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2025

digital

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Review

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

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Abstract

The integration of Artificial Intelligence (AI) in construction project management is revolutionising the industry; offering innovative solutions to enhance efficiency, reduce costs, and improve decision making. This structured literature review explored the current applications, benefits, challenges, and future trends of AI in construction project management. This study synthesised findings from 135 peer-reviewed articles published between 1985 and 2024; representing Industry 3.0 (3IR), Industry 4.0 (4IR), and Industry 4.0 Post COVID-19 (4IR PC). Analysis showed that the Planning and Monitoring and Control phases of the project have the greatest application of AI, while decision making, prediction, optimisation, and performance improvement are the most common purposes of AI use in the construction industry. The drivers of AI adoption within the construction industry include technology availability, project outcome and performance improvement, a competitive advantage, and a focus on sustainability. Despite these advancements, the review revealed several barriers to AI adoption, including data integration issues, the high cost of AI implementation, resistance to change among stakeholders, and ethical concerns surrounding data privacy, amongst others. This review also identified future ongoing applications of AI in the construction industry, such as sustainability and energy efficiency, digital twins, advanced robotics and autonomous construction, and optimisation. By providing a comprehensive analysis of the evolution of practices and the future direction of AI application, this study serves as a resource for researchers, practitioners, and policymakers seeking to understand the evolving landscape of AI in construction project management.

Keywords: artificial intelligence; construction industry; construction project; project management; literature review

Academic Editors: Phivos Mylonas, Akrivi Krouska, Christos Troussas, Dimitrios Kardaras and Cleo Sgouropoulou

Received: 29 May 2025
Revised: 23 June 2025
Accepted: 3 July 2025
Published: 9 July 2025

Citation: Adebayo, Y.; Udoh, P.; Kamudyariwa, X.B.; Osobajo, O.A. Artificial Intelligence in Construction Project Management: A Structured Literature Review of Its Evolution in Application and Future Trends. *Digital* **2025**, *5*, 26. https://doi.org/10.3390/digital5030026

1. Introduction

With the emergence of Artificial Intelligence (AI), the construction industry, traditionally characterised by manual and labour-intensive processes, has experienced noteworthy transformation and development. AI is multifaceted, with diverse definitions reflecting its broad scope and complexity. McCarthy et al. [1] defined AI as the science of making a machine behave in ways that would be called intelligent if a human behaved similarly. This is consistent with Minsky's [2] definition of AI as the science of making machines carry things out that would require intelligence if completed by humans. These definitions emphasise the existence and relevance of systems that can learn and intelligently execute tasks.

As a result, Poole and Mackworth [3] referred to AI as an intelligent computational agent. This is consistent with Russell and Norvig's [4] definition of AI as a computational agent that acts intelligently and maximises chances of success by perceiving the environment. These definitions further emphasise AI decision-making capabilities and adaptability in understanding their environment and, with some degree of autonomy, taking actions to achieve specific objectives.

Scholars have also defined AI as a system used to acquire information for the purpose of interpreting the data, learning from the data, and using the findings to achieve specific tasks and goals [5]. This is consistent with Wang's [6] definition of AI as an information processing system with the ability to adapt to its environment with insufficient resources and knowledge. Thus, Dignum [7] concluded that AI is a purpose-driven system capable of processing information intelligently. Organisations' commitment to transformation and innovation has further strengthened the need for AI, which is becoming more significant today with the introduction of Industry 4.0. Other AI technologies include machine learning, natural language processing, deep learning, problem solving, and pattern recognition [7].

AI technologies have been instrumental in redefining various aspects of construction project management, from design and planning to execution, handover, and maintenance, consequently fostering efficiency, safety, and cost-effectiveness enhancements [8]. AI technologies, such as computer vision, neural networks, and machine learning, have proved useful in improving various aspects of construction projects. They present apt solutions to persistent challenges in construction project management, such as delays, safety concerns, cost overruns, and quality control challenges. AI-powered predictive analytics, for example, play a crucial role in accurately forecasting project timelines and risks, surpassing traditional methods. Similarly, autonomous machinery, a product of AI, is adept at handling hazardous and repetitive tasks, thereby significantly enhancing productivity and safety [8,9].

Despite AI's potential benefits, the industry is perceived to be experiencing low productivity growth rates, largely due to its slow adoption of new technologies. This is consistent with Regona et al.'s [9] assertion that AI adoption in construction projects remains relatively limited compared to other sectors, such as finance and manufacturing. With a rapidly changing AI landscape, it becomes increasingly important to understand the changes occurring over time in terms of the needs of the construction industry and its adoption trends. These insights would provide construction stakeholders with the most up-to-date information on the use of AI, current drivers, major barriers, and its future direction to enable the best decision making when intending to shift to more AI-oriented construction project management.

This study thus aims to conduct a structured literature review on the adoption of AI in construction projects to understand the evolution to the current landscape, identify how trends and future direction have changed, while proposing future research and practice directions. Therefore, this paper seeks to answer the following questions:

1. How has AI application in construction projects evolved?
2. What are the main barriers and challenges to AI application in construction projects?
3. What is the future outlook for AI application in the construction industry?

By answering these questions, this study will offer a holistic understanding of how AI applications are used in the construction industry, the potential of AI for transforming the industry, and what the future holds in terms of AI-driven efficiency and innovation. This paper is structured as follows: Section 2 describes the structured, systematic literature methodology adopted for this study. Section 3 presents this study's findings and discussion from evaluating the selected journal articles, while Section 4 considers the drivers of and barriers to AI application in the construction industry. The study conclusions, implications, and future directions are presented in Section 5.

2. Research Methods

In this study, we adopted a systematic literature review to offer a structured and critical overview of the current knowledge and understanding of the research topic [10,11]. Systematic literature reviews are crucial in critically analysing and synthesising existing research. Thus, our structured review process builds on Mayring's process model [12], which has been validated in different research contexts [13]. This process encompasses four sequential steps: material collection, descriptive analysis, category selection, and material evaluation, as shown in Figure 1.

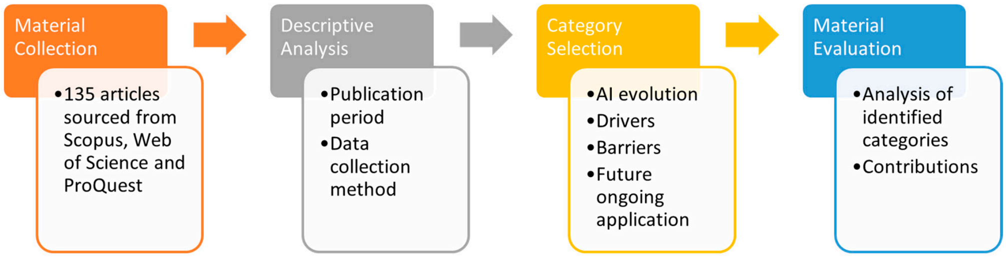

Figure 1. Application of Mayring's process.

2.1. Material Collection

Material collection involves defining the unit of analysis for journal articles to be collected for the study. As a result, a set of structured keyword searches was conducted in three databases, Scopus, Web of Science, and ProQuest, to identify journal articles related to artificial intelligence in project management. The following keyword combination searches were used: "artificial intelligence AND construction", "AI AND construction", "artificial intelligence OR AI AND construction", "machine learning OR AI AND construction", "AI techniques in construction", "AI in construction", and "artificial intelligence in construction". The material collection step included only peer-reviewed journal articles written in English. Figure 2 presents the filtering process, resulting in the journal articles being considered in the rest of the steps.

As presented in the flow chart, the selection of the final set of peer-reviewed journal articles for this study went through five filters, (1) language, (2) journal type, (3) duplicates, (4) abstract, and (5) text analysis, after the structural keyword search, resulting in identifying 135 peer-reviewed journal articles related to this study's theme.

2.2. Data Analysis

The data analysis employed an approach of combining qualitative content analysis with quantitative visualisation techniques. Downe-Wamboldt [14] defined "content analysis as a research method that provides a systematic and objective means to make valid inferences from verbal, visual, or written data to describe and quantify specific phenomena". This approach was selected to convert the text-based insights into structured data, facilitating a clearer interpretation. This study systematically extracts findings from 135 articles, categorises and quantifies these findings through bar graphs to profile AI evolution trends, AI types, AI purposes, and AI use by lifecycle phases in order to answer the first research question on how the application of AI in the construction industry has evolved. The lifecycle of construction projects includes a series of sequential stages that guide the development of a project from initiation to handover [15]. Although the names of the stages may slightly vary in various studies, they generally point to initiation, planning, execution, monitoring and control, and handover [16–18]. Therefore, this study categorises the construction lifecycle phases into initiation, planning, execution, monitoring and control, and handover.

Thematic coding was employed to systematically analyse the textual data. Based on the readings of the findings and review of the selected literature, AI types such as machine learning, knowledge-based systems, Natural Language Processing (NLP), etc., were identified across the findings. Also, the AI purpose and lifecycle phase were deduced from the findings of the selected literature.

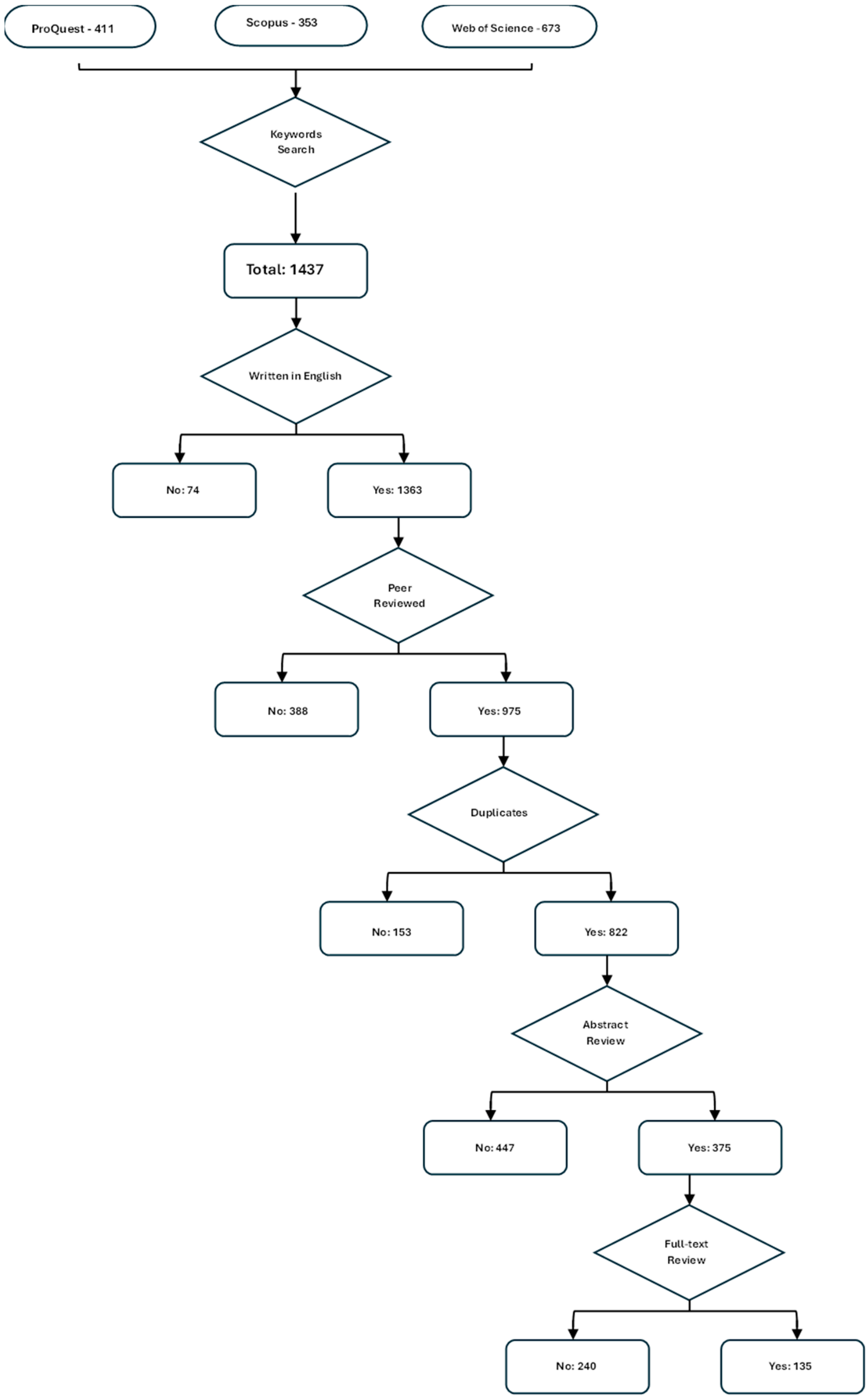

Figure 2. Material collection filtering process.

After categorising the findings into themes, as shown in Table 1, the frequency of each theme was calculated. This process involved counting the number of times each theme appeared across the articles, thus transforming the qualitative data into a quantitative form.

Table 1. Purpose categorisation themes.

Themes	Purpose Category
Expert systems for decision making in control and monitoring, financial decisions, scheduling, project control, collaborative project management, project management processes, information analysis, and conflict management **Various models for decision making,** e.g., computer models for conflict resolution, metaheuristic modelling for scheduling, fuzzy logic for uncertainty and risk management, probabilistic simulation for preconceptual estimates, graph theory and matrix methods for contractor selection, and web-based applications for planning **Deep learning** for contractor selection and manager selection **Natural language processing** for risk management	**Decision Support**
Intelligent systems for optimising resources, planning, and scheduling **Case-based reasoning** for optimising decision making **Deep learning for optimising** pricing and bidding, time and cost, waste reduction, design, planning and production, resource management, information management, and PM practices **Various algorithms for optimization,** e.g., genetic algorithm for planning, control and monitoring, structural efficiency, sustainability, evolutionary algorithms for project cash flows, and moth–flame optimisation for time and cost	**Optimisation**
Various models for improvement, e.g., metaheuristic modelling for project duration and Bayesian approach for design process **Deep learning systems for improving** scheduling critical paths, costing, resources and scheduling, budgeting, conflict resolution improvement, minimisation of delay and waste, and monitoring employees **Machine learning for improving** estimating at project completion and resource allocation **Evolutionary algorithms for improving** conceptual phase costing and cost estimating **Natural language processing for improving** building evaluation	**Performance Improvement**
Expert systems for automating project planning **Various tools for automating,** e.g., WBS mind map and semantic network for WBS, integrated planning tool for productivity monitoring, and resource management **Deep learning for automating** project plans, scheduling, monitoring, image recognition and decision support, collision risk warning, and daily construction reporting	**Automation**
Machine learning for predictive conflict resolution **Deep learning for predictive** costing, scheduling, conflict management, cash flow, risk management, delay estimating, safety management, and waste management **Various types of learning,** e.g., unsupervised learning for predictive safety management and reinforcement learning for predictive energy performance **Natural language processing for** predictive risk management	**Predictive**
Deep learning for forecasting performance, schedule, cost, risk, productivity, and pricing	**Forecasting**
Deep learning for evaluation of initiation performance, PM competency, and engineering management **Fuzzy logic for evaluating** planning performance **Genetic algorithms for evaluating** investment management	**Evaluation**

3. AI Application in the Construction Industry

3.1. General Observations

A total of 135 papers were utilised for this research. These comprised papers from 1985 to 2024 and were categorised into three time periods. Specifically, Industry 3.0 (3IR), representing the latter years of Industry 3.0 which spanned from 1970 to early 2010, had 38 papers, Industry 4.0 (4IR), which began in 2010, had 31 papers, and Industry 4.0 Post COVID-19 (4IR PC), which represents the period from 2020 to 2024, had 66 papers. Where Industry 3.0 was more focused on automation, Industry 4.0 focused on digital transformation. The COVID-19 pandemic, on the other hand, accelerated the digital transformation from Industry 4.0, making industries more open to the use of technology and, in some cases, more speedily adopt it [19]. Figure 3 reflects the studies completed over these time periods, showing an explosion in AI research in the years since COVID-19.

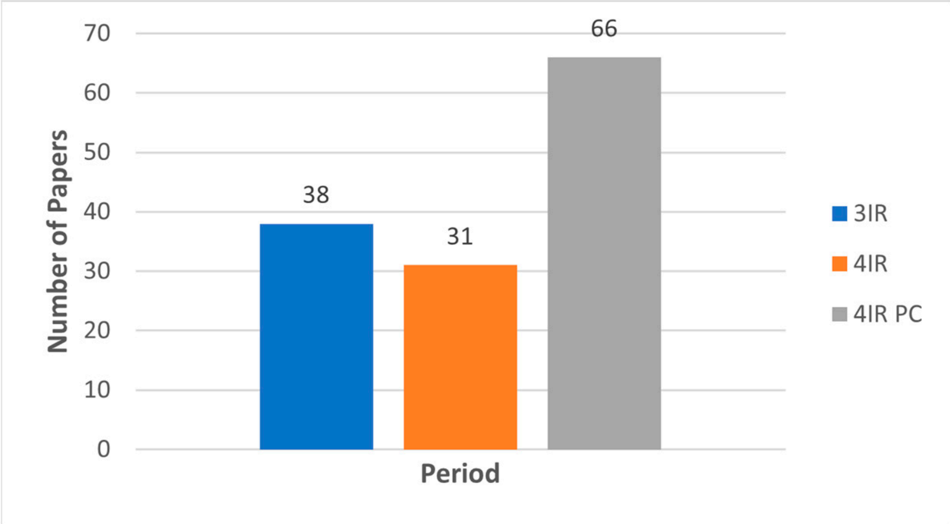

Figure 3. Profile of papers by period.

The data collection types for the papers were varied, with 69 of 135 (51%) papers comprising computational experiments. These experiments typically involved the development and testing of AI models. Data collection categorised as a case study represents 40 of 135 (29.6%) papers where a specific developed model is being applied to a particular context. Figure 4 shows the categorisation of the data collection methods.

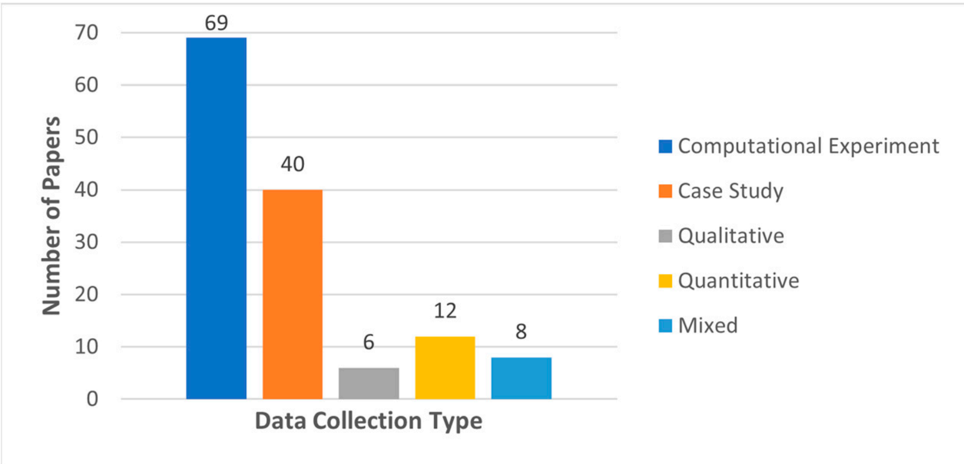

Figure 4. Profile of papers by data collection type.

3.2. AI Type and Purpose Under Research in the Construction Industry

Based on Abioye et al. [20], there are seven subfields of AI, namely: Machine Learning, Knowledge-Based systems, Computer Vision, Robotics, Natural Language Processing, Automated Planning, and Scheduling and Optimisation. A review of the existing literature identified various types of AI applications under research within the construction industry. Specifically, knowledge-based systems were discussed in 21 studies [21–23], machine learning in 77 studies [24–26], optimisation in 13 studies [27–29], natural language processing in 6 studies [30], and basic (non-AI) tool in 18 studies [31–33].

Most of the studies utilised machine learning and knowledge-based systems. Those termed basic (non-AI) were more focused on the digitisation of processes as opposed to the development of artificial intelligence models or tools and included tools such as Excel. This use of basic tools was not surprising as the construction industry has been slow in using AI. Figure 5 represents the most common AI types.

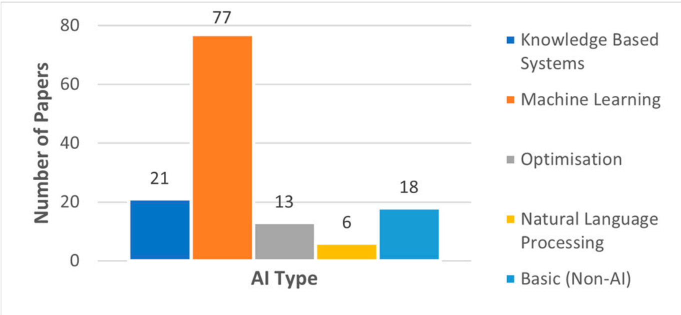

Figure 5. Profile of AI and non-AI type in research.

Based on Table 1, seven categories were identified for AI purpose. Among the reviewed studies, 28 focused on decision support, 14 addressed automation, 28 explored performance improvement, 22 examined optimisation, 28 focused on prediction, 10 on forecasting, and 5 on evaluation.

First, AI tools were employed to support decision making based on existing knowledge [34–37]. Second, AI was utilised to automate various processes such as planning, scheduling, and monitoring [31,38,39]. Third, AI enhanced productivity and improved functions such as cost estimation and budget accuracy, thus improving the performance [40–42]. Fourth, AI facilitated the optimisation of processes, resource utilisation, and cost efficiency [28,43–45].

Fifth, predictive AI tools were used to anticipate risks, detect wear patterns, forecast potential failures, and identify schedule delays [46–49]. Sixth, forecasting AI supports a shift from reactive management to proactive, insight-driven operations, enabling risk forecasting, resource planning, project performance assessment, and cash flow prediction [50–52]. Lastly, AI is used to evaluate competence, quality, performance, and compliance [33,53]. These applications collectively illustrate the transformative role of AI in enhancing the efficiency, accuracy, and foresight in construction project management.

The most prominent categories were decision support, predictive, performance improvement, optimization, and automation tools. This again is in line with the Industry 4.0 agenda on connectivity, data, computational power, analytics, intelligence, and human–machine interactions [54]. Figure 6 shows the identified AI categories.

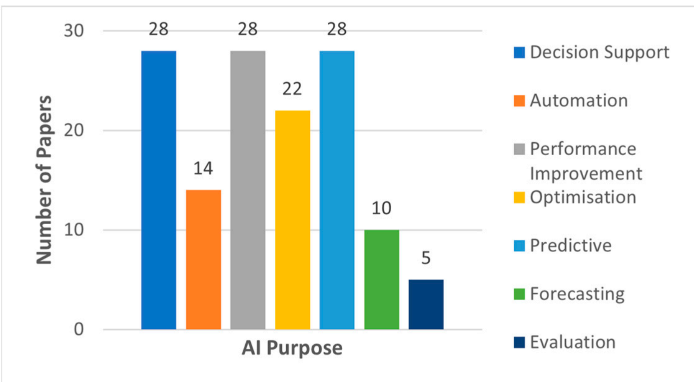

Figure 6. Profile of AI purpose in research.

3.3. Analysis of the Progression of AI Research in Construction

During the Third Industrial Revolution (3IR, 1970–2010), the primary focus of artificial intelligence (AI) research was on knowledge processing, as highlighted by Lu [55]. This aligns with the findings of the current study, which indicated that knowledge-based systems were a prominent form of AI application in the construction industry during Industry 3.0, with 13 of 37 (35%) articles focused on knowledge-based systems. These systems facilitated the collection and organisation of diverse data types, which, in turn, created a demand for more advanced methods to process and analyse such data.

This necessity spurred the development of machine learning (ML) tools in the early 2000s. As Lu [55] notes, ML has evolved from its initial shallow learning phase into the more sophisticated deep learning phase seen today. This trajectory mirrors this study's findings, which show a clear progression in the research on the adoption of machine learning from 11 of 37 (29.7%) articles during 3IR to 47 of 64 (73.4%) articles during 4IR PC.

The post-COVID-19 era, particularly during the Fourth Industrial Revolution (4IR), saw a notable surge in the use of Natural Language Processing (NLP) in sectors like healthcare. As reported by Chen et al. [56], NLP was crucial in managing the vast information demands brought on by the pandemic. This trend is consistent with the study's findings, which reveal that NLP was also increasingly adopted in the construction industry post-COVID, largely in response to greater digitisation and the shift toward remote communication. Although AI-based optimisation tools were widely used in industries such as manufacturing and logistics during 4IR [57], our study found no significant research focus on optimisation AI in the construction sector during that time. However, there was a noticeable increase in research interest with 8 of 64 (12.5%) articles focusing on optimisation tools in the 4IR post-COVID-19 era, indicating a delayed but growing recognition of their potential value in construction.

Basic tools increased in use which aligns with the construction industry being a late adopter of AI over the 3IR and 4IR period. However, with the uptick of machine learning, optimisation, and natural language processing, the use of basic tools and knowledge-based systems faces a drastic decrease. This progression is illustrated in Figure 7.

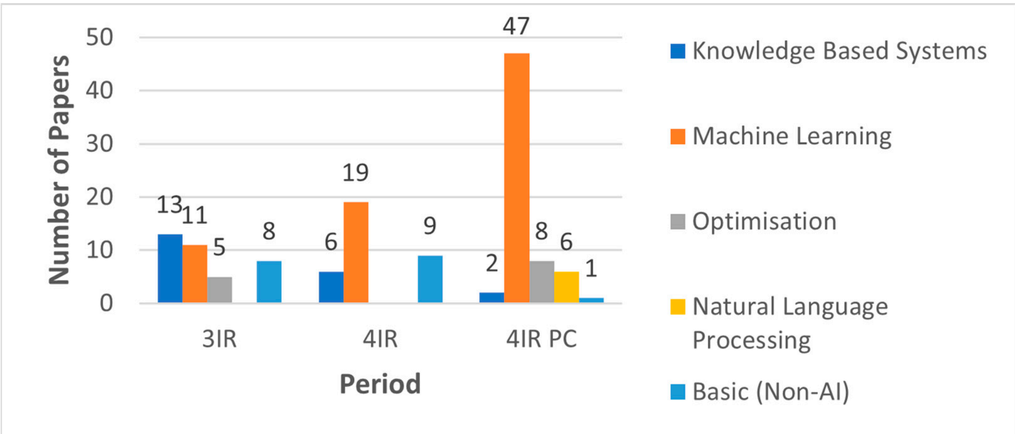

Figure 7. AI-type progression over periods.

Of note is the fact that AI was not used for evaluation purposes in the Industry 3.0 period; its use built up from Industry 4.0. Decision support systems have been widely used, although their usage has declined somewhat since 2020. Performance improvement and forecasting though have maintained their consistency of use. Increases have been observed in the use of optimisation and predictive tools as organisations aim for better efficiency and project outcomes. Automation experienced a slowdown at the onset of Industry 4.0. However, its significance has surged since the COVID-19 pandemic, as the circumstances have necessitated greater reliance on technology to perform tasks. This evolution is reflected in Figure 8.

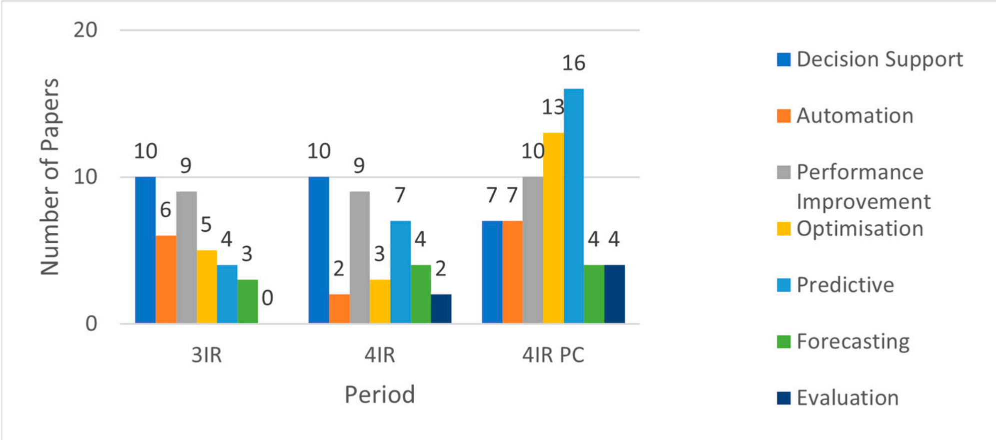

Figure 8. AI purpose progression over periods.

An analysis of the literature highlighted the range of project lifecycle stages where AI technologies were implemented in the construction industry across Industry 3.0, Industry 4.0, and Industry 4.0 post COVID-19. AI usage varied across different lifecycle phases, with planning being the phase where AI is most utilised. Figure 9 reflects how from Industry 3.0, planning has consistently been the focus of AI in construction. Any change occurring later in a project means more risk and expense, making the planning phase one of the most crucial for hedging positive project outcomes. Monitoring and control is another phase where AI has consistently been in use. It is interesting to note that in recent years, the handover phase has started using AI software such as Assai.

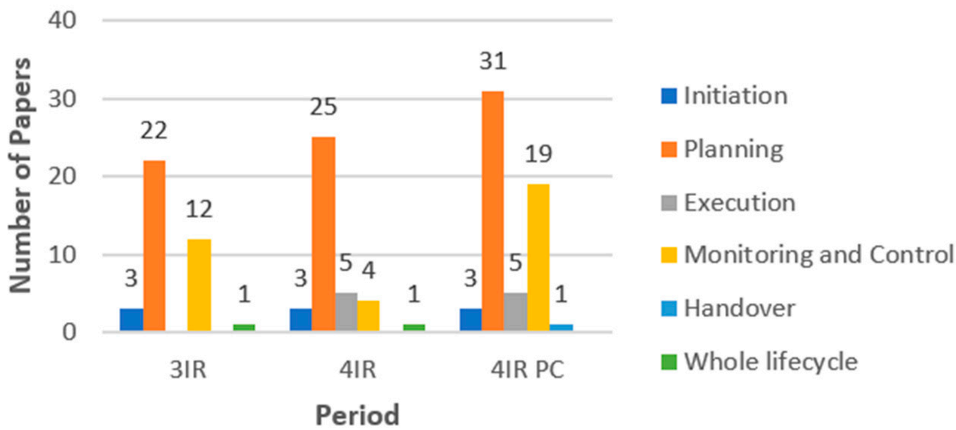

Figure 9. Progression of AI use over the lifecycle.

Machine learning appears to be widely used throughout the project lifecycle with notable emphasis on the planning phase, as noted in 43 of 79 (54%) articles, and monitoring and control phases, referenced in 25 of 37 (68%) articles. Basic tools are also commonly used in the planning phase as noted by 18 of 79 (23%) articles. Knowledge-based systems are mentioned less frequently with 8 of 79 (10%) articles focusing on their application in the planning phase and 9 of 27 (24%) articles highlighting their use in the monitoring and control phase. Optimisation tools have proven useful in the planning and execution phases of the project where they are mostly needed for efficiency such as cost savings, process improvement, and optimal resource utilisation. Figure 10 shows the use of AI over the various phases.

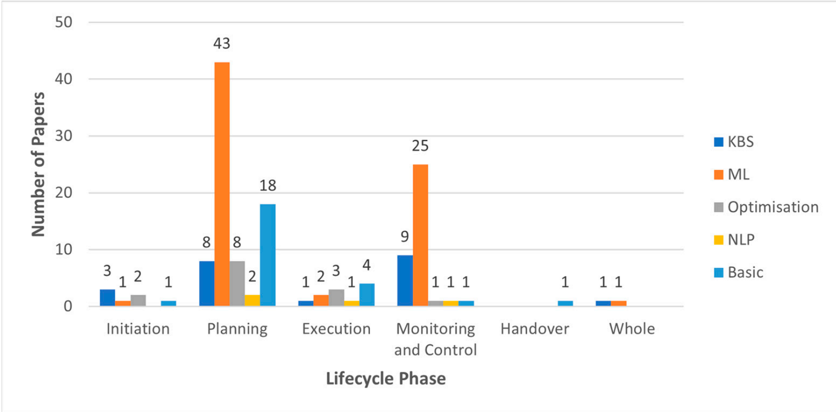

Figure 10. AI types over the lifecycle.

As shown in Figure 11, the planning phase has been identified as the primary stage where AI is currently utilised. The most frequently cited purposes of AI within this phase in the literature include predictive functions (22.6%), optimisation (20%), decision support (12.6%), and performance improvement (24%). In the monitoring and control phase, AI is predominantly used for predictive functions (22%) and decision support (25%).

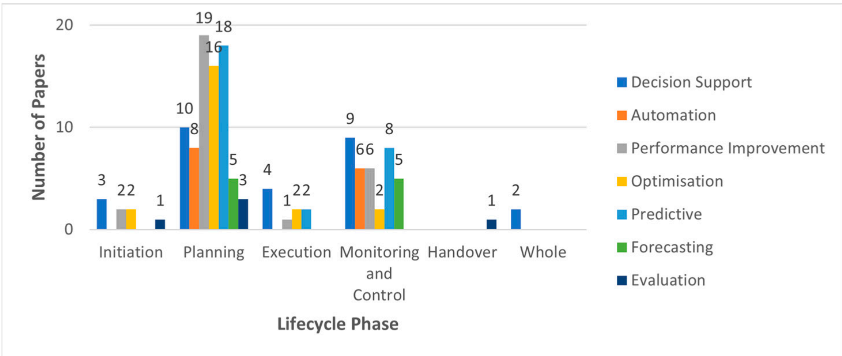

Figure 11. AI purpose over the lifecycle.

Based on the analysis of AI types by purpose, as illustrated in Figure 12, machine learning is predominantly used for predictive functions—cited in 24 out of 77 articles (31%)—and for performance improvement, noted in 17 out of 77 articles (22%). Additionally, knowledge-based systems (47% of articles) and basic (non-AI) tools (44% of articles) are primarily employed for decision support functions.

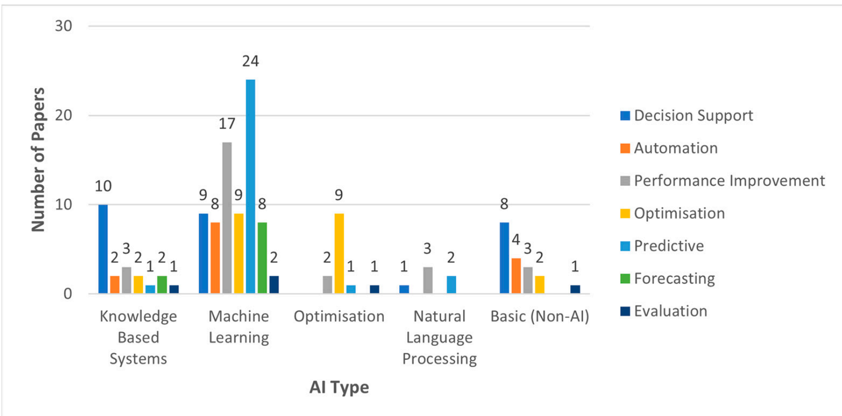

Figure 12. Analysis of AI type by purpose.

4. Barriers and Drivers of AI Adoption in Construction

4.1. Global Adoption of AI in Construction

The adoption of AI within the construction industry is accelerating and it has been driven by a range of factors that are set to revolutionise how construction is designed, managed, and executed [58]. The rise in the need for infrastructural development and urbanisation necessitates the adoption of artificial intelligence to improve productivity and efficiency in construction. In their study, Sacks et al. [43] stated that the implementation of digital twin technologies is essential for effective decision making concerning production planning and detailed product design during construction, using well-informed and reliable what-if scenario assessments which greatly reduce waste, thus improving efficiency in construction.

Research indicates that the AI adoption rate in construction is higher in countries within North America, Asia, and Europe than in countries within Latin America, the Middle East, and Africa. In 2023, North America dominated the global AI landscape in the construction market while Latin America, the Middle East, and Africa had the smallest market share [59]. The robust construction industry within the North American region coupled with technological advancements in artificial intelligence enables the high integration rate of AI in construction. Also, the huge presence of technology companies and AI innovators in the region provides adequate infrastructure and expertise needed to support the adoption of AI. The substantial investment in smart city initiatives and infrastructure projects also creates an enabling environment for using AI in construction. Similarly, Asia and Europe are experiencing an increase in the adoption of AI in the construction industry due to the rise in infrastructural development, government regulatory frameworks and policies, focus on sustainability, and smart city projects. In the UK, the government acknowledges the potential of AI to proactively mitigate issues such as delays and cost overruns in construction projects, while South Korea's government has invested heavily in research and development funds to develop smart construction [60] and Singapore has been proactive in integrating technologies into its construction sector, as evident in their Construction Industry Transformation Map [61].

The adoption of AI in other regions has proven slow due to limited access to advanced technologies, the technological readiness of the construction industry, and low government support. While several countries are increasing investments in AI technologies for construction, the rate of technology adoption varies between nations [60]. This variation in the adoption of AI is influenced by various cultural, socioeconomic, and institutional differences among countries [62,63].

In contrast, as shown in Figure 13, the regional data from this study shows the Asia Pacific region dominating in AI application research, with 59 of 135 (44%) articles. This is in line with growing AI initiatives in the region fuelled by a very-strong-capacity building plan in China and similar projects in other Asian countries. The Middle East and Africa also show growing AI recognition driven by numerous greening opportunities in places like South Africa.

4.2. Drivers of the Adoption of AI

Various factors are driving the adoption of AI in construction. These include the availability of different technologies, improvement of productivity and project outcomes, competitive advantages, and an emphasis on sustainability.

As shown in Figure 14, some changes have been observed in the drivers of AI adoption as its advantages are being realised over time. Identified factors from 3IR are still relevant, with additional factors emerging in 4IR PC. The global awareness of sustainability is a major driving factor in an industry that needs to reduce the waste it produces, improve its safety records, and ensure better productivity and better project outcomes. The most current and pervasive drivers are provided in the sections below.

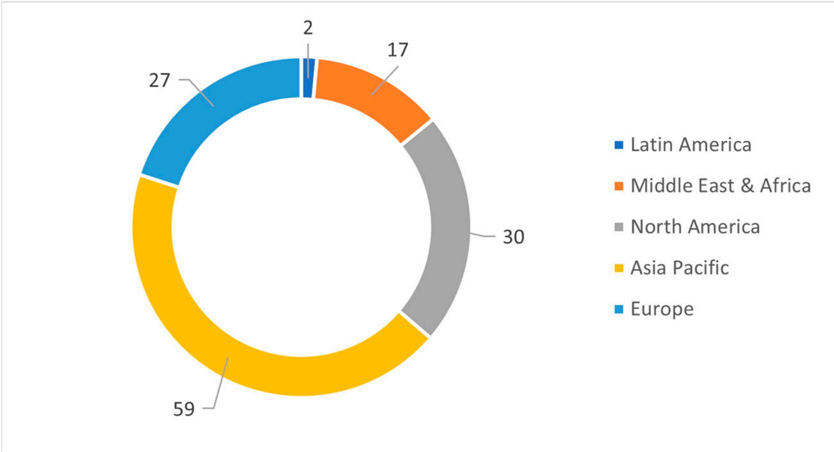

Figure 13. AI research by region.

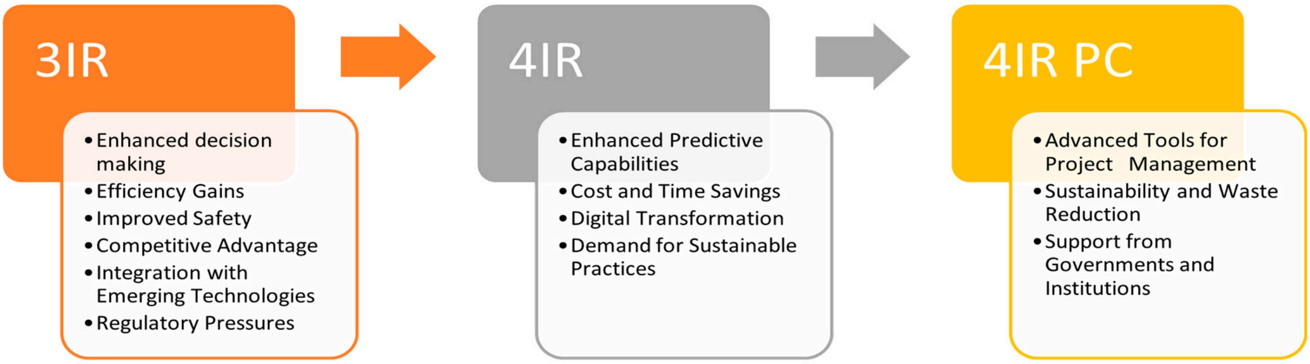

Figure 14. Evolution of drivers.

4.2.1. Technology Availability

The construction industry has varied needs that can be met through the use of AI-making technology availability, a driver of AI adoption. Where precise and data-driven decision making is necessary, predictive risk modelling is available for reducing uncertainty and enhancing performance [64]. The decision-making efficiency is also improved through advanced models such as graph-based models [65] and deep learning techniques [66]. Enhanced project visualisation is possible through the integration of technologies such as BIM and Digital Twins [43,67–69]. Health and safety is a major concern in construction, and technologies for accident prediction using hybrid machine learning models have been shown to significantly reduce workplace hazards [48], while monitoring systems enhance safety through predicting and mitigating risks [70–72]. Enhanced communication is also possible through chatbot technology, reducing administrative burdens in construction management [73].

4.2.2. Improved Productivity and Project Outcomes

The construction industry is plagued with traditional construction processes that suffer from inefficiencies, causing delays, cost overruns, and material waste. To improve productivity and project outcomes in the industry, the use of AI is accelerating. AI is an asset for the automation of repetitive tasks, reducing manual interventions [74] while improving the accuracy of cost and scheduling estimations [69,75–77] and enabling better resource allocation [22]. AI also enhances safety management through monitoring and predictive analytics [51,78] while enabling quicker decision making through the real-time analysis of safety metrics [79].

4.2.3. Competitive Advantage

Growing demands for improved project outcomes, higher efficiency, and better quality in construction are forcing organisations to innovate and adopt digital tools to maintain a competitive edge [80]. Tools such as BIM are increasingly considered essential [81] and considered mandatory for successful bidding for some projects.

4.2.4. Growing Emphasis on Sustainability

As global sustainability efforts take on momentum, conserving resources used in construction has become increasingly important. AI tools are proving indispensable in supporting energy optimisation and carbon emission evaluations [68,82,83]. AI is also proving effective in green retrofitting projects where it more accurately predicts and implements energy-efficient designs [84]. The better optimisation of material usage and minimisation of waste is also possible through AI tools [75]. The pressure the construction industry is under to reduce its environmental impact, particularly in terms of energy consumption, carbon emissions, and waste production is proving a driver of AI adoption.

4.3. Barriers and Limitations to the Adoption of AI

Despite its potential benefits, AI adoption has previously proven slow in the construction industry. This seems to be changing as advancements in algorithms and deep learning have spread AI use across different industries, including the construction industry, leading to sporadic innovation, creativity, and efficiency [85]. Despite this, several barriers (challenges to the adoption of AI) and limitations (challenges after adoption) have been identified throughout this review. These may impede the actualisation of the benefits associated with effectively adopting and harnessing the technology [9]. Figure 15 shows the evolution of the barriers.

As shown below, data and integration issues in their evolving forms are proving an ongoing concern when using AI. Interestingly, some uncertainty on the value of AI use has also been cited. The following sections expound on the most prominent and ongoing challenges when considering AI adoption.

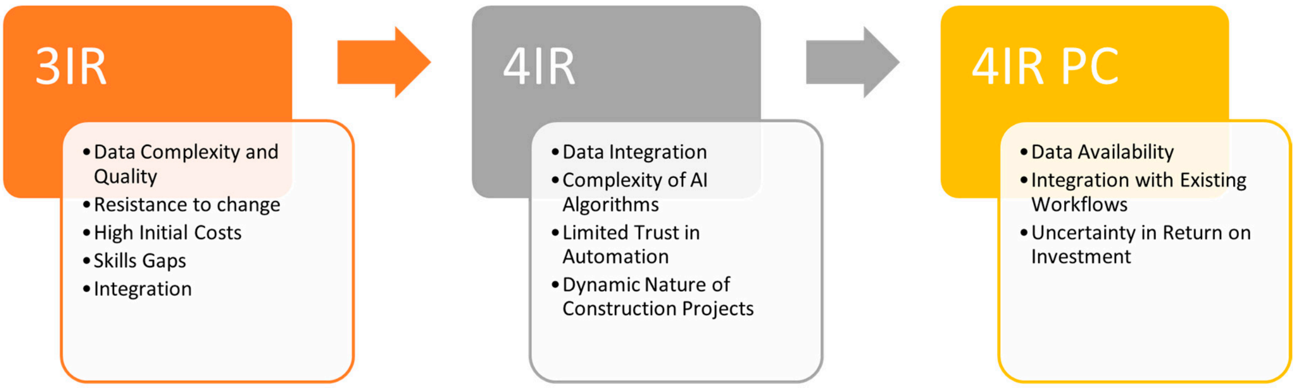

Figure 15. Evolution of barriers.

4.3.1. Barrier: Resistance to Technology

The adoption of AI has been slow in the construction industry and this in part has been due to a number of barriers. As one of the oldest industries, it has thrived on the use of conventional methods that make it risk-averse, resistant to perceived drastic changes [86], slow to innovate due to organisational inertia, and lag in AI adoption in comparison to other industries. Despite perceived gains, as noted by Doukari et al. [81], there tend to be reservations about replacing conventional practices with AI methods and further skepticism on AI's benefits [87] and reliability in comparison to human decision making [88]. Ayhan et al. [70] and Momade et al. [89] found that resistance from construction personnel occurred due to unfamiliarity with AI tools.

4.3.2. Barrier: AI Skills Gap

The adoption of AI requires skill in data analytics, machine learning, and digital tools, but unfortunately, there tends to be a noted lack of AI literacy [33] and technical expertise in the construction industry [80,90]. The need for extensive training to enable staff to use AI has proven a barrier to AI adoption [29], with professionals lacking the required knowledge for implementing and managing AI systems [70,91,92].

4.3.3. Barrier: High Implementation Costs

Depending on the type of system, the initial implementation of AI often takes a hefty upfront financial investment [48,93]. Exacerbating the cost is the significant customisation necessary in some cases [94]. Retrofitting existing systems tends to be prohibitively expensive [69], while maintenance can also prove time-consuming and costly [95]. These costs tend to be a deterrent, especially to small- and medium-sized enterprises [96].

4.3.4. Barrier: Regulatory and Ethical Concerns

Accountability and liability are major concerns for organisations when it comes to AI adoption. Concerns come about as it is not clear where the responsibility lies if errors occur from decisions made through AI [75,97]. The lack of adequate legal frameworks to regulate AI's dynamic pace creates uncertainty in its adoption [49]. Where monitoring systems are in place, there are major concerns regarding data privacy as sensitive information may be inadvertently captured [39,98], creating problems in regions with strict privacy laws [79].

4.3.5. Limitation: Data Quality and Quantity Issues

Data extracted from the construction industry tends to be unstructured, fragmented, and incomplete, posing a challenge for models that require high-quality data. Integrating these types of data into a useful form can be a hurdle [87,99] due to data inconsistency and a lack of standardisation [100]. Historical data are also a major problem as records are often unavailable or collected inconsistently, preventing the effective performance of models [85,101,102]. The integration of heterogenous datasets required for training adaptive machine learning models also proves complex and resource-intensive [103], exacerbating data issues in the construction industry.

4.3.6. Limitation: Technical Shortcomings

While AI technology is readily available, interoperability issues tend to be a concern. Those transitioning from traditional systems may be hindered by the lack of compatibility between traditional or existing systems and AI systems [43,81,91]. Liu et al. [95] also found that scalability can be problematic when AI models cannot be generalised to different projects. Another noted limitation is that of algorithm bias caused by models relying on skewed training data [73]. This tends to lead to inaccurate reporting or estimates which have the potential to undermine stakeholder confidence in AI.

5. The Future of AI in Construction

AI has become a critical tool in reshaping the way construction companies approach design, project management, safety, and operations. As construction projects grow more complex, the need for innovative solutions that increase efficiency, reduce costs, and improve safety will become more imperative, making AI an indispensable tool for the future. It is expected that in the construction industry, AI will continue to integrate with existing digital technologies to further improve decision-making, forecasting, predicting, and evaluating processes [104,105] within the project life cycle.

As the construction industry continues to evolve, the need for more advanced AI solutions will grow. Several emerging trends indicate that future AI applications will focus on sustainability, digital twins, optimization, and more sophisticated automation technologies.

5.1. Sustainability and Energy Efficiency

One of the major challenges for the future of construction is the need for sustainable and energy-efficient buildings. The role of AI has been emphasised in the use of technologies such as BIM for optimising waste-efficient buildings in a circular economy [106].

Another growing area of AI application is that of sustainable construction which involves the optimisation of energy use and efficiency in buildings through deep learning [84,93,107], the improvement of resource efficiency and usage [75,82,87], and green retrofitting [82]. The use of AI will thus enable the optimisation of the environmental performance of buildings and better decision making for sustainable construction.

5.2. Digital Twins for Predictive Maintenance

The concept of digital twins—virtual replicas of physical structures—will become increasingly important in the construction industry. Their value when coupled with AI foster a data-driven approach to project execution [43], allowing intelligent decision making which reduces time and cost overruns in complex projects [108], real time monitoring, the adaptive management of the various construction processes, and predictive maintenance. This better ensures improved coordination, error prediction, and optimisation of performance throughout the lifecycle of the project [69,79,81] and the extended lifespan of structures.

5.3. Advanced Robotics and Autonomous Construction

While robotics is already making an impact in construction, the future will see more advanced autonomous construction technologies powered by AI. Robotic systems will continue to be especially useful for excavation [109], site monitoring [39] and material handling [82].

Automated monitoring is another key area where deep learning is utilised for aligning long-term and short-term plans effectively [99], automating daily reporting and progress tracking [98], and also enabling the monitoring of employee performance monitoring on-site [110].

These technologies can significantly speed up construction activities and reduce human error, increasing productivity and precision in construction tasks. It is also expected to improve efficiency and safety on construction sites by coordination between machines and human workers.

5.4. Optimisation and Enhancements

AI is proving increasingly useful in optimising the iron triangle components of time, cost, and quality in projects. Through data-driven approaches, AI is expected to continue improving costing and scheduling, thus helping reduce overruns and delays [76,77,111] and improving project outcomes.

Materials optimisation is another developing field with AI utilised for quality control and performance measurement purposes in the development of sustainable construction material [112,113].

AI is proving indispensable when it comes to safety enhancements. Deep learning models are increasingly used for hazard detection to reduce accidents [49] and also for accident prevention through real-time construction site monitoring [114] and machine learning prediction [48].

Another expectation is that more decision making on projects will be AI-based. Where previously the focus was on decision support, the future will look at more data-driven decision making, which will assist in predictive risk modelling [64] and the evaluation of the impact of decisions made [33]. All these will provide further protection for projects and improve the prospect of successful project outcomes.

While the use of AI in the construction industry has been slower than in other industries, growth is being observed in the adoption of technologies to assist in the different phases of the project lifecycle. AI has the potential to turn around the construction industry into one known for safety standards, efficiencies, and sustainability implementation.

6. Conclusions and Future Research

This study conducted a systematic literature review on the application of Artificial Intelligence (AI) in the construction industry, analysing 135 peer-reviewed articles published between 1985 and 2024 from the Web of Science, Scopus, and ProQuest databases. The review followed a structured approach, including a material collection, descriptive analysis, category selection, and material evaluation.

The findings indicate a significant increase in AI research in construction during the Industry 4.0 and post-COVID-19 era, with computational experiments being the predominant data collection method. This highlights an opportunity for researchers to explore alternative methodologies. The primary purposes of AI in construction include decision support, predictive analytics, performance improvement, optimisation, and automation, aligning with Industry 4.0's emphasis on data, connectivity, computational power, and human–machine interactions. This study also notes a growing adoption of machine learning, particularly post-COVID-19, as the demand for predictive tools increased.

AI adoption in construction is driven by factors such as technological advancements, productivity improvements, competitive advantage, and sustainability goals. However, several barriers persist, including resistance to technology, a shortage of AI-related skills, high implementation costs, regulatory and ethical concerns, data challenges, and technical limitations. Future AI applications in construction are expected to focus on sustainability, energy efficiency, digital twins for predictive maintenance, advanced robotics, and autonomous construction.

This paper contributes to the body of knowledge of AI in construction by synthesising previous research and providing insight into future explorations in the field. Despite its contributions, this study is limited to peer-reviewed articles published in English, excluding international conferences that may offer additional perspectives. Additionally, while this review examines technological drivers and barriers, future research can explore the role of labour in AI adoption, especially in regions where labour-intensive practices are upheld by legislation. Further investigation into the practical solutions to overcome AI adoption barriers in the construction industry would be apt. Finally, future research can consider algorithmic ethics and regulatory impact assessments in construction AI application, which could inform robust bills to be passed into law on AI safety regulations and AI ethics guidelines by construction firms to ensure the responsible use of AI.

Author Contributions: Conceptualization, Y.A. and O.A.O.; methodology, Y.A. and X.B.K.; software, P.U. and O.A.O.; validation, O.A.O.; formal analysis, Y.A., P.U. and X.B.K.; writing—original draft preparation, Y.A. and O.A.O.; writing—review and editing, X.B.K. and Y.A.; visualization, P.U.; supervision, O.A.O. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No data, models, or code were generated or used during this study.

Conflicts of Interest: The authors declare no conflict of interest.

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