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Leveraging Artificial Intelligence for Digital Transformation of Construction and Project Management Practices

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Abstract

The construction and project management (CPM) sector is increasingly leveraging Artificial Intelligence (AI) to enhance efficiency, decision-making, and risk management. Despite its potential, AI adoption in CPM faces challenges, including fragmented implementation, workforce-readiness gaps, and concerns about governance and data security. This study conducts a systematic literature review (SLR) of peer-reviewed articles, industry reports, and grey literature from 2018 to 2025. The review identifies key thematic dimensions, including AI application areas, impacts on efficiency, cost, and time management, and adoption challenges related to governance, digital infrastructure, stakeholder engagement, workforce capacity, and ethical considerations. Drawing on these insights, a comprehensive implementation strategy is proposed that integrates technical, organisational, and ethical perspectives to support effective AI integration in CPM. This study advances knowledge by conceptualising an AI-integrated CPM ecosystem and proposing an evidence-based strategic implementation framework that bridges theoretical discourse and industry practice. The primary limitation is the lack of empirical validation of the proposed strategy through local case studies or pilot implementations, which are recommended to assess its practical applicability across diverse project contexts.

Keywords: Artificial Intelligence, Construction, Implementation Strategy, Project Management, Systematic Literature Review.

1. Introduction

The construction and project management sectors, traditionally characterised by labour-intensive processes and fragmented workflows, are undergoing a profound transformation driven by advancements in digital technologies. Among these technologies, artificial intelligence (AI) has emerged as a pivotal force, reshaping how projects are planned, executed, and monitored (Lu et al., 2024).

Artificial Intelligence (AI) denotes computational systems capable of performing tasks that typically require human cognitive capabilities, including learning, reasoning, problem-solving, perception, and natural language understanding (Sarker, 2021). It comprises a diverse set of approaches, such as symbolic reasoning, machine learning, neural networks, and evolutionary computation, that enable machines to exhibit adaptive, goal-directed behaviour. According to Rane, Choudhary, and Rane (2024), AI is the creation of intelligent systems that perceive their environment and act rationally to pursue defined objectives. Contemporary AI research emphasises data-driven techniques, particularly machine learning and deep learning, in which algorithms identify patterns in large datasets to generate predictions or decisions with minimal reliance on explicit programming (Taye, 2023).

By leveraging AI, stakeholders can enhance efficiency, reduce costs, and mitigate risks, thereby addressing long-standing industry challenges. AI is reshaping every stage of the construction project lifecycle, from smart design software that optimises architectural plans to predictive maintenance systems that anticipate equipment failures (Baduge et al., 2022). The integration of Artificial Intelligence (AI) within Building Information Modelling (BIM) underscores its transformative potential in the construction domain. AI enhances BIM capabilities by automating design optimisation, facilitating clash detection, and

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improving resource allocation, thereby streamlining stakeholder collaboration and promoting more efficient and effective project outcomes (Timilsena et al., 2024). This transformation is about adopting new technologies and fostering a culture of innovation, collaboration, and adaptability. The adoption of Artificial Intelligence in the construction and project management sectors offers a strategic response to persistent challenges, including project delays, cost overruns, and resource inefficiencies, while simultaneously facilitating the development of sustainable and resilient infrastructure. (Shamim, 2024).

Across the African continent, awareness of AI applications in construction and project management has increased significantly among policymakers, major contracting firms, and academic institutions; however, practical implementation remains limited and uneven. Continental assessments show that no African country has surpassed an estimated 20% overall AI diffusion, with adoption largely concentrated in regions with comparatively stronger digital infrastructure and cloud readiness, notably parts of Southern and North Africa. In contrast, many countries continue to lag due to persistent deficits in electricity supply, connectivity, data-centre capacity, and specialised technical skills (Mutambara, 2025). Sector-specific literature and national case studies further reveal that awareness and favourable perceptions of AI frequently exceed actual deployment. Although large firms and research-intensive institutions are piloting AI-enabled tools, such as BIM for advanced planning, risk detection, predictive scheduling, and quality control, most small and medium-sized contractors remain at stages of limited awareness, minimal capacity, or early experimentation (Awe et al., 2025).

Despite its benefits, adopting AI in construction and project management faces challenges, including resistance to change, data privacy concerns, and the need for skilled personnel to operate advanced systems (Shoushtari, Daghighi & Ghafourian, 2024). Addressing these barriers is critical to unlocking the full potential of AI and fostering a culture of innovation in the industry. This study outlines the foundational principles and key components of designing an AI implementation strategy for construction and project management. Grounding the discussion in scholarly research and industry best practices provides a comprehensive strategic framework for stakeholders seeking to harness AI's transformative power in the construction industry.

2. Literature Review

Historically, construction processes were marked by hierarchical systems and rudimentary project management principles, emphasising craftsmanship and manual labour with minimal reliance on formalised planning or scheduling tools. The introduction of computers in the 1990s, as Eastman (2018) noted, revolutionised project management by enabling the adoption of systems theory. This enabled integrated management of resources, time, and costs. In the 21st century, advanced digital technologies have further transformed construction and project management. According to Lu et al. (2024), these technologies emphasise sustainable practices and lean construction principles that minimise waste and risk while improving overall efficiency.

AI adoption within the construction and project management sector remains comparatively modest relative to industries such as manufacturing, healthcare, education, and transportation. Whereas manufacturing and transportation have achieved significant advancements in automation, predictive analytics, and robotics, the construction sector continues to face challenges stemming from fragmented workflows and limited digital integration (Bang & Olsson, 2022). Similarly, healthcare and education exhibit higher levels of technological maturity, increasingly employing AI for diagnostic support, personalised learning, and administrative efficiency (Faiyazuddin et al., 2025). By contrast, Adebayo et al. (2025) observed that AI deployment in construction is still emerging and is predominantly concentrated in domains such as safety monitoring, schedule optimisation, and design automation.

According to Adebayo et al. (2025), the advancement of artificial intelligence (AI) has generated considerable interest in its potential to transform construction and project management by improving cost estimation, scheduling, risk management, quality control, and safety monitoring. A growing body of literature documents promising AI applications, such as machine learning models for predictive cost and schedule performance, computer vision for site inspection and safety compliance, natural language processing for contract analysis, and digital twins coupled with Building Information Modeling (BIM) for integrated project simulations (Akhmedov, 2023; Korke et al., 2023; Khan et al., 2024). The authors underscore the transformative role of artificial intelligence in improving project efficiency, productivity, accuracy, and decision-making, while simultaneously addressing persistent challenges of cost overruns, schedule delays, ineffective risk management, and resource misallocation. These studies collectively demonstrate AI's capacity to automate repetitive tasks, augment decision-making under uncertainty, and enable near-real-time feedback loops across project lifecycles.

However, Allouzi and Aljaafreh (2024) emphasised that results vary widely across contexts and that adoption is uneven, suggesting that technical feasibility alone does not guarantee successful implementation. Al-sarafi et al. (2022) examined the adoption drivers and barriers, highlighting organisational, technical, and socio-cultural factors that mediate the translation of AI pilots into scaled benefits. Organisational readiness, including executive sponsorship, cross-functional governance, and change management capabilities, is repeatedly identified as a precondition for AI adoption in the construction industry (Fasasi et al., 2024; Khan et al., 2025).

Furthermore, Regona et al. (2022) identified data-related constraints, including fragmented data sources, poor data quality, limited interoperability between BIM and enterprise systems, and limited information technology (IT) infrastructure, as pervasive technical bottlenecks. Shang et al. (2023) highlighted human factors, skills shortages in data science and AI, while Oke et al. (2023) pointed to employee resistance rooted in perceived job threat or low trust in opaque models. Besides, Shakibaei (2024) described regulatory compliance, contractual complexities, and ethical concerns as critical barriers to implementing AI in the construction and project management sector.

A significant strand of the literature focuses on governance, ethics, and risk management for AI in construction. For instance, Shakibaei (2024) called for clear data governance frameworks, model validation and explainability protocols, and mechanisms to mitigate algorithmic bias, especially where models influence safety-critical decisions or contractual outcomes. Asadollahi et al. (2025) highlighted the value of external partnerships with technology vendors, academic institutions, and industry consortia to accelerate capability building and diffuse best practices.

Nevertheless, cost–benefit analysis in the literature is often context-specific and rarely accounts for longer-term organisational change costs, leaving decision-makers seeking scalable project cases with a gap. This has called for interdisciplinary research that integrates technical performance metrics with socio-technical assessments to examine how governance, trust, and legal frameworks shape AI's ultimate effectiveness in construction project ecosystems. Addressing this gap will allow a move beyond isolated proofs of concept toward developing a comprehensive AI implementation strategy that fuses digital infrastructure, skill development, policy support, stakeholder engagement, and industry collaboration, and is technically robust and organisationally sustainable to drive the adoption of AI in construction and project management.

3. Research Methodology

The study employs a systematic literature review methodology, adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021) in the identification, screening, selection, and synthesis of relevant academic and grey literature to ensure a rigorous and transparent analysis of existing literature. Review research involves applying scientific methods to analyse and synthesise previous studies, thereby generating new knowledge for academic, practical, and policy-making purposes (Kunisch et al., 2023). The primary motivation for reviewing and analysing academic articles is to identify research gaps, explore under-researched areas, and facilitate the development of new theories or ideas (Marzi et al., 2024).

This research study review follows a series of steps to achieve the desired outcome. In the initial phase, a comprehensive keyword search was conducted across leading academic databases: Scopus, Google Scholar, and Web of Science and from other databases for book chapters and conference proceedings using terms like Artificial Intelligence in Construction, Construction Industry, Construction Project Management, Construction Automation, Construction Design, and Predictive Analytics in Construction.

Search keywords were derived from the study's core concepts, with Boolean operators (AND, OR) and wildcards applied to optimise the retrieval of relevant literature. The search strings used were: ("Artificial Intelligence" OR "AI" OR "AI Technologies") AND ("Construction" OR "Construction Project Management" OR "Construction Automation" OR "Predictive Analytics in Construction") AND ("Global South" OR "Africa") AND ("Digital Transformation"). The sample of the search strings used in the database is: ABS-KEY ("Artificial Intelligence "AND (Construction" OR "Construction Project Management" OR "Construction Automation" OR "Predictive Analytics in Construction") Global South AND Africa) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "re")) AND (LIMIT-TO (LANGUAGE, "English")).

The inclusion and exclusion criteria were defined to maintain a clear focus on the research area. Studies were included if they met the following criteria: they examined the impact of artificial intelligence in construction and project management; were published in peer-reviewed journals, academic conferences, or reputable research reports; and were written in English. Conversely, studies were excluded if they were purely theoretical or conceptual, lacked empirical evidence on the adoption of artificial intelligence in construction and project management, or focused broadly on digital technologies rather than artificial intelligence specifically. The study spans 2018 to 2025 to capture the latest trends and advancements, and specifically addresses aspects of construction and project management. At this stage, 872 peer-reviewed articles and 29 grey literature articles were identified for the study.

A thorough screening process was then carried out, following the defined inclusion and exclusion criteria, to ensure relevance and quality. Duplicate entries and articles unrelated to the construction industry or without AI applications were removed. Following the exclusion of duplicate, irrelevant, and out-of-focus studies, 82 articles and nine grey literature items, consisting of conference proceedings, book chapters, and policy reports, were assessed for eligibility. The deduplication features of the specialised screening tool, Systematic Review Accelerator, were used to identify duplicate records, which were then further examined through side-by-side comparison to confirm their validity as accurate duplicates.

The study progressed to a comprehensive thematic analysis phase to clarify the current status, limitations, and future trends of AI applications in construction and project management. The focus was primarily on key findings and conclusions from the reviewed articles, specific challenges, identified opportunities, and recommendations for policy, practice, and further research. A final set of 54 peer-reviewed articles, six book chapters, and three conference proceedings was selected for thematic analysis.

A PRISMA flow diagram for the study is shown in Figure 1, illustrating the document selection process and thereby enhancing methodological rigour and ensuring transparency in the review.

iterative analytical procedure. Relevant information was first systematically extracted from the selected studies using a predefined coding framework designed to capture conceptual, empirical, and contextual insights related to artificial intelligence, construction automation, construction project management, and predictive analytics in construction. The coded data segments were then analysed thematically to identify patterns, points of convergence, and conceptual linkages, which were subsequently synthesised into higher-order themes representing dominant narratives and recurring constructs within the literature. Through axial coding, the interrelationships among these themes were further examined to elucidate underlying structural connections, dependencies, and potential causal pathways.

The quality appraisal process followed PRISMA guidelines, ensuring methodological transparency, rigorous evaluation of evidence, and reducing potential bias throughout the review process. All eligible studies and reports were assessed using the Critical Appraisal Skills Programme (CASP) Qualitative Checklist, a structured instrument designed to evaluate the methodological rigour and credibility of qualitative research. The appraisal criteria were applied independently by the two authors to strengthen consistency and limit subjectivity, with any divergences resolved through discussion. The outcomes of this appraisal informed decisions

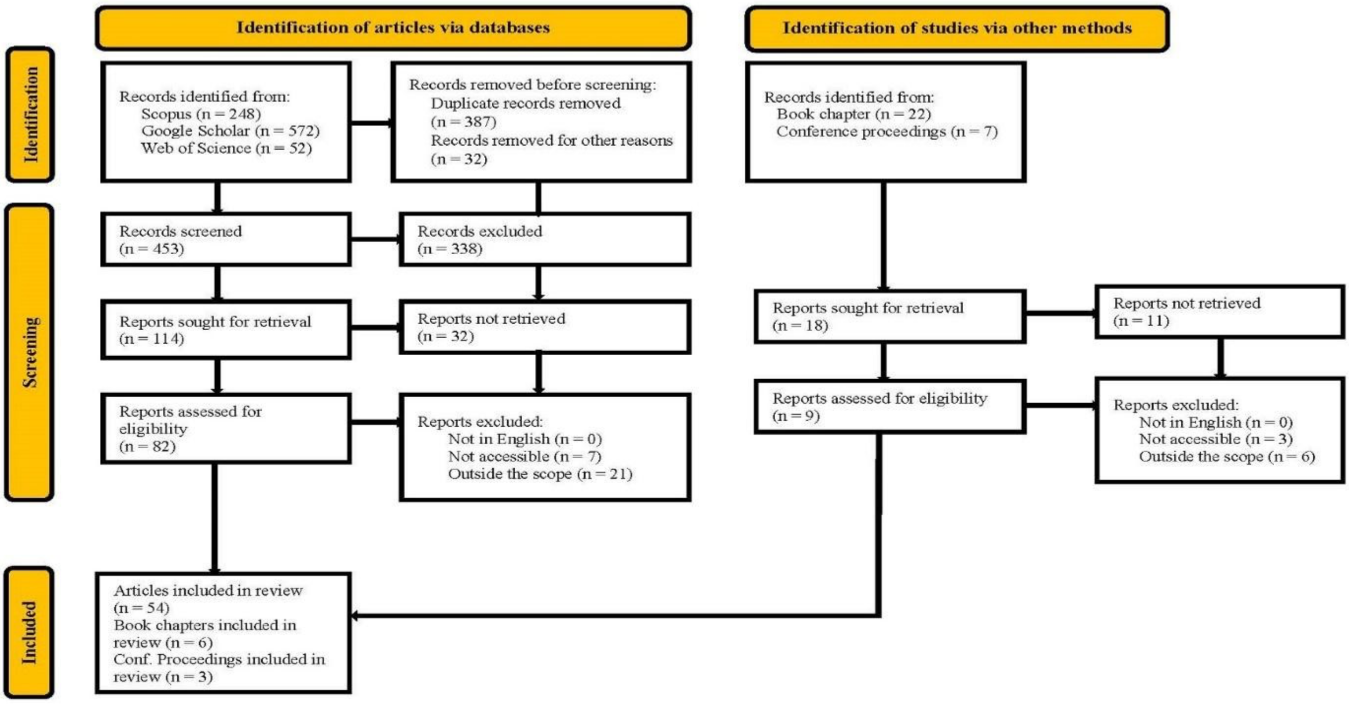

Figure 1: Prisma Flow Diagram for the Study (Source: Authors)

The transition from data extraction to thematic categorisation, and the subsequent development of the implementation strategy, were guided by a rigorous,

regarding the inclusion, exclusion, and weighting of studies within the synthesis, thereby enhancing the reliability, credibility, and overall methodological integrity of the systematic review.

4. Findings

4.1. Application of Artificial Intelligence in Construction and Project Management

The literature indicates that the adoption of AI technologies in construction and project management is accelerating but remains uneven. In contrast, pilot projects and academic studies show substantial gains in scheduling, cost forecasting, safety monitoring, and design optimisation; the full-scale, organisation-wide deployment lags in the leading industries (Ivanova et al., 2023). Recent structured reviews and empirical studies report a surge in research and applied pilots across machine learning, computer vision, robotics, and decision-support systems. However, they repeatedly note that the construction sector is still catching up in turning these pilots into routine practice (Adebayo et al., 2025).

Artificial Intelligence (AI) in construction and project management involves exploiting advanced technologies to improve efficiency, accuracy, and decision-making. According to Akhmedov (2023), AI-driven tools, such as generative design software, enable architects and engineers to rapidly explore numerous design alternatives while optimising key factors, including cost, sustainability, and structural integrity. Baduge et al. (2022) posited that AI algorithms leverage historical data to predict project timelines, identify potential risks, forecast delays, and propose corrective actions. These are made possible through the optimisation of project schedules using generative scheduling, resource allocation, and risk assessment.

Yu and Wang (2022) asserted that adopting AI-powered systems in construction projects enables organisations to identify trends, predict potential issues, and make informed decisions based on accurate, up-to-date information. This assertion is supported by Khan et al. (2024), who confirm the excellent performance of AI systems in analysing real-time data from Internet of Things (IoT) devices, digital twins, cameras, and sensors, making them highly effective in predicting and preventing accidents on construction sites. Technologies such as computer vision and AI-driven drones enhance site safety by providing real-time monitoring and ensuring compliance with project specifications (Khan et al., 2024).

Integrating AI-driven predictive maintenance into construction projects enables machine learning algorithms and advanced data analytics to analyse large-scale sensor data generated by construction equipment, thereby detecting patterns and anomalies that signal potential equipment failures (Putha, 2022). According to Qi and Tao (2018), predictive maintenance is an advanced equipment management strategy that employs AI algorithms to analyse real-time data, predict potential failures, and implement preventive measures. It adopts a proactive approach, unlike traditional maintenance methods that rely on scheduled inspections or reactive repairs.

Furthermore, the adoption of artificial intelligence (AI) models in construction and project management enhances the accuracy of risk assessment and management by enabling the systematic analysis of large and diverse datasets, including weather patterns, financial trends, and stakeholder behaviours (Pan & Zhang, 2021). Construction projects are inherently complex and multifaceted, demanding effective coordination and streamlined material procurement and logistics management. Okoye et al. (2024) argued that the success of construction projects hinges on the efficiency of the construction supply chain, encompassing the acquisition and movement of materials throughout the project lifecycle. The integration of AI into project management platforms enhances inventory tracking, demand forecasting, and procurement processes through smart procurement strategies, ensuring the timely delivery of materials and equipment (Culot et al., 2024). Regona et al. (2022) observed that the adoption of AI in construction and project management is leading to a more cost-effective, efficient, productive, proactive, safe and sustainable construction industry.

Table 1 (See Appendix 1) presents additional findings on the application of artificial intelligence in construction and project management, specifically in progress monitoring, BIM integration, predictive analytics, robotics, and safety, detailing the contextual settings, AI techniques employed, associated project functions, and key outcomes.

4.2. Impact on Efficiency, Cost, and Time Management

4.2.1. Efficiency

AI-driven digital transformation substantially raises operational efficiency by automating routine tasks, improving information flow across lifecycle stages, and enabling data-driven decision-making. Rinchen, Banihashemi and Alkilani (2024) contended that integrating BIM, IoT and cloud platforms with AI enables real-time clash detection, automated progress-tracking from site sensors and images, and smarter logistics planning, leading to reduced rework, improved worker utilisation, and increased productive output per labour hour. Measurable gains in productivity are observed when artificial intelligence is applied to coordinate design–construction handovers and to automate repetitive scheduling and quality control processes (Adebayo et al., 2025).

Similarly, AI systems utilise condition-based monitoring and predictive analytics techniques to analyse sensor data, enabling proactive maintenance, minimising equipment downtime, and enhancing the efficiency of construction projects (Singh et al., 2023; Shoushtari et al., 2024).

Besides, sustainability and risk management are identified as two domains in which AI's contributions are increasingly documented. AI supports life-cycle carbon estimation by linking design data to material-impact databases, optimises sequencing to reduce waste and transport emissions, and enhances risk quantification across the project lifecycle, helping project managers to prioritise mitigation actions with probabilistic outputs rather than binary judgements (Tian et al., 2025). Also, coupling AI with sustainability metrics creates value for both compliance and operational cost savings, particularly when data fidelity and governance are adequate (Demeke, 2025). By digitising data capture and transforming documents into structured signals, AI tools such as natural language processing and reinforcement learning reduce rework cycles and shorten decision loops from days to hours, a key driver of construction projects' execution efficiency.

4.2.2. Cost

Artificial Intelligence is already reshaping core project-management activities. On cost, AI has a dual effect: it lowers variable and lifecycle costs while raising certain upfront and transition costs. Advanced machine learning models and hybrid deep-learning approaches produce more accurate cost and duration estimates, improving bid accuracy and reducing contingency loading due to uncertainty (Cheng, Vu & Gosal, 2025). AI systems leverage historical project data and external variables to predict risks such as cost overruns, delays, and quality issues (Korke et al., 2023). They improve schedule and cost forecasting by learning from historical project data to flag risks and potential overruns earlier than conventional methods; computer vision systems applied to site imagery automate safety compliance checks and progress quantification; and optimisation algorithms assist resource levelling and logistics for complex supply chains (Nenni et al., 2025).

Datta et al. (2024) observed that predictive maintenance and waste-optimisation models shrink material and downtime costs over a project's life. These targeted applications deliver measurable benefits by reducing rework, fewer safety incidents, tighter schedule control, and improved tender accuracy when integrated with existing workflows and Building Information Modelling (BIM) data. The benefit of adopting the technology is a reduction in the total project cost. Shamim et al. (2025) further argued that integrating AI into project management enhances upfront cost estimation by reducing bias and error, while also enabling more timely mid-course corrections. Together, these effects help mitigate cost overruns that typically arise from the late discovery of project issues.

However, the literature consistently flags significant initial investments (software, sensors, data management), training, and integration costs. It warns that without careful change management, these can offset short-term savings (Khan et al., 2024). Cost-benefit outcomes therefore depend heavily on organisational readiness, data maturity, and scale of deployment.

4.2.3. Time Management

Regarding time management and schedule performance, AI enables earlier and more reliable detection of delay risks and can generate optimised schedules from historical BIM data (Alsulamy, 2025). According to Al-Sinan et al. (2024), machine-learning predictors, such as XGBoost, CatBoost, and deep-learning hybrids, outperformed traditional heuristics in forecasting delays and in prioritising interventions, thereby reducing time to recovery and minimising cascading schedule impacts in construction projects. The authors also maintained that automated schedule generation and continual resequencing reduce manual planning and shorten decision cycles, resulting in faster project delivery across many tested projects. Although these gains are contingent on the availability of clean historical data and integrated workflows that let AI outputs be actioned quickly on site.

Ivanova et al. (2023) stated that AI in infrastructure construction provides safety monitoring, such as personal protective equipment compliance, worker and equipment tracking, and process management, as the most mature application clusters, resulting in fewer stoppages and smoother workflows, which ultimately lead to optimal time usage in projects’ execution and timely delivery of projects.

4.3. Challenges of Artificial Intelligence Implementation in the Construction Industry

Incorporating artificial intelligence (AI) into the construction and project management sector holds significant promise for enhancing efficiency, accuracy, and decision-making. Despite this potential, its widespread adoption faces several challenges. These challenges can be broadly classified into five categories: technological, organisational, financial, environmental, and regulatory and ethical challenges.

4.3.1. Technological Challenges

Data issues, including fragmentation, poor quality, and interoperability, repeatedly constrain AI in construction. Construction data comes from heterogeneous sources, such as BIM, sensors, drones, schedule logs, and procurement systems, and is often incomplete, noisy, or stored in proprietary formats, which prevents ready reuse for machine learning (Asadollahi et al., 2025).

According to Regona et al. (2022) and Obiuto et al. (2024), construction projects often lack standardised data collection processes, leading to inconsistent, incomplete, or siloed data that limit the effectiveness of AI functionalities. The lack of standardised data formats and protocols in the construction sector further complicates AI implementation, as AI systems rely heavily on large volumes of accurate, structured data (Pan & Zhang, 2021). Du et al. (2024) contended that efforts to link BIM semantics to AI-ready feature sets remain immature, as many promising algorithms fail at the pre-processing stage or produce unreliable outputs when fed with inconsistent data. These data-readiness and transformation problems are considered the most-cited technical barriers to deployment.

Besides, the technical limitations of AI models also pose significant risks in construction, as reliance on restricted or biased datasets often yields unreliable and non-generalisable predictions. Such inaccuracies compromise safety-critical decisions and contract documentation in construction (Sinha & Lee, 2024). Furthermore, black-box behaviour, limited explainability, and domain drift, arising from model degradation as site conditions and materials evolve, erode trust among engineers and clients, thereby constraining adoption in high-stakes construction tasks (Ghimire, Kim & Acharya, 2024).

4.3.2. Organisational Challenges

Manpower capability gap, resistance to change, and leadership commitment have been identified as major human and organisational limitations for adopting AI in the construction and project management sector. Obi, Osuizugbo and Awuzie (2025) posited that construction’s traditional workforce and management structures are less familiar with data science, AI lifecycle management, or digital-first work processes. Therefore, the construction industry faces a shortage of professionals skilled in AI and data science, creating a bottleneck for AI implementation (Shang et al., 2023).

Also, resistance to change, low on-site digital literacy, and weak top-down sponsorship reduce the likelihood that construction experiments will become business-as-usual. Many construction professionals hesitate to adopt new technologies due to a lack of familiarity with AI technology or fear of job displacement (Oke et al., 2023). Fasasi et al. (2024) noted that the industry's conservativeness and high fragmentation, characterised by numerous small players and subcontractors, complicate collaboration on AI initiatives. Besides, the concerns about the transparency of AI decision-making processes further erode trust and acceptance among stakeholders (Pan & Zhang, 2021). Singh et al. (2023) assert that without targeted training, clear change management, and executive commitment, AI pilots tend to wither despite technical promise.

4.3.3. Financial Challenges

The high cost and infrastructure burden are also identified as significant challenges to the adoption of AI systems in the construction and project management sectors. The initial capital outlay for sensors, edge devices, cloud services, and integration with legacy enterprise systems is substantial, especially for SME contractors with thin margins. Oke et al. (2023) highlighted the financial and economic hurdles the construction industry faces, particularly the high costs associated with developing and deploying AI solutions, and Korke et al. (2023) argued that implementing AI requires substantial initial investments in software, hardware, and skilled personnel. These upfront costs can be prohibitive, particularly for smaller construction firms.

Additionally, the ongoing costs of model retraining, data storage, cybersecurity, and the uncertainty around short-term return on investment (ROI) make investments risky. Shang et al. (2023) identified cost and unclear economic benefits as primary inhibitors of uptake. Consequently, many organisations either pilot isolated proofs of concept that never scale or delay investment until clear vendor solutions emerge.

4.3.4. Environmental Challenges

The literature presents environmental factors as significant challenges for AI adoption in the construction industry. AI models struggle to handle the unstructured, unpredictable nature of construction sites, while high computational demands often limit their capacity for real-time decision-making (Khan et al., 2025). According to Yang et al. (2024), the operational realities of construction sites, such as temporary setups, dynamic layouts, varied weather conditions, and unstructured human activities, make implementing real-world automation technologies like robotics, autonomous vehicles, and continuous vision monitoring far more difficult than laboratory results suggest.

Unlike controlled environments such as factories and mines, urban construction sites are far more complex. Najafzadeh and Yeganeh (2025) contend that AI deployments in construction frequently require extensive customisation, safety interlocks, and hybrid human–machine workflows, which drive up costs and complexity. Consequently, many of AI's most promising applications remain confined to pilot or demonstration projects rather than achieving full-scale commercial adoption.

4.3.5. Regulatory and Ethical Challenges

Legal, ethical, and cybersecurity issues have been further classified as limitations restricting the use of AI applications in construction environments. Singh et al. (2023) argued that construction collects personal data, such as workers' images, locations, and health metrics, as well as commercial data, such as contracts and bids, raising privacy, compliance, liability, and intellectual property concerns. Cyber-attacks on connected construction assets and poisoned training data can produce safety hazards or commercial losses, just as regulatory ambiguity about AI accountability in many jurisdictions can exacerbate procurement and insurance frictions (Pärn & de Soto, 2020).

Regulatory and ethical barriers, such as data privacy concerns, algorithmic bias, and accountability for AI-driven decisions, have been flagged as challenges to AI adoption in the CPM sector (Re Cecconi, Khodabakhshian & Rampini, 2025). Similarly, Shakibaei (2024) underscored the need for AI systems to adhere to regulations that remain inadequately defined in the construction sector. These governance and trust issues, therefore, slow the mainstreaming of AI.

Therefore, Korke et al. (2023), Obiuto et al. (2024), Oke et al. (2023), and Shakibaei (2024) underscore the importance of developing a comprehensive artificial intelligence implementation strategy specifically tailored to the construction industry, emphasising that such a strategy is essential for unlocking the full potential benefits that artificial intelligence offers to the construction and project management sectors. Table 2 summarises AI-related challenges and their impacts in the construction and project management industries.

5. Discussion

5.1. Synthesis of Findings

The literature indicates a growing trend in the adoption of AI tools across the construction and project management sectors, reflecting industry-wide recognition of AI's transformative potential. Tools such as predictive analytics for risk management, automated scheduling systems, and AI-driven design optimisation are increasingly being integrated into workflows. This adoption signals a shift toward data-driven decision-making and automation, which aligns with global trends toward digital transformation in the construction sector. However, the extent of adoption varies significantly across organisations, often influenced by factors such as organisational readiness, technological infrastructure, and managerial attitudes toward innovation.

In terms of impact on efficiency, cost, and time management, the results suggest that AI has delivered notable improvements in project delivery. Findings reported enhanced forecasting accuracy, reduced project delays through real-time monitoring, and cost optimisation achieved by minimising material waste and resource misallocation (Nenni et al., 2025). These findings underscore AI's potential to address traditional inefficiencies in construction projects, particularly in complex and large-scale developments where time and budget overruns are common. Moreover, AI's ability to facilitate predictive maintenance and optimise resource allocation contributes to better risk management and improved overall project performance.

Despite these benefits, the findings highlight persistent challenges and limitations in AI implementation within the construction sector. High initial investment costs, lack of skilled personnel, and resistance to change

Table 2: Summary of Challenges of AI Implementation in CPM (Source: Authors)

Category	Challenges	Impact
Technological (Regona et al., 2022; Obiuto et al., 2024; Du et al., 2024; Asadollahi et al., 2025)	Lack of standardised & quality data; Black-Box Models & Lack of Explainability; Integration with legacy systems; Data & cybersecurity threats	Inaccurate predictions; Unreliable models; Poor decision-making; Reduced trust from Engineers and clients; Risk in safety-critical decisions; Disruptions in workflows; Loss of sensitive project data
Organisational (Oke et al., 2023; Fasasi et al., 2024)	Workforce Resistance; Shortage of professional skills; AI decision-making bias	Slows AI implementation; Social & legal implications; Productivity loss; Underutilisation.
Financial (Korke et al., 2023; Shang et al., 2023)	High initial investment for AI infrastructure; Skilled personnel investments; Limited ROI Evidence	Hesitation among investors and contractors; Slow adoption rates; Limited adoption among SMEs; Delays in scaling AI solutions.
Environmental (Yang et al., 2024; Khan et al., 2025)	Conflicting views on the creation of robots; AI adaptability to unstructured environments;	Models degrade over time, leading to inaccurate outputs, delayed AI adoption, and incorrect AI results and predictions.
Regulatory and Ethical Challenges (Shakibaei, 2024; Re Cecconi, Khodabakhshian & Rampini, 2025)	Cybersecurity & data privacy concerns; Algorithmic bias; Accountability for AI-driven decisions; Legal & Ethical Uncertainty.	Data breaches; Loss of sensitive project data; Reputational damage; Delays in AI adoption, Resistance to data provision, and a Lack of accountability.

emerged as critical barriers (Shoushtari et al., 2024). Furthermore, interoperability issues between AI tools and existing systems, coupled with concerns about data privacy and security, hinder seamless integration (Regona et al., 2022). There is also uncertainty about return on investment (ROI), particularly among small and medium-sized enterprises (SMEs), which limits wider adoption. These challenges suggest that while AI adoption offers substantial benefits, its implementation requires strategic planning, continuous training, and supportive regulatory frameworks to maximise its value in the construction industry.

5.2. Implications for Industry and Practice

The digital transformation of construction and project management through artificial intelligence (AI) carries significant implications for the industry, offering both opportunities and challenges. On the positive side, AI enables data-driven decision-making, real-time monitoring, predictive analytics, and automation of routine tasks, which can lead to improved efficiency, reduced project delays, and optimised resource allocation (Khan et al., 2024). For project managers, AI tools can enhance risk forecasting, schedule optimisation, and cost estimation, while for contractors and clients, they provide greater transparency, accountability, and overall productivity. This transformation aligns with broader industry goals of increasing sustainability, minimising waste, and ensuring projects are delivered on time and within budget.

However, the path to AI integration is not without challenges and risks that shape its practical implications. The cost of adoption, both financial and organisational, remains a barrier, especially for small and medium-sized firms (SMEs) that lack the resources to invest in AI infrastructure and training. Issues of bias and reliability also pose risks, as AI systems trained on incomplete or skewed datasets may produce flawed outputs that can compromise safety-critical decisions or contract documentation (Obiuto et al., 2024). Moreover, the black-box nature of many AI models can erode trust among engineers, project managers, and clients who demand explainability in high-stakes environments. Concerns about data governance, cybersecurity, and compliance further complicate adoption, while workforce resistance to technological disruption may hinder organisational change.

Taken together, these opportunities and risks suggest that while AI can transform construction and project management into a more efficient, predictive, and resilient industry, its implementation must be guided by careful governance, ethical safeguards, and capacity-building strategies. Firms must weigh the tangible benefits of efficiency and competitiveness against the risks of trust erosion, implementation costs, and technological dependency.

A balanced approach that emphasises explainable AI, phased adoption, and workforce upskilling will be critical for ensuring that digital transformation strengthens rather than destabilises the industry, particularly the small and medium construction enterprises (SMEs).

The need for an adaptive, actionable AI implementation strategy for construction and project management, particularly for small and medium-sized enterprises, has become a necessity to exploit the benefits of AI technologies.

5.3. Construction and Project Management Ecosystem

At the heart of the digital transformation of the construction and project management sector through artificial intelligence is the recognition of the inherent complexity and variability of construction projects (Lu et al., 2024). From fluctuating material costs and labour availability to unpredictable weather conditions and regulatory changes, construction project stakeholders face many challenges that demand precision, adaptability, and foresight.

The construction and project management ecosystem is a complex network of stakeholders, processes, and technologies that work together to deliver projects from conception to completion, ensuring that projects are completed on time, within budget, and to the desired quality standards. It includes owners and clients, architects, engineers, contractors, subcontractors, suppliers, regulators, and financial institutions. Each actor contributes to the planning, design, execution, and monitoring of projects, while ensuring compliance with legal, safety, and sustainability standards. The ecosystem is also shaped by broader factors such as policy frameworks, labour markets, technological developments, and environmental considerations, making it both dynamic and multifaceted.

Traditionally, the ecosystem has been characterised by fragmented communication, siloed operations, and manual processes, often leading to inefficiencies, cost overruns, and delays. However, the ongoing wave of digital transformation driven by artificial intelligence (AI) and related technologies offers opportunities to reconfigure these interactions. AI can streamline project planning through predictive analytics, optimise resource allocation, improve safety monitoring, and enable real-time decision-making across stakeholders. This technological infusion is gradually reshaping the ecosystem into a more integrated, data-driven, and collaborative environment, therefore positioning construction and project management for enhanced efficiency, transparency, and sustainability in the digital era. Figure 2 presents the authors' construction and project management ecosystem, taking into

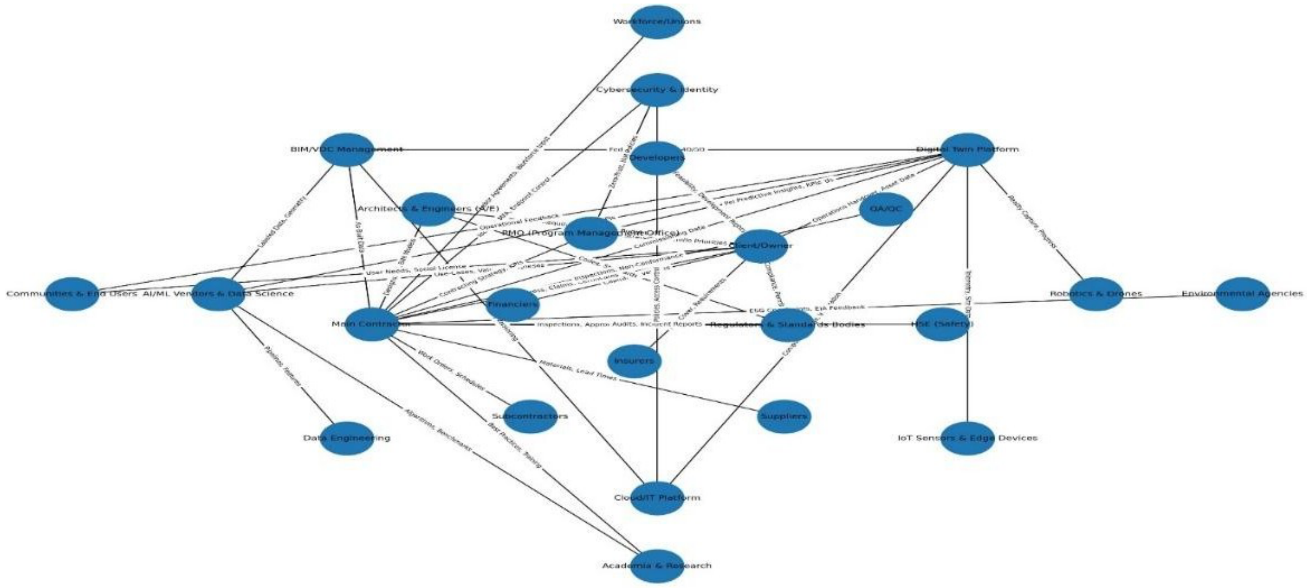

Figure 2: An AI-Integrated Construction and Project Management Ecosystem

consideration the dynamic interactions among the stakeholders.

The ecosystem begins with the governance layer**,** where the Client/Owner, Programme Management Office (PMO), Financiers, Insurers, and Regulators establish the strategic, financial, and compliance framework for projects. These decisions shape feasibility, risk cover, and regulatory approvals, which are then translated into project strategies and key performance indicators (KPIs) by the PMO. From that point, the delivery core takes over, with developers, architects, engineers, and contractors coordinating design, procurement, and construction activities. Subcontractors and suppliers provide specialised services and materials, while Health, Safety and Environment (HSE) and Quality Assurance and Quality Control (QA/QC) ensure that safety, compliance, and quality standards are maintained.

The digital and AI layer amplifies the delivery processes through BIM, IoT sensors, drones, and digital twins that capture real-time data, optimise operations, and support predictive insights. AI/ML models and cloud platforms process this data into actionable intelligence, while cybersecurity safeguards the integrity and trust of digital systems. Finally, the external stakeholders**,** comprising communities, unions, academia, and environmental agencies, provide essential feedback, innovation, and oversight. This creates a continuous flow where governance defines the project direction, delivery executes it, digital technologies optimise and secure it, and external actors regulate and refine it, ensuring sustainable, efficient, and transparent project outcomes. Figure 3 shows a simplified linear ecosystem, with the major layers and their interactions.

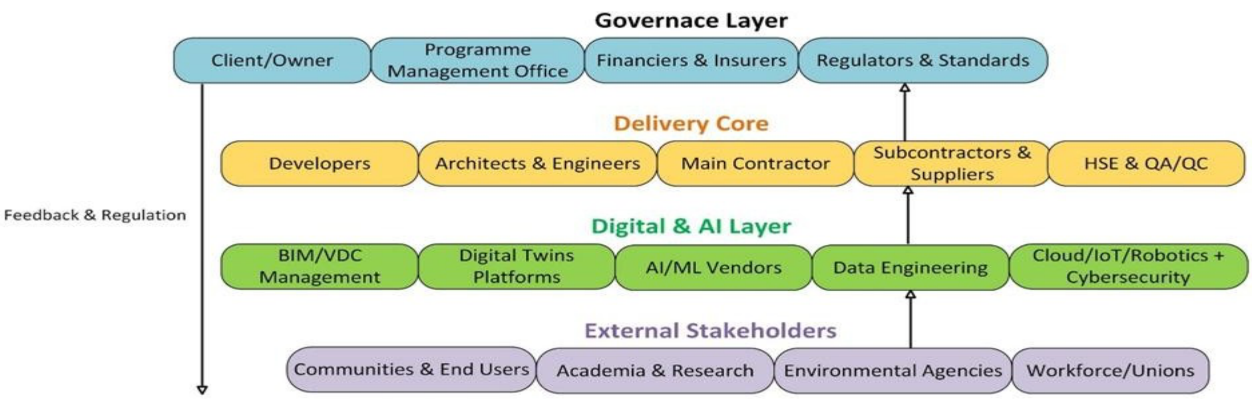

Figure 3: The Simplified Linear Construction and Project Management Ecosystem

5.4. Artificial Intelligence Implementation Strategy for CPM

Although artificial intelligence (AI) holds significant transformative potential for construction and project management, its implementation has been impeded by several challenges, including organisational resistance to change, concerns about data privacy, and a shortage of skilled personnel to manage advanced digital systems. Overcoming these barriers is essential to fully realise the benefits of AI and cultivate a culture of innovation across the industry. To this end, a comprehensive AI implementation strategy is developed that emphasises capacity building, supportive policy frameworks, and enhanced collaboration among stakeholders and industry actors to facilitate effective and sustainable AI adoption in construction and project management. The diagram for the proposed Artificial Intelligence Implementation Strategy for CPM is represented in Figure 4.

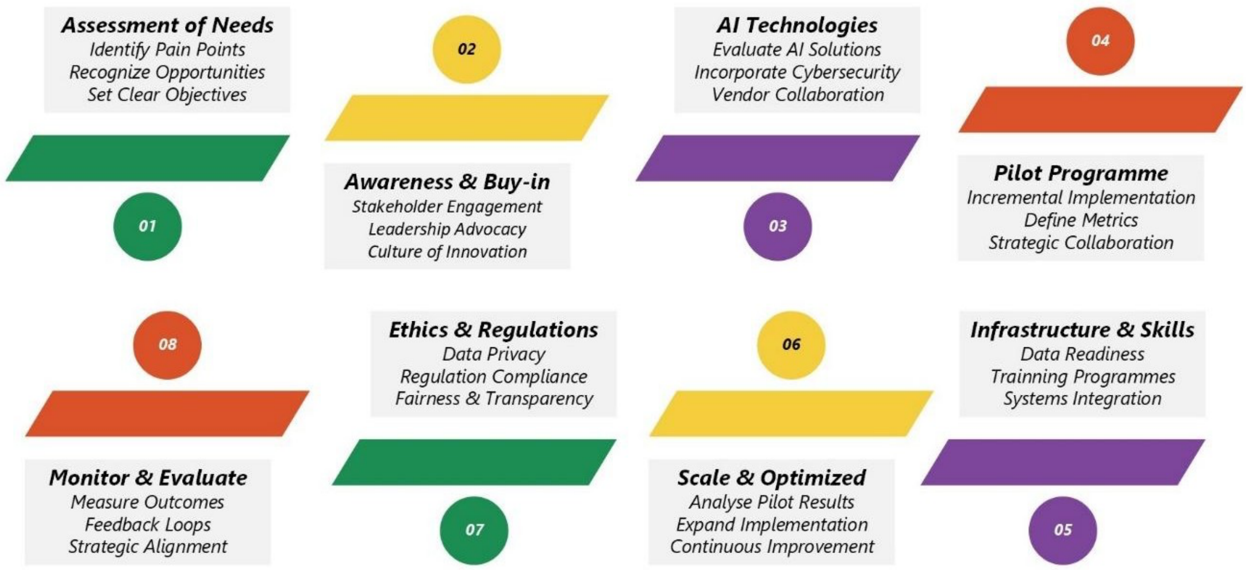

Figure 4: Proposed Artificial Intelligence Implementation Strategy for CPM

The implementation strategy begins with a clear assessment of an organisation's needs and opportunities**.** Organisations must identify critical pain points such as delays in project scheduling, inefficient resource allocation, safety risks, and challenges in quality control or predictive maintenance. Once these are evaluated, clear objectives should be set, for example, minimising project delays, improving safety compliance, and optimising material usage, ensuring that AI adoption is aligned with business priorities and measurable goals.

The next step is to build awareness and buy-in across the organisation. Engaging stakeholders, such as project managers, engineers, contractors, and site workers, is essential to fostering understanding and addressing concerns about AI's role. Equally important is leadership advocacy from senior management to champion AI initiatives and ensure that adoption supports broader organisational strategies. Choosing the right AI tools is central to success. Tools such as Building Information Modelling (BIM) for design optimisation, predictive analytics for risk anticipation, and computer vision for site safety monitoring can provide direct value to construction projects.

To reduce risks, organisations should implement a pilot programme**,** starting small with a specific use case such as predictive scheduling using machine learning or drone-based site inspections. Success metrics, such as cost savings, efficiency gains, or error reduction, should be established to evaluate the pilot's impact. Strategic collaboration with reputable vendors experienced in the construction domain ensures the selected solutions are both practical and robust. Supporting this is the need to build infrastructure and skills**,** ensuring data readiness through clean, structured datasets, providing training programmes to upskill employees, and integrating AI tools with existing project management systems to ensure seamless workflows.

Once the pilot demonstrates value, organisations can scale and optimise AI applications. Insights from early adoption should inform refinements, after which implementation can be expanded across multiple projects. Continuous monitoring and improvement, including updating algorithms and adapting to new project requirements, will maintain long-term effectiveness. In parallel with scaling, organisations must also address ethical and regulatory considerations**,** particularly by ensuring data privacy, regulatory compliance, and fairness in AI decision-making. Maintaining transparency in how AI systems make recommendations builds trust with stakeholders.

Finally, measuring return on investment (ROI) and long-term impact is vital for sustaining AI implementation. This includes evaluating outcomes such as reduced costs, improved project timelines, enhanced safety, and higher-quality outputs. A feedback loop with architects, engineers, and project managers helps refine AI tools. At the same time, continuous alignment with the organisation's strategic vision ensures AI delivers sustainable benefits to construction and project management practices.

5.5. Development of the Proposed Implementation Strategy Based on Literature Findings

The developed implementation strategy is directly derived from the study's empirical findings and is structured to respond systematically to the identified thematic insights. The theme on the application of Artificial Intelligence in construction and project management informed the assessment of needs and AI technologies components by identifying priority use cases, functional areas, and suitable AI tools aligned with industry practices. Findings on the impact of AI on efficiency, cost, and time management underpin the pilot programmes, and scale and optimisation components, providing evidence-based justification for incremental adoption, performance benchmarking, and the expansion of successful AI applications. These impact-related findings also guided the monitor and evaluate component, ensuring that measurable productivity, cost, and scheduling indicators are embedded in implementation and review processes.

The theme on the challenges of AI implementation, including technological, organisational, financial, environmental, and ethical constraints, informed the remaining strategy components. Specifically, organisational and cultural barriers shaped awareness and buy-in, while technological and skills gaps guided infrastructure and skills development. The financial challenge reinforced the need for phased pilot programmes before large-scale deployment. Furthermore, ethical, regulatory, and governance concerns directly informed the ethics and regulations component, ensuring responsible and compliant AI adoption. Collectively, these thematic linkages ensure that the implementation strategy is empirically grounded, context-sensitive, and aligned with both the opportunities and constraints identified in the study.

6. Conclusion

This study synthesises recent AI in construction and project management (CPM) literature, conceptualises an AI-integrated CPM ecosystem, and develops a strategic framework for the implementation of artificial intelligence (AI) in the construction and project management sector, addressing the industry's increasing demand for digital transformation and enhanced operational efficiency. The study's findings highlight AI's substantial potential to improve project outcomes through more informed decision-making, accurate forecasting, optimised resource allocation, and effective risk management. Moreover, the study underscores that realising the full benefits of AI extends beyond mere technological adoption, necessitating a comprehensive strategy that encompasses organisational leadership, capacity building, stakeholder engagement, and supportive policy measures.

From an industry perspective, the proposed AI implementation strategy provides a roadmap for both practitioners and policymakers to embed AI in ways that are context-sensitive, scalable, and sustainable. By situating AI within broader organisational and regulatory ecosystems, the framework encourages innovation while mitigating risks related to trust, cost, and operational disruption. In doing so, it advances the digital maturity of the construction and project management domain, offering a pathway toward more resilient, data-driven, and future-ready industry practices.

Finally, the major limitation of this study is the lack of validation of the development strategy. Future research may focus on developing standardised data collection processes that prioritise data privacy and cybersecurity—empirically validating the proposed strategy through case studies and pilot projects to assess its practical applicability across different project scales and contexts. In addition, longitudinal research could examine how the AI implementation strategy evolves, capturing the dynamic interplay among technological advancement, industry adaptation, and governance structures.

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Appendix 1

Table 1: The application of artificial intelligence in construction and project management

Author/Year/ Ref	Context (Setting)	AI Technique	CPM Function	Main Outcomes
Ekanayake et al. (2021). Computer vision for interior progress monitoring.	On-site interior finishing works (case studies).	Convolutional neural networks (CNNs), image processing, and photogrammetry	Progress monitoring, productivity measurement, and quality assurance.	Automated image-based progress monitoring reduced manual reporting time, improved the accuracy of per cent-complete estimates, and enabled near real-time productivity tracking.
Yu & Wang (2022). Real-Time Data Analytics.	Case studies & simulations in feasibility/scheduling contexts.	Predictive ML (time-series, ensemble models), scenario simulation.	Feasibility analysis, schedule risk forecasting, and decision support.	Demonstrated improved uncertainty quantification in feasibility studies and better schedule risk prediction.
Alateeq et al. (2023) Construction Site Hazards Identification.	Construction site image datasets / real projects.	Deep learning (CNNs, image classification/ object detection).	Site safety monitoring; hazard identification; automated alerts.	Validated deep-learning pipelines for multi-class hazard detection; highlighted data scarcity and annotation challenges.
Musarat et al. (2024). Robotics & workforce substitution in construction.	Empirical studies on robotic deployments on-site.	AI-driven robotics for control/ planning, autonomous navigation.	Automation of repetitive tasks, labour substitution, and productivity.	Robotics increase productivity for specific tasks and reduces exposure to hazardous work; adoption is constrained by cost, task variability, and integration with human crews.
Liu et al. (2024). Computer vision for construction safety monitoring.	Active construction sites (video surveillance datasets).	Deep learning (YOLO family adaptations), multi-task CNNs.	Safety monitoring, Personal Protective Equipment (PPE) detection.	Multi-task models detected PPE non-compliance and unsafe behaviours with high precision, supporting proactive safety interventions and lowering incident risk.
Valdebenito et al. (2025). Integrating AI and BIM — review & synthesis.	Recent literature synthesis (2022–2025).	ML, knowledge graphs, and semantic rule engines integrated with BIM.	Planning, clash detection, lifecycle data analytics.	Shows convergent trend: AI services plugged into BIM workflows enable predictive asset management, automated code checking, and improved handover.
Alazawy et al. (2025). Machine Learning to Predict the Construction Cost.	Power-plant construction case studies.	Explainable ensemble ML (feature-importance, SHAP-style explanations).	Early cost prediction; model interpretability for stakeholder buy-in.	Demonstrated improved prediction accuracy from ensembles and provided feature-level explanations to increase trust and practical uptake in project planning.
Ranjan (2025). Addressing Construction Claims Using Natural Language Processing.	Claims and contract correspondence (construction projects).	NLP (Python-based models) for timeline & factor extraction.	Claims management, documentation analysis, and dispute timeline mapping.	Extracted timeline events and 26 influencing factors from contract correspondence; demonstrated how NLP can speed claim resolution and highlight documentation gaps.