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Review Article

Artificial Intelligence in Construction Project Management: A Structured Literature Review of Its Evolution in Application and Future Trends

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ABSTRACT

The review examines 130 peer-reviewed works from 1985 to 2025 on the application of Artificial Intelligence (AI) and Machine Learning (ML) in construction project management, covering Industry 3.0, Industry 4.0, and the post-COVID-19 era. The trend in articles demonstrated that AI and ML are widely employed in planning and monitoring to support decision-making, prediction, performance, and optimisation, as technological development, improved productivity, a competitive edge, and sustainability are drivers of AI adoption. However, data integration issues, high implementation costs, resistance to change, and ethical concerns posed persistent challenges. The review further discussed future AI and ML applications in the construction project management industry, including sustainability, digital twins, robotics, and optimisation, and noted that future research should examine how workforce training, leadership readiness, and change management affect AI adoption to overcome the identified challenges.

Keywords: *Artificial Intelligence, Machine Learning, Construction Industry, Construction Project, Project Management*

1 Introduction

1.1 Background: AI and ML in Construction

It is also a very important, multifaceted, and resource-intensive industry, involved in almost all economic and infrastructural development worldwide (Cucos and Turcan, 2025). The new dynamics in the industry, that is, the digital transformation, are taking time, and the new technologies can indicate a new level of productivity, efficiency and interest in the decision-making process. The technologies that have received significant focus in this category are Artificial Intelligence (AI) and Machine Learning (ML), as they can transform the core practices of construction project management. AI: an automated type of computer system, which otherwise would have required an intelligent system with humans, to include reasoning, learning, and problem solving (Souza et al., 2021), although ML, a sub-specialisation of AI, is pattern matching, where deep learning operations versus a basic computer code are improved upon, without explicit computer code (Sarker, 2021). Integration of these technologies in the construction industry has moved beyond theory and is being applied in practice through predictive analytics, automated scheduling, cost forecasting, safety monitoring, and risk assessment.

1.2 Importance of Construction Project Management

AI and ML can be utilised in the construction sector because the industry faces common issues, including cost increases, construction time and schedule delays, accidents, and resource underutilisation (Datta et al., 2024). Industry reports recommend that, worldwide, the majority of major construction projects have experienced significant deviations in budgetary allocations and development timelines, leading to failures and losses of finances and consumer services (Rivera et al., 2016). Conventional project management techniques, such as those that rely more on human judgment and manual systems, fail to effectively address the complexity of large, multidisciplinary projects. The possibility of overcoming those restrictions by presenting the facts of the work, facilitating the work process, and enabling real-time decision-making is made possible by AI and ML projects. Among them are AI-based predictive models, which can predict delays based on historical project data, and ML algorithms, which can recognise possible hazards at construction sites by identifying patterns (Baker, Hallowell, and Tixier, 2020). The accentuating trend is the focus on improvements in relation to the growing importance of AI and ML in enhancing the overall performance and stability of construction project management.

Such potential revolutionary changes in the segments of the project performance, time, cost, quality, and safety are what make AI and ML so valuable in managing the project. Project managers do not always have structured data as a picture of the specific area of interest, along with analogous data recorded by sensors, financial reports, and various documents regarding resource allocation (Nabeel, 2024). The standard tool used in the data analysis process is insufficient to infer useful results from such types of data. AI and ML technologies better process data, detect trends, and enable predictive modelling, giving decision-makers in the project management sector the opportunity to take a step ahead and make informed decisions. Moreover, AI may lead to significant success in communication among stakeholders, as this tool provides a centralised setting in which real-time communication and information can be shared (Brodny and Tutak, 2025). Furthermore, WMT tools have been shown to be promising for automating homogeneous operations, such as scheduling and progress monitoring, thereby enabling project managers to allocate more time to strategic planning and communicating with stakeholders.

1.3 Problem Statement and Research Gap

Nevertheless, these opportunities, such as relatively young AI and ML, are adopted less in the construction industry than in other industries, such as manufacturing, healthcare, and finance. Several obstacles contribute to this gap, including the enormous costs of implementation, a lack of technical knowledge, concerns about data privacy, and the aversion to change among stakeholders who have already adapted to traditional practices. Moreover, the construction industry, due to its fragmented nature and reliance on subcontractors and consultants, can be characterised by greater challenges in standardising and scaling AI-based solutions. The theoretical basis for using historical data to build ML models is also subject to the same arguments about the quality, availability, and relevance of such data, which can jeopardise the accuracy of the forecasts.

Among the greatest limitations of the existing literature is the lack of access to studies that provide a balanced overview of the prospects and obstacles of AI/ML adoption in construction project management. Whereas some studies focused on particular applications, i.e., AI in safety monitoring or ML in cost estimation, a few have offered a critical and integrative view of the overall presence of these technologies in project delivery. Furthermore, most prior research focuses on developed nations, with little consideration of developing countries, where the need for infrastructure development is skyrocketing. Nevertheless, technologically sophisticated use can be incorporated through a small number of resources. Such literature indicates a serious gap that cannot be resolved without considering whether the global applicability of AI/ML can be investigated not only without reference to different contexts and challenges but also in relation to them.

1.4 Aim of the Study

The current research is primarily designed to critically examine the application of Artificial Intelligence (AI) and Machine Learning (ML) to the management of construction projects, focusing on the opportunities offered by AI and ML and the obstacles that hinder their adequate introduction. The work will aim to provide a solution to the theme of how the use of these technologies can transform the process of delivering projects and will illustrate recommendations for increasing their use in the construction industry.

1.5 Objectives of the Study

To fulfil the mentioned goal, the study has the following objectives:

- To analyse the existing usages of AI and ML in the field of construction project management.
- To examine the opportunities that AI and ML provide in improving the timing performances of projects in terms of cost, quality, and safety.
- To determine the issues and obstacles related to the use of AI and ML in construction.
- To evaluate the implications of AI and ML integration for industry practitioners, policymakers, and researchers.
- To propose recommendations for overcoming challenges and enhancing the effective implementation of AI and ML in construction project management.

1.6 Research Questions

Based on the above objectives, this study addresses the following research questions:

1. What are the current states and purposes of AI and ML that provide for improving project performance and efficiency? (Aligned with Heading 3)
2. What drivers and barriers limit the adoption of AI and ML in construction? (aligned with Heading 4)
3. How can the construction industry address these challenges to accelerate the integration of AI and ML in the future? (Aligned with Heading 5)

2 Research Methods

The study adopted a systematic literature review (SLR) to analyse the current state of industrial AI and ML implementation in construction project management because, according to Snyder (2019), systematic reviews are effective for synthesising and critically assessing the literature in a structured manner. The review followed Mayring's methodological model (Mayring, 2021), which has already been validated across multiple research contexts to ensure analytical rigour (Creuza et al., 2017). The process is divided into four key steps (Figure 1); thus, the method allowed for constant and systematic literature evaluation while ensuring valid and transparent results.

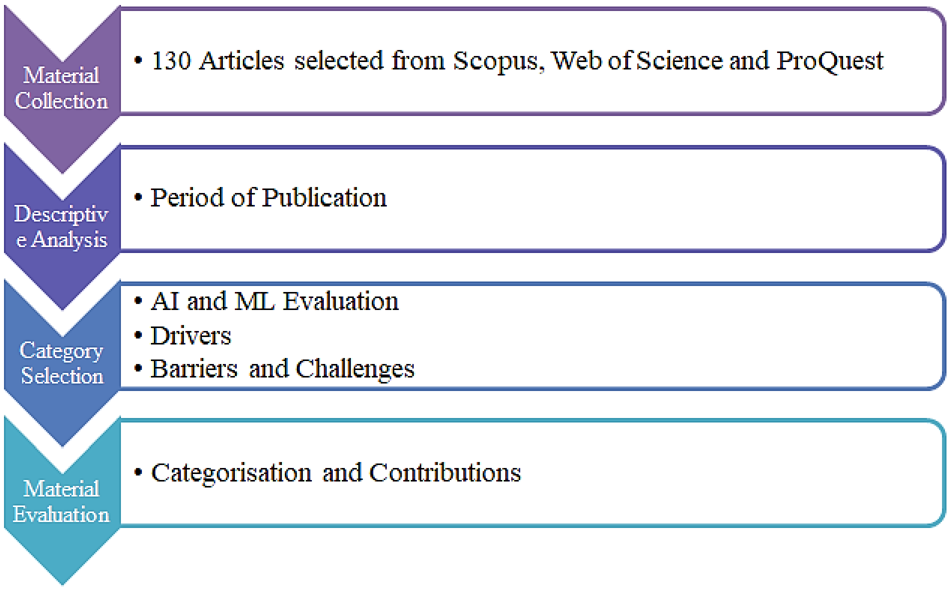

Figure 1: Mayring Process Application

2.1 Materials Collection

The collection of necessary material (data) is important as the unit of analysis was peer-reviewed scholarly articles on construction project management using AI and ML, under which three major databases, Scopus, Web of Science, and ProQuest, were searched using structured keywords to obtain complete coverage. The search strategy used different keyword combinations to find different ways to achieve the results, such as "artificial intelligence AND construction," "AI AND construction," "AI OR ML AND construction," "machine learning OR AI AND construction," "AI techniques in construction," "AI in construction," and "artificial intelligence in construction." Multiple criteria within the inclusion/exclusion criterion are employed to ensure the quality and relevancy of the datasets, as only English-language peer-reviewed journals are examined, while conference proceedings, editorials and non-academic sources are ignored; after the initial search, the elements of language, journal type, duplication removal, abstract screening and full-text analysis were utilised for systematic filtering. Following the specified inclusion and exclusion criteria, the most relevant studies were selected for the review, and the final dataset comprised 130 peer-reviewed academic papers for analysis. The filtering and selection process is illustrated in the PRISMA diagram (Figure 2).

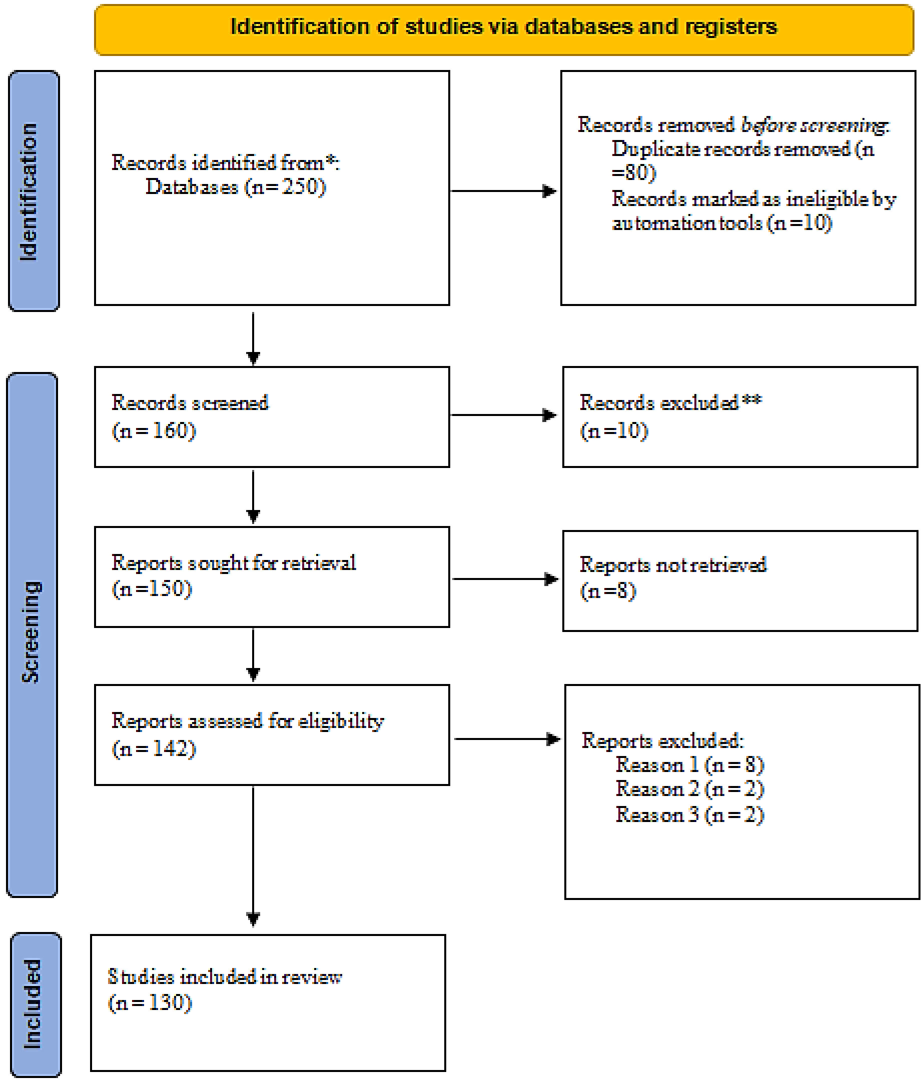

Figure 2: PRISMA-based Data Selection Strategy

2.2 *Data Analysis*

The methodology utilised qualitative content analysis and quantitative visualisation to analyse the data, as content analysis is a methodical and impartial way to develop insights from text or images (Roumell, 2024), while the dual method is employed to better assess the literature and organise textual results into quantitative data. The review comprehensively classified results from the final 130 papers and categorised them thematically to identify themes such as AI types, AI application purposes and their utilisation throughout the construction project management. Thematic coding made the identification of the patterns within the literature easy, and once the primary themes are categorised (Table 1), their frequency was quantitatively analysed within the dataset, and this process quantified qualitative inputs via bar graphs and charts; the graphics visually illustrate the trend of AI and ML applications within construction management. The qualitative coding and quantitative visualisation established a complete analytical framework because they categorised the patterns and illustrated the proficiency of the existing literature, while the methodological approach further allowed the research to address its main research question about the progress of AI and ML applications in construction project management, with the identification of their potential opportunities and challenges.

Table 1: Purpose Themes Categorisation

Themes	Purpose Category
Expert systems, models, and AI tools for decision making in control, finance, scheduling, and project management	Decision Support
Intelligent and deep learning systems for resource optimisation, planning, bidding, and scheduling	Optimisation
Genetic algorithms, Bayesian models, and machine learning for cost, scheduling, and resource improvement	Performance Improvement
Expert systems, automation tools, and deep learning for project planning and monitoring	Automation
Machine learning and natural language processing for predictive conflict, safety, and risk management	Predictive
AI models for forecasting project performance, cost, risk, and productivity	Forecasting
AI and deep learning for evaluating performance, competencies, and investment	Evaluation

3 AI & ML APPLICATIONS IN THE CONSTRUCTION INDUSTRY

3.1 General Observation

The SLR examined 130 peer-reviewed academic articles published between 1985 and 2025, and these articles were divided into three groups to demonstrate the evolution of AI and ML within construction project management. The series of 20 articles (1985-2010) covers the ending years of Industry 3.0 (3IR) and the increasing interest within automation technologies in civil engineering defined the developmental approach of the specific period while the other series of 35 articles (2010-2020) associated with Industry 4.0 (4IR) under which the digital transformation research in civil engineering increased because the construction companies employed data-driven tools and technology to promote production and efficiency. The most significant and latest category of Industry 4.0 Post-COVID-19 (4IR PC), comprised of 75 articles (2020-2025) and the rapid increase in the publications reflected the active role of COVID-19 pandemic in promoting digital technology adoption in construction management; driving construction to adopt AI and digital solutions (McKendrick, 2021) while the rapid increase of research is visually illustrated in Figure 3.

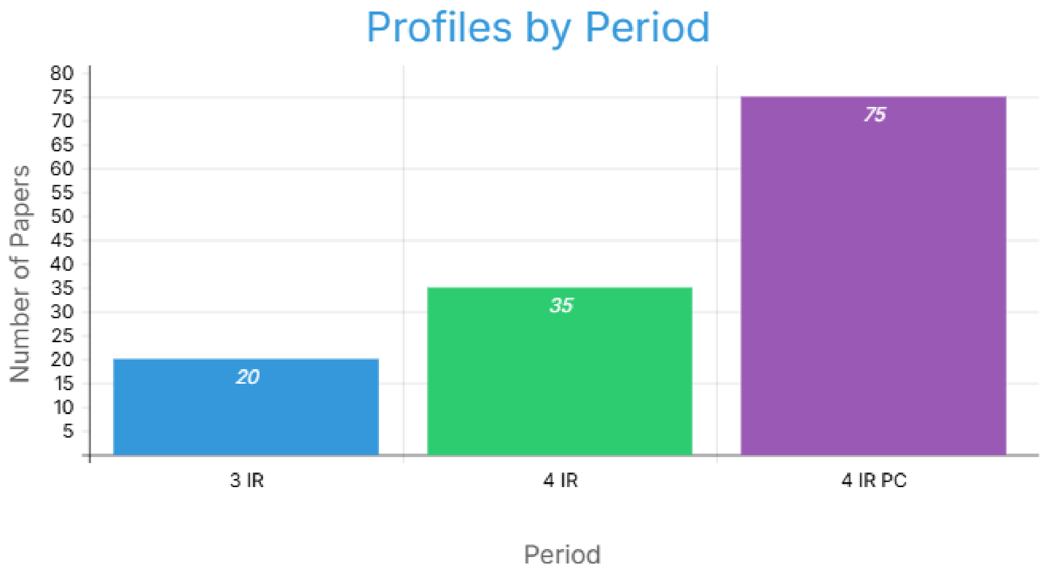

Figure 3: Profiles of Research by Period

Different data collection methods were employed in the selected research articles but majority of the publications (52% or 67) were based on computational experiments by using AI model building, ML modelling and testing within controlled or experimental situations while the second most prevalent method was caste study analysis of construction project across 30% of the selected articles (Oliveira et al., 2021). The selected articles adopted AI models in construction projects or organisations to demonstrate practical applications and assess AI system viability but despite being effective in civil engineering (Nyokum and Tamut, 2025), survey and other primary frameworks were employed in very limited articles while Figure 4 provide the break-down of data collection methods and reflected the domination of experimental and case-study approaches in AI or ML research works within civil engineering.

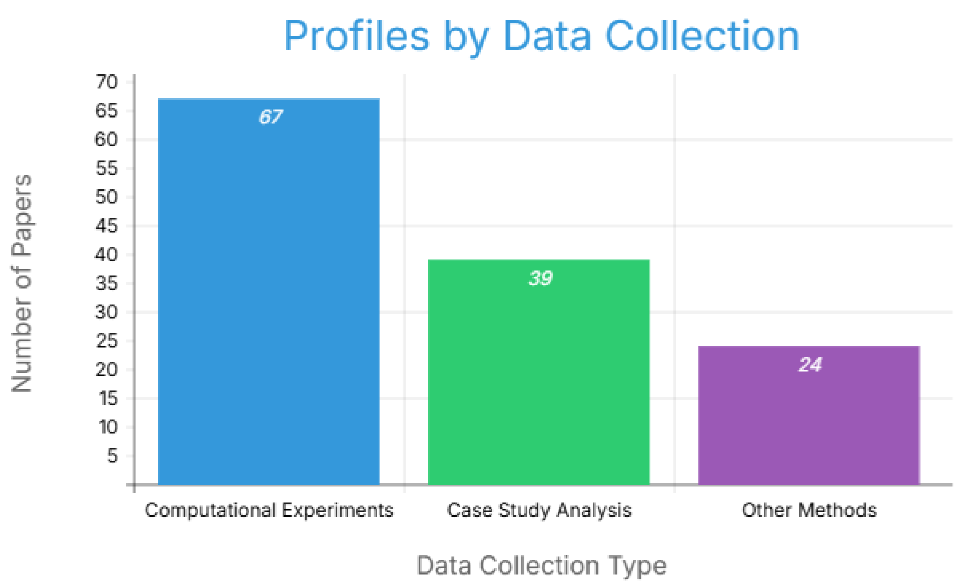

Figure 4: Profiles of Research by Data Collection Approaches

3.2 Types and Purposes of AI and ML in the Construction Industry

According to Abioye et al. (2021), the application of AI is divided into seven subfields, including "*Machine Learning (ML), Knowledge-Based Systems, Computer Vision, Robotics, NLP, Automated Planning, and Scheduling and Optimisation*", and the systematic review found that machine learning and knowledge-based systems are the most researched AI applications within the construction project management. Machine learning approaches were covered in 77 articles (Cheng et al., 2010; Ghazal and Hammad, 2020), while knowledge-based systems were emphasised across 22 articles (Ngai et al., 2021; Parsamehr et al., 2022); however, 13 articles discussed optimisation and 10 articles analysed process digitalisation via Excel (Chevallier and Russell, 1998; Karki and Hadikusumo, 2021), followed by only eight articles stressed natural language processing (Ko et al., 2021). Figure 5 below further illustrates the distribution of AI subfields in the literature, and it is established that construction project management primarily relies on basic AI tools such as ML and knowledge-based systems, which aligns with the findings of Regona et al. (2022) that the construction industry is slow to adopt modern AI technologies.

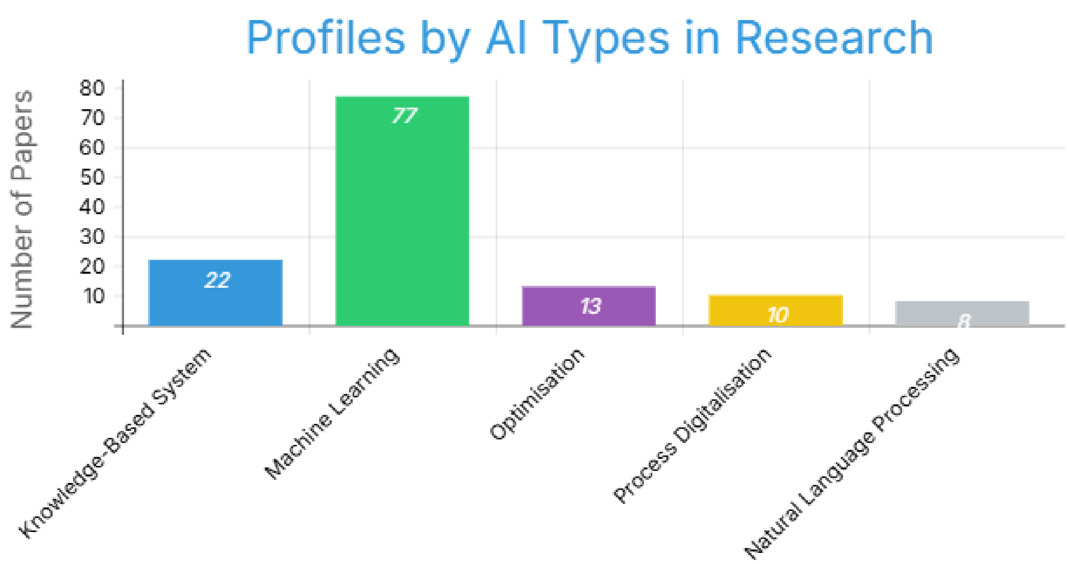

Figure 5: Categorisation of AI Types Prevalence across Selected Articles

4 DRIVERS AND CHALLENGES OF AI AND ML IN CONSTRUCTION

4.1 AI and ML - Global Adoption

The adoption of AI and ML within the global construction industry accelerated significantly over the past ten years, modifying the planning, management and execution of engineering-based project management processes (Kabalisa and Altmann, 2021). Technologies like AI are supporting the smarter decisions with better performance within the construction project cycles because, according to Sacks et al. (2020), an advanced AI-driven technique, "digital twin technologies", provides real-time production planning and design optimisation in project management, while modern construction management already requires planning for reducing material waste and improving operations. The global AI and ML adoption within the construction sector is uneven because regions like the U.S, Asia and Europe are ahead of the world in AI-based construction, but the Middle East, Africa and Latin America are still in the early phase of adoption due to technological, financial, and institutional challenges (Precedence Research, 2025). North America led AI construction worldwide in 2023 with 75% of the global share, supported by the strong engineering and infrastructure industries and preparedness for new technologies, under which the prevalence of IT businesses, strong digital infrastructure and a well-established project management culture made the AI and ML adoption easy at every stage of the project (Srivathsan et al., 2024). The AI-enabled construction management is also growing in Europe and Asia, as Seunguk et al. (2023) cited that AI and ML applications in construction planning, scheduling and risk management have expanded in the Asia-Pacific due to growing industrialisation, population expansion and government-led digital transformation; South Korea has funded major R&D programs to improve smart construction technology.

Moreover, the strategic policy frameworks can assist digital integration of engineering projects which is exemplified by the "*Singapore Construction Industry Transformation Map*" (Gao et al., 2018) and China also leads construction project management AI research and use due to its large infrastructure projects and AI-driven capacity building hence; all of these regions recognises the potential of AI and ML in reducing project management issues like cost overruns and schedule delays (Seunguk et al., 2023). Contrary to this, Adebayo et al. (2025) cited that in Latin America, the Middle East and Africa, the adoption of AI and ML is still very slow because the lack of access to advanced digital infrastructure, an unprepared local construction industry and insufficient government incentives for innovation are the key causes for gradual adoption. The adoption of ML in project management is further complicated by the labour capabilities, budget and data governance standards, but some new projects in the region of Middle East region reflected that ML is being promoted within sustainable and "green" construction methods for predictive maintenance, energy optimisation and automated monitoring systems (Mahmood et al., 2024).

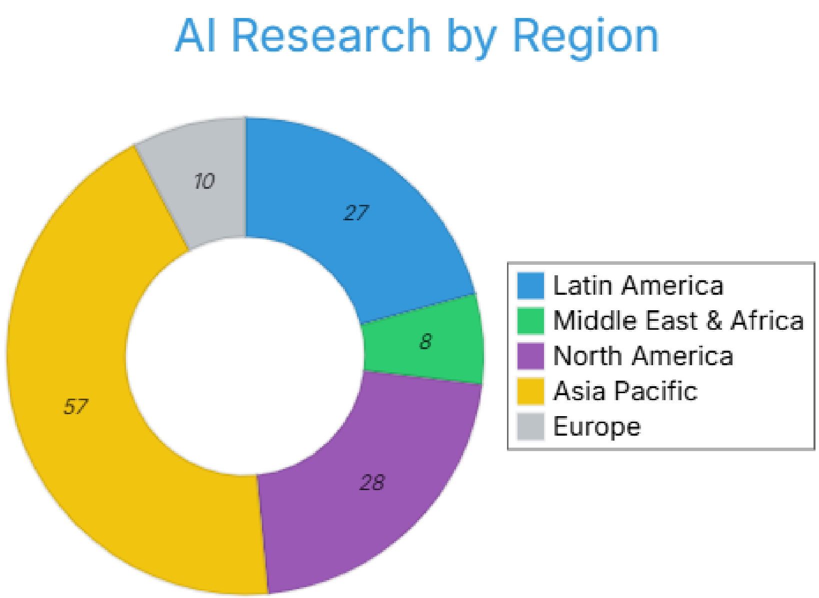

Figure 6: AI-Research by Region in Selected Articles

Following the global pattern of adoption, Figure 6 highlighted the global variance within the selected AI-related construction project management research articles, as the Asia Pacific appeared as the dominant region (44%) with 57 out of 130 peer-reviewed articles, while the trend further established that China, South Korea and Singapore are focusing on digital skills and AI integration via large national programs. The adoption of AI and ML across the globe is uneven but efficiency, sustainability, and digital transformation of the construction project management appeared as the common goals under which the mature infrastructure and innovation ecosystems supported the practical implementation of AI and ML in the regions like North America and Asia Pacific however, awareness, investment and digital readiness are slowly adoption other areas (Ejohwomu et al., 2021). Zairul and Zaremohzzabieh (2023) affirmed that the global improvements indicated that AI and ML modified engineering project management by delivering data-driven accuracy, greater forecasting abilities and long-lasting approaches to provide sustainable projects for future construction.

4.2 AI and ML Adoption Drivers

Artificial Intelligence (AI) and Machine Learning (ML) are providing diverse opportunities to modern engineering project management because the need to increase productivity and project outcomes, market challenges and a growing focus on sustainability within the new technologies are driving the rapid adoption. Figure 7 highlighted that some of these drivers appeared in Industry 3.0 (3IR), but their effects have evolved, and new drivers have emerged in post-COVID Industry 4.0 (4IR PC) while Erfani and Cui (2022) cited that the understanding of AI benefits ranging from improved safety and efficiency to reduced waste, made it crucial technology for construction project management performance and innovation.

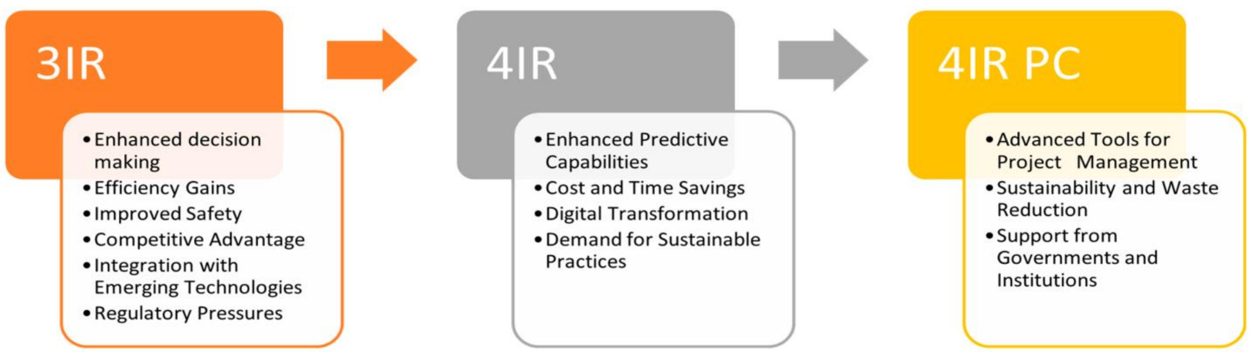

Figure 7: Drivers Evolution of AI and ML (Adebayo et al., 2025)

The access to technology with rapid development and general availability of AI-related construction technology promoted their adoption because modern engineering projects require adaptability and smart decision-making, while predictive and data-driven solutions are improving to fulfil these needs, under which Erfani and Cui (2022) reported that predictive risk modelling helps project managers with early identification of uncertainty for improving performance and reducing delays. Graph-based models (Wu et al., 2022) and deep learning algorithms (Zheng et al., 2020) also provide data intelligence for complex project scheduling, quality control and optimisation, while Piras et al. (2024) further added that BIM and Digital Twins transformed visualisation and simulation because they allow designing checking and anticipation of outcomes by test simulation for the project teams before the actual implementation. Improved productivity and project success are also key drivers and opportunities with the adoption of AI and ML, because cost overruns, delays, and material waste have long negatively impacted the success of the construction industry. According to Cheng et al. (2019), AI and ML are increasingly utilised to automate repetitive tasks, improve workflows and support data-driven decision-making because the automation reduces human error and speeds up work completion. According to Son and Khoi (2023), AI solutions simplify cost estimation, scheduling, and forecasting, making project outcomes more predictable.

In the competitive construction industry, organisations must adopt digital transformation to sustain a competitive edge, as AI technologies accelerate project delivery, lower costs, and improve quality. Smart technology for predictive analytics, automated scheduling and data-driven decision-making can help companies in overcoming their competition Sousa et al. (2023) while BIM as a project management technology is becoming increasingly vital for competitiveness under which some clients and public-sector contracts even need it for project eligibility Doukari et al. (2022) thus; AI improves operations of a construction company and supports the competition within the evolving digital construction industry. The sustainability priority is also a key driver to the adoption because sustainability drives engineering project management AI adoption, as the construction industry faced the external pressure to reduce its environmental impact due to excessive energy and resources utilisation (Yevu et al., 2023), but as per Liu et al. (2024), AI optimises energy utilisation with carbon footprints to achieve sustainability goals. The ML technologies also make the green retrofitting easier by allowing predictive analysis for energy-efficient design and restoration plans (Mahamedi et al., 2023) while the smart construction planning and optimisation using AI-driven solutions reduces material waste (Bang and Andersen, 2022) under which AI and ML integrated to current construction management systems to reduce emissions, save resources and improve project performance as the construction industry transforming with global sustainability standards.

4.3 AI and ML Adoption Challenges

The adoption of AI and ML in engineering project management remains uneven despite significant advancements enabled by digital transformation; structural and cultural challenges limit full-scale adoption in the construction and engineering sectors (Shang et al., 2023). Figure 8 demonstrated the evolution of these challenges and barriers, indicating that data, integration, cost, and regulatory uncertainties persisted as barriers even with the rise in awareness and demand for modern technologies.

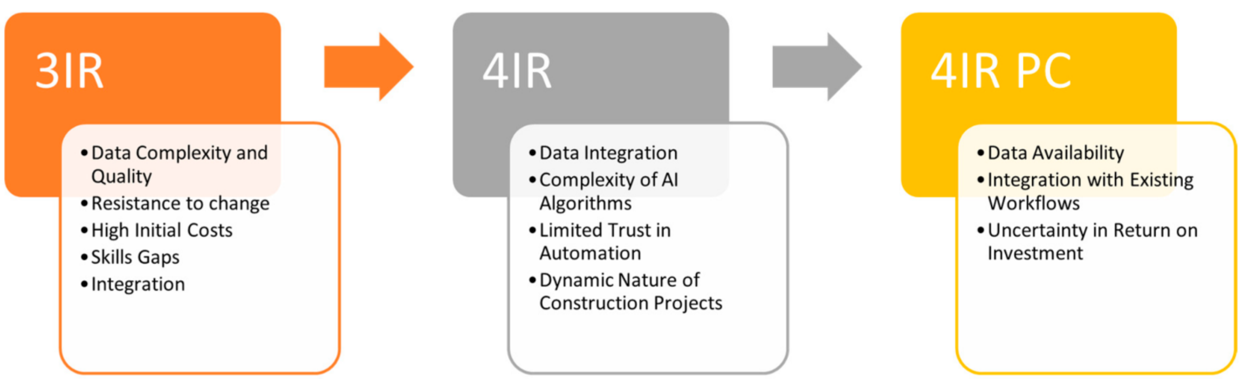

Figure 8: Evolution of Challenges (Adebayo et al., 2025)

Resistance to technology adoption is the ultimate challenge because stakeholders are not willing to change with technology, under which the construction industry is still risk-prone and heavily dependent on old methods, leading to uneven adoption of efficient modern technologies like AI (Chen et al., 2021). According to Aljawder and Al-Karaghouli (2022), the organisational inertia and scepticism about trustworthiness and transparency of AI delayed the adoption, as many stakeholders still fear that AI would undermine knowledge and are unwilling to replace traditional techniques with algorithmic decision-making (Rafsanjani and Nabizadeh, 2023). Doukari et al. (2022) argued that criticism of AI and ML integration within conventional engineering project management often originates from unfamiliarity with AI methods and a lack of comprehension of their practical benefits, while engineering projects need staff engagement and change management solutions to overcome this challenge. The high cost of implementation is another significant challenge because the integration of AI and ML within the construction project management is expensive, which small and medium-sized enterprises have not been able to invest in due to the high costs of technology, data infrastructure, and staff training (Elshaboury et al., 2023; Tang and Leung, 2009). The modification and update of the existing systems also required substantial investment, while the maintenance and system changes also require technical and financial resources along with the technological hardware (Liu et al., 2022).

Furthermore, the data quality and quantity for training the AI model further served as a challenge to adoption because AI and ML in engineering rely on structured high-quality data, yet construction datasets often demonstrate fragmentation, incompleteness and inconsistency (Amer et al., 2021). Historical project data is sometimes missing or not gathered consistently, making machine learning training unreliable (Martínez-Rojas, 2016). Combining datasets into working systems is challenging and time-consuming (Amini et al., 2024); hence, the persistent data issues make AI models less useful for project planning, scheduling and risk analysis. Legal and ethical issues impacted the IP adoption in engineering project management because organisations are concerned about AI-driven decision liability without clear legislation (Mahfouz and Kandil, 2011), under which it is difficult to determine the causation between people and technology on project failure or site accidents. Jung et al. (2024) further established that AI-driven monitoring and prediction systems collect sensitive data, leading to data privacy risk, while the particular risk is even more significant in regions like the EU, which has strict data privacy laws (Di Minin et al., 2021). Thus, AI and ML are difficult to employ due to inconsistent rules and standards.

5 AI and ML Future in Construction

AI and ML are rapidly changing engineering project management by modifying design, planning, execution, and operational procedures, as they actively contribute to creativity, efficiency, and safety (Maruthi et al., 2022). Future engineering and construction projects will prioritise efficiency and sustainability, as the adoption of AI-driven sustainability frameworks is required by global efforts to reduce carbon emissions, save energy, and reduce material waste. According to Ganiyu et al. (2020), AI and BIM can help engineers design energy- and waste-efficient structures for the circular economy, while deep learning models can aid sustainable retrofitting, resource consumption, and energy utilisation prediction, with optimisation across project phases (Li et al., 2021). AI systems assist project managers in making sustainable choices by assessing the environmental impacts of designs and construction (Aljawder and Al-Karaghouli, 2022). Thus, AI will be crucial to data-driven sustainability plans and environmental compliance as the construction industry is inclined towards net-zero ambitions. Digital twin technology for predictive maintenance has emerged as an important future advancement in engineering project management because Digital Twins, as virtual replicas of actual assets, enable real-time construction monitoring and simulation, leading to proactive maintenance (Sacks et al., 2020). The teams of construction projects can predict errors, evaluate performance, and take corrective measures before costly disruptions by using data from the digital models under which Sun and Liu (2022) cited that a smart feedback loop improves collaboration, design accuracy, and rework and delay reduction while Doukari et al. (2022) further added that AI-powered Digital Twins provide adaptive management which optimises project performance in real time.

The technologies of AI and ML strengthen their position in engineering project management optimisation, as predictive analytics and machine learning support project managers in enhancing the "iron triangle" by simplifying cost estimation, resource scheduling, and risk prediction, thereby reducing costs and improving performance (Bakhshi et al., 2022). AI applications are also improving material performance by analysing quality control requirements and predicting structure behaviour to make materials more efficient (Chao et al., 2022), while, as per Kim and Jang (2023), the data is also important in safety management as the AI systems apply deep learning models to identify risks, predict accident likelihood and conduct real-time precautions. The AI-powered robots are also providing future-modifying opportunities for the construction industry, as Feng et al. (2022) reported that future construction sites will use autonomous systems for digging, inspecting and transferring materials. Robotics, computer vision, and deep learning can automatically track progress, identify flaws, and evaluate performance, while effective machine-human collaboration will enable project managers to work with smart machines and staff to ensure data-driven operations (Dharani et al., 2022). Thus, these innovations would speed up project timetables and reduce human error with safety risks. AI-assisted decision support will give way to data-driven decision-making in engineering project management, as predictive risk modelling and impact analysis allow managers to consider numerous project options before execution, thereby boosting engineering productivity and transforming the industry into one that values safety, sustainability and operational excellence.

6 Conclusion and Future Recommendations

The use of Artificial Intelligence (AI) and Machine learning in construction and engineering project management was investigated in this study as we examined 130 peer-reviewed journal publications from 1985 to 2025 from Web of Science, Scopus and ProQuest, and we used a four-step approach to collect materials, descriptive analysis, manual categorisation and thematic evaluation. AI research increased significantly between Industry 4.0 and COVID-19 because the industry is increasingly using digital transformation and automation, under which computational trials are the most common study method; thus, future studies should benefit from a wider range of empirical and qualitative methods to better contextual comprehension. The review revealed that construction and engineering project management uses AI and ML for decision support, predictive analytics, performance optimisation, process automation, and resource allocation, while these applications support the focus of Industry 4.0 on data-driven intelligence, real-time networking, computational power, and human-machine collaboration.

The peer-reviewed articles further revealed that rapid technological advancement, the need to improve productivity and project outcomes, industry competition, and sustainability imperatives drive AI adoption; however, persistent challenges prevent comprehensive applications. The challenges include resistance to change, a lack of AI skills, high implementation and maintenance costs, ethical concerns, data quality issues, and system integration challenges; hence, these must be addressed to successfully apply AI and ML in engineering project management. The utilisation of AI and ML in sustainable design, energy efficiency, and digital twins for predictive maintenance, with robotics for building, will shape the future of construction, as these technologies enable real-time project monitoring, resource optimisation, and better decision-making throughout the project. Future research should examine how workforce training, leadership readiness and change management affect AI adoption to overcome the identified challenges. Under which the researchers should also explore algorithmic ethics, regulatory compliance, and project governance to create frameworks that improve transparency, accountability, and safety in AI-driven construction; hence, these initiatives will ensure that AI improves operational efficiency and drives strong engineering project management transformation.

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