. This allows for the early identification of errors and deficiencies during the initial stages of the project, enabling timely interventions. Furthermore, by analyzing historical quality data, AI can learn the conditions under which specific defects tend to occur and provide recommendations to prevent similar issues in future projects. Quality checklists, audit plans, and compliance reports can also be automated, saving time and reducing the risk of human error. Another significant contribution lies in predictive quality analytics. AI can assess various variables—including environmental conditions, labor density, and material supply lead times—during the project to anticipate situations that may pose quality risks in specific work packages. This offers managers the opportunity to take preventive action and directly enhances overall project performance. In line with this, recent studies underscore the growing role of AI-based visual inspection, drones, and ML algorithms in real-time quality assurance, particularly for defect detection and site progress monitoring (Hasan et al., 2025).

In terms of practical implementations, one notable example is Doxel AI, a system designed to support product-level quality control by collecting real-time data from the field, identifying faulty work, and verifying alignment between planned and actual production (Doxel AI, n.d.). This system enables immediate error reporting and corrective action. By transforming quality management from a reactive inspection process into a continuous improvement and data-driven decision-making mechanism, AI has the potential to enable the development of more reliable, cost-effective, and sustainable construction projects.

### *4.2.4. Occupational Health and Safety Management*

The construction industry continues to be one of the sectors with the highest rates of occupational accidents. Each year, a significant number of work-related injuries and fatalities occur within the sector, posing substantial risks in terms of occupational health and safety (OHS). The rate of accidents during construction activities is considerably higher than in most other industries. Among the most notable causes are falls from heights, trips and slips, electric shocks, and being caught between objects. Due to factors such as working at height, use of heavy machinery, insufficient safety measures, and human error, accidents frequently occur—resulting not only in loss of life but also in significant financial losses (Hinze et al., 2013). In this regard, making OHS management more proactive and data-driven is of critical importance. Artificial intelligence (AI) has the potential to offer novel solutions in areas such as early risk detection, development of pre-incident warning systems, and the design of safer work environments.

The primary objective of AI applications in construction site safety is to monitor and report safety-related events, alert workers regarding safety protocols, and provide real-time safety cues (Blanco et al., 2017). Current AI-based research in this field mainly focuses on: (1) identifying workers who are not wearing required protective equipment, (2) detecting potential physical hazards on the construction site, (3) analyzing past accidents by comparing incident reports with captured images to predict possible future risks, and (4) generating preliminary warnings for identified potential hazards.

AI-supported computer vision systems and sensor data can analyze workers' movements and their use of safety gear (such as helmets and vests) in real time, promptly detecting anomalies and notifying relevant personnel. For example, using computer vision, unsafe worker behavior or presence in restricted areas can be identified before an accident occurs, allowing for preemptive intervention. In addition, machine learning algorithms trained on historical accident records and site data can predict which types of work, under what conditions and timeframes, are more prone to safety risks. This enables project managers to plan hazardous activities in advance, take necessary precautions, and update worker training programs accordingly. When integrated with virtual reality (VR) technologies, AI can also provide interactive, simulation-based training to workers, enhancing risk awareness and strengthening the overall safety culture. This approach not only helps prevent accidents but also contributes to reducing long-term safety-related costs within the industry.

Moreover, the use of AI in construction safety management significantly enhances efficiency and accelerates decision-making processes for project managers. For instance, in one study, an AI system was able to process 1,080 site photos in under five minutes to detect potential safety risks, whereas a human expert team required over five hours to conduct a similar review (Smith & Kanner, 2017). This finding demonstrates that AI can substantially reduce the time required for implementing safety measures, thereby improving both operational efficiency and on-site safety conditions. More recently, language models such as ChatGPT have also been adapted to extract and explain safety protocols, offering site teams faster and more accessible guidance from regulatory documents (Tran et al., 2024).

#### *4.2.5. Risk Management*

Due to their inherent complexity and the involvement of numerous stakeholders, construction projects are characterized by a high degree of uncertainty and risk. These risks can be multifaceted, encompassing cost overruns, schedule delays, quality deficiencies, environmental impacts, and occupational safety threats (Zou et al., 2007). The accurate identification, assessment, and prioritization of these risks is of critical importance for effective project management. At this point, artificial intelligence (AI) has the potential to offer a data-driven approach that enables a more efficient and predictive risk management process. However, despite these capabilities, AI also introduces a new layer of complexity and uncertainty in decision-making. As Kovačević and Bouder (2023) highlight, AEC professionals often encounter “model uncertainty,” “parameter uncertainty,” and “person uncertainty,” making it difficult to trust AI-generated recommendations without extensive validation or contextual awareness.

Machine learning algorithms, trained on data derived from past projects, can predict potential risks likely to emerge in similar projects and analyze their potential impacts (Elghaish et al., 2019). These machine learning algorithms are capable of evaluating numerous variables—including contract type, project scale, supply chain configuration, site conditions, and contractor history—to conduct project-specific risk assessments. In doing so, they provide decision-makers with the opportunity to take proactive measures against high-probability risks. Moreover, natural language processing (NLP) techniques can automatically analyze uncertainty and risk-related statements in project documents, contracts, and other textual records. This enables the systematic identification of sources of uncertainty even during the early stages of the project.

AI-assisted simulation and scenario analysis tools can model how project performance may be affected under various risk conditions, thereby offering project managers a range of decision-making alternatives. However, as Mohamed et al. (2025) point out, the integration of generative AI models introduces new risks—ranging from input data bias and lack of transparency to cybersecurity threats and governance failures. These risks must be addressed to ensure reliable AI adoption in construction project risk management. AI-integrated risk analysis tools also enable project managers to perform dynamic risk evaluations based not only on historical data but also on real-time field information. This capability is particularly valuable in situations that require rapid response, as it supports more accurate and timely decision-making. Emerging research also highlights the use of generative AI tools, such as ChatGPT, for project risk assessment, showing promising results in modeling ISO 31000-based risk decisions (Al-Mhdawi et al., 2023). In this context, AI technologies have the potential to become powerful tools for reducing uncertainties, accelerating risk prioritization processes, and developing decision support systems—thereby enhancing the overall robustness of risk management in construction projects. A recent bibliometric and systematic review of AI-driven risk management in construction underscores growing attention to explainable AI methods and the need to address bias, model transparency, and dataset limitations—suggesting these remain critical challenges for mainstream adoption (Tian et al., 2025).



#### *4.2.6. Resource Management*

Resource management is one of the key determinants of success in construction projects. The accurate planning and efficient utilization of resources such as labor, materials, equipment, and time are essential for controlling costs, meeting schedule targets, and achieving quality standards (Kerzner, 2017). However, traditional resource management approaches often fall short in dynamic project environments, resulting in unforeseen deviations. At this point, artificial intelligence (AI) emerges as a promising tool for optimizing resource management through complex data analysis.

AI systems can analyze historical project data to forecast labor and equipment requirements, as well as predict the timing and intensity of resource utilization. This predictive capability helps prevent common issues such as over- or under-allocation of resources, thereby supporting continuous project flow. Furthermore, material procurement processes can be more accurately managed through AI-powered demand forecasting models, minimizing problems such as overstocking or shortages. Machine learning algorithms can analyze real-time data collected from the field to reveal patterns in resource utilization and detect potential bottlenecks at early stages. For instance, AI can identify whether delays in a particular work item are due to labor shortages, equipment malfunctions, or logistical challenges. This enables managers to revise resource plans and optimize operations in real time (Akinosho et al., 2020).

AI-based resource management systems also offer holistic solutions by accounting for interdependencies among different types of resources. For example, how will a delay in one work item cause resource conflicts in other activities? AI systems capable of answering such questions not only analyze the current state but also generate alternative planning scenarios, providing managers with strategic advantages. In this way, AI technologies offer a digital support system that strengthens both strategic planning and operational execution in resource management. As a result, construction projects can benefit from increased efficiency, reduced waste, and more rational resource utilization—ultimately contributing to the overall sustainability of project delivery.

#### *4.2.7. Organizational Learning*

Construction projects are inherently complex and dynamic endeavors involving numerous stakeholders working simultaneously, which makes them susceptible to errors and deviations. In this context, documenting and transferring the knowledge and experiences gained at the end of each project for use in future projects constitutes the foundation of organizational learning. Commonly referred to as the “lessons learned” approach, this practice is strategically important for learning from the past and fostering continuous improvement (Ajmal et al., 2010). However, conventional methods of collecting, analyzing, and disseminating such knowledge across the organization are often insufficient. At this point, artificial intelligence (AI) holds significant potential to enhance the effectiveness and sustainability of organizational learning processes. Organizational learning is a critical process within firms as it supports knowledge-based risk management practices (Alashwal et al., 2017), enhances overall performance, and sustains competitive advantage (Zhai et al., 2013). Although the acquisition and reuse of new knowledge are particularly important in project-based industries, knowledge management practices in the construction sector are predominantly informal and human-dependent (Oti et al., 2018). AI tools can offer a more systematic approach, enabling more efficient acquisition and reuse of knowledge. These tools can ensure the retention of learned knowledge within the organization and facilitate its reuse in future projects. They are capable of simulating scenarios and predicting their impact on organizational processes.



With its capabilities in big data processing and natural language processing (NLP), AI can analyze large datasets derived from completed projects—including construction logs, audit reports, site notes, and communication records—to build a robust organizational memory. Pattern recognition algorithms trained on such data can identify frequently recurring problems or successful practices, thus supporting the generation of post-project evaluation reports (Love et al., 2012). In this way, the lessons learned from past experiences can be systematically documented and categorized. Moreover, AI can play a key role in surfacing “tacit knowledge” by facilitating information sharing among project teams. For instance, AI-powered knowledge management systems can analyze the challenges encountered, decisions made, and their outcomes in previous projects, offering guidance for new projects. These systems can also establish learning bridges across different teams within the organization, minimizing redundancy, preventing repeated mistakes, and fostering the dissemination of innovative solutions. AI-assisted organizational learning practices contribute to transforming post-project evaluations into institutional knowledge assets, thereby generating long-term strategic benefits. The support offered by AI in this area not only helps avoid past mistakes but also enables the development of more successful, efficient, and low-risk strategies for future projects. In doing so, AI facilitates the emergence of learning organizations within the construction sector and contributes to the achievement of sustainable success.

#### *4.2.8. Information Management*

Construction projects, by their very nature, involve the collaboration of numerous stakeholders and disciplines, resulting in information-intensive processes. From project plans and drawings to contract documents and site data, a wide array of information must be managed effectively to ensure project success. One of the greatest challenges in this process is the inability to store and analyze information in a consistent, accessible, and usable manner. While the goal of information management is to overcome these challenges, artificial intelligence (AI) technologies has the potential to provide significant contributions to this process.

Organizational communication and efficient information flow are crucial components of any operational process. Without proper information flow, financial or material flows cannot occur. An optimally organized flow of information can provide a company with competitive advantages through reduced costs, enhanced customer service, and more efficient business processes (Nousiainen, 2008). The timeliness of information is also of utmost importance because data is continuously updated; staying current in information flow is essential to avoid issues in understanding and interpretation. Consequently, ensuring the transfer and readability of information is the paramount objective in software related to information flow. In construction project management, effective information flow is vital and has become even more important with technological advancements.

AI is revolutionizing information management processes through big data, natural language processing (NLP), and automatic classification algorithms. By integrating with digital technologies such as Building Information Modeling (BIM), AI can automatically organize project documents, detect inconsistencies within documents, and facilitate quicker access to information. Moreover, by extracting meaningful insights from semi-structured data—such as email traffic, site reports, and meeting notes—AI-powered systems can provide decision support to project managers. These systems can also establish contextual relationships among the various datasets generated throughout a project, thereby optimizing search processes for critical information. For example, using NLP techniques, a project team can retrieve related contract clauses, technical drawings, or change records instantly by simply posing a short query (Khosrowshahi & Arayici, 2012). This capability not only contributes positively to time management but also enhances the quality of information-based decision making. Another strong aspect of AI in information management is its role in ensuring data security and version control. By establishing automatic audit systems related to data access permissions, version tracking, and change histories, AI both preserves data integrity and prevents potential information losses. As a result, information flow in complex construction projects becomes more sustainable and transparent. AI-supported information management applications thus make the flow of information in construction projects smarter, more efficient, and more reliable, thereby contributing significantly to overall project success. With rapid access to accurate information, robust validation processes, and powerful analytical capabilities, AI assumes a strategic role in the digital transformation of the construction industry.

#### *4.2.9. Design Management*

Creativity is one of the most fundamental attributes of human intelligence and simultaneously represents an inevitable challenge for artificial intelligence (AI). The potential of AI to transform the discipline of architectural design—by introducing novel possibilities and unexplored pathways—remains a subject of ongoing debate. As one of the core phases of construction projects, the design process is critical in determining a project's functionality, aesthetics, and feasibility. It typically involves the simultaneous evaluation of multiple variables and the making of numerous decisions. While traditional design approaches largely rely on professional experience and are conducted through manual methods, the integration of AI technologies promises more rational, efficient, and optimized solutions (Alanne, 2004). AI's iterative, data-driven processes have begun to tackle multilayered design challenges – from form-finding and spatial programming to performance optimization – revealing a rapidly growing body of literature that maps nearly a decade of applications (Bölek et al., 2023).

AI's potential contributions to the design process are multifaceted. Foremost among these is the advent of generative design, an AI-driven methodology that enables designers to define a set of parameters, upon which the system generates a wide array of design alternatives. This approach not only saves time but also facilitates the discovery of creative options that might otherwise be overlooked in conventional design processes. Architectural and engineering solutions can thus be optimized not only for form and function, but also in terms of cost, energy efficiency, and sustainability. A notable example is Autodesk Generative Design, an AI-based tool that generates numerous high-performance design alternatives based on user-defined inputs such as desired daylight levels, orientation toward specific views, or a maximum allowable construction budget. The tool then evaluates these alternatives through AI-driven generative design processes, assessing their functionality accordingly. Furthermore, it provides cost estimates, projected energy consumption metrics, and documentation for quality and budget considerations related to each proposed design (Autodesk, n.d.).

AI-supported design systems can also analyze data from previous projects to highlight the most effective solutions within specific contexts. In this way, systems empowered by pattern recognition and machine learning capabilities not only offer creative suggestions but also support more robust, feasible, and risk-mitigated design decisions by learning from past mistakes. Additionally, AI can be integrated with Building Information Modeling (BIM) platforms to enhance consistency in multidisciplinary design processes. Through such integration, potential clashes between architectural, structural, and mechanical systems can be automatically detected and resolved using AI-generated recommendations. This helps reduce the number of design revisions and prevents errors during the construction phase (Bock & Linner, 2015). AI-assisted design tools can enhance decision quality in the early stages of construction projects, thereby exerting a direct influence on overall project success. While accelerating design workflows, AI can simultaneously foster flexibility, creativity, and sustainability. By combining engineering logic with data analytics, AI contributes to shaping the intelligent buildings of the future. Recent frameworks emphasize the integration of AI with digital twins and real-time data streams, enabling synchronous design, simulation, and performance monitoring across the entire building lifecycle (Jiang et al., 2024).

### 4.2.10. Environmental Sustainability

The construction sector is responsible for approximately 50% of global resource consumption, nearly 40% of energy use, and a significant share of greenhouse gas emissions (UNEP, 2021). As such, achieving environmental sustainability within the sector is of paramount importance—not only for meeting global climate goals but also as a matter of social responsibility. While traditional construction methods often fall short of supporting sustainability objectives, artificial intelligence (AI) has the potential to offer innovative solutions that contribute to reducing the sector's environmental impact.

AI-supported systems are capable of estimating energy consumption, carbon footprint, and waste generation during construction processes. Based on these data, they can develop alternative scenarios to identify the most environmentally friendly option. For instance, in material selection, AI can holistically evaluate criteria such as recyclability, carbon emissions during production, and the environmental impact of transportation, thereby recommending the most sustainable alternatives. Furthermore, AI systems integrated with sensor data and Internet of Things (IoT) technologies can monitor energy and water consumption on construction sites in real time. These systems can issue automatic alerts in the case of inefficiencies or waste, enabling prompt intervention. Additionally, AI is increasingly used for optimizing sustainability performance by modeling energy usage, emissions, and materials efficiency—especially in green building retrofits (Adebayo et al., 2025). Thus, environmental impact is controlled not only at the planning stage but also during the execution phase.

AI applications can also facilitate optimized waste management by minimizing material waste and promoting sustainable practices throughout the construction lifecycle. Additionally, AI can enable the modeling and enhancement of buildings' energy performance over their entire life cycle. For example, AI-enhanced life cycle assessment tools can forecast the environmental impacts of a building during production, operation, and demolition stages, thereby supporting more sustainable design decisions (Asadi et al., 2012). By promoting the adoption of sustainability principles in construction, AI technologies help reduce environmental impacts, ensure the efficient use of resources, and contribute to the creation of more livable built environments. As a digital enabler of environmentally friendly transformation in the sector, AI is increasingly recognized for its strategic importance.

## 5. Discussion

The analysis presented in this study affirms that artificial intelligence (AI) holds significant transformative potential in construction project management, particularly in addressing long-standing challenges related to efficiency, uncertainty, risk, and sustainability. Although construction sector is slow in digital transformation, the reviewed literature demonstrates that AI applications are increasingly being adopted across core project management functions, including time and cost estimation, quality assurance, safety monitoring, risk analysis, and resource optimization. These functions are central to project success and have traditionally relied on human intuition and heuristic methods. The shift toward AI-supported decision-making marks a substantial evolution in management philosophy—moving from reactive to predictive and from subjective to data-driven. The practical value of AI in construction project management is most apparent in its predictive and prescriptive capabilities, which allow for proactive identification of risks, optimization of schedules, and real-time performance monitoring. For example, machine learning-based tools exemplify the growing use of autonomous systems for real-time site data analysis and predictive scheduling. These applications mirror the broader trend observed in other sectors, where AI is used not merely to automate but to augment strategic decision-making (Abioye et al., 2021; Burger, 2017).

When compared with previous reviews (e.g., Bang & Olsson, 2022; Aladağ et al., 2024), this study provides a more holistic and function-oriented synthesis, mapping AI applications to specific project management domains. While Bang and Olsson (2022) offered a systematic scoping review, they largely focused on technical implementations. In contrast, this paper extends the discussion to organizational, cultural, and strategic dimensions, highlighting factors such as resistance to change, ethical concerns, and skill gaps—elements that are often underexplored in technologically focused studies. These concerns are echoed in the findings of Kovačević and Bouder (2023), who observe that many construction professionals view AI as ambiguous and overly reliant on visual interfaces that may conceal data weaknesses. Their study reveals that skepticism toward AI stems from a lack of algorithmic understanding and the fear that poorly contextualized AI tools may introduce new risks rather than mitigating existing ones. Moreover, the findings echo the concerns raised by Khosrowshahi & Arayici (2012) and Bilal et al. (2016) regarding data fragmentation and interoperability challenges in the construction industry. These technical hurdles, coupled with organizational resistance and cultural inertia (Perera et al., 2020), illustrate that AI adoption is not merely a technological endeavor but a socio-technical transformation. The need for structured, high-quality datasets is a recurring theme, as poor data quality significantly hampers the training and generalization of AI models, is particularly critical in the construction sector, where project conditions are highly variable and context-specific.



In terms of occupational health and safety (OHS), the study affirms that AI can significantly enhance proactive risk mitigation strategies through real-time monitoring, image recognition, and behavioral analysis. These findings are supported by Smith and Kanner (2017), who demonstrated that AI can drastically reduce the time needed to detect on-site safety hazards compared to human inspection. However, widespread adoption remains limited due to ethical and legal concerns, especially regarding the black-box nature of AI algorithms (Bai et al., 2020), which can undermine user trust in safety-critical decisions. Another noteworthy contribution of this study is the emphasis on organizational learning and knowledge retention, areas often neglected in earlier AI discussions. As Ajmal et al. (2010) and Zhai et al. (2013) suggest, continuous learning from past projects is a key component of project success. AI's role in capturing, structuring, and disseminating tacit knowledge offers a promising avenue for embedding institutional memory into future project planning and execution—thus reinforcing strategic project management capacity. Another thing is, the convergence of AI with digital twins is emerging as a transformative paradigm for construction project control. By combining real-time sensor data, BIM models, and ML algorithms, digital twins enable predictive monitoring, adaptive scheduling, and scenario-based simulation. This integration supports dynamic decision-making and aligns with Construction 4.0 maturity objectives (Jiang et al., 2024).

Despite these advances, the gap between academic innovation and real-world implementation persists. Much of the literature reflects conceptual enthusiasm but lacks empirical validation, particularly in large-scale, diverse project environments. This discrepancy underscores the need for interdisciplinary collaboration, where construction engineers, data scientists, software developers, and project managers co-develop and test AI solutions under field conditions. Hereby, this study underscores that while AI technologies are progressing rapidly, their integration into construction project management is constrained by a combination of technical, organizational, and human factors. The findings support the growing consensus that a multi-dimensional and interdisciplinary approach is essential to unlock AI's full potential in this domain. For example, Recent studies such as Mohamed et al. (2025) and Al-Mhdawi et al. (2023) highlight the rising use of generative AI and LLMs for automated document analysis, risk prediction, and regulatory compliance. However, concerns over explainability, adversarial risk, and model bias remain major barriers to adoption.

## 6. Conclusion

This study has provided a multi-dimensional examination of AI in construction project management across core domains—including time, cost, risk, safety, quality, resource and information management, organizational learning, design, and environmental sustainability—through a narrative literature review. It makes three key contributions to the literature on AI in construction project management. First, it offers a comprehensive and function-oriented synthesis—mapping AI methods to core project management domains—thereby bridging the gap between fragmented technical studies and holistic management frameworks. Second, it integrates technical applications with organizational and cultural dimensions, highlighting both AI's transformative potential and the systemic barriers—such as data governance, explainability, and skills gaps—that must be overcome. Third, by grounding the thematic analysis in the PMBOK framework, it adds methodological rigor and produces a practical roadmap that researchers and industry partners can use to scope AI pilots, design live validation studies and evaluate performance using standardized criteria.

Building on these contributions, the study generates clear practitioner takeaways. Project managers are encouraged to move beyond reactive monitoring by leveraging AI-augmented scheduling tools that predict potential delays and trigger early warnings. BIM coordinators can embed generative design plugins within their workflows, automating clash detection and embedding sustainability analyses directly into building models. Safety officers can adopt explainable AI dashboards to visualize hazard predictions and compliance gaps in real time, thereby bolstering stakeholder trust and accelerating on-site implementation of safety protocols. These implications demonstrate how academic insights can translate into actionable strategies, improving both efficiency and resilience on live construction sites.

Beyond practical guidance, the findings underscore AI's broader transformative potential: not merely as a set of tools, but as a catalyst for shifting traditional project management paradigms toward predictive, data-driven, and adaptive practices. Yet, realizing this vision requires overcoming persistent barriers—fragmented data ecosystems, interoperability issues with legacy BIM and ERP systems, limited digital literacy, and organizational resistance deeply rooted in industry culture. To bridge the gap between theoretical promise and real-world impact, future research must prioritize empirical validation of AI applications in diverse project environments, develop sector-specific AI frameworks tailored to construction's unique characteristics, and foster interdisciplinary collaboration among engineers, data scientists, and managers. Parallel efforts in professional education and policy incentives will be essential to upskill the workforce and cultivate a culture of digital innovation.

In sum, AI stands poised to become the cornerstone of intelligent, sustainable, and high-performing construction project management. By addressing both technological capabilities and organizational realities, this study advances theoretical understanding and informs practical strategies, laying the groundwork for resilient, adaptive, and future-ready project delivery ecosystems.

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## Resume

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