Applying Artificial Intelligence in Construction Management: A Scoping Review

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Abstract

With the growth of artificial intelligence (AI) and Industry 4.0, construction management has entered a phase of rapid digital transformation. In order to effectively adopt digital applications of construction management, this paper aims to identify the specific applications of AI in construction management from the perspective of Construction 4.0, especially when applying technologies from Industry 4.0. A scoping review methodology was used to explore the limited literature in this research area. 60 articles were selected to analyze the state of the art of AI applications in construction management, especially for schedule management, cost management, quality management, and health and safety management. This review shows that AI has mainly been used in the preliminary design and construction phases of the above management areas, and proposes a research framework to highlight the contemporary development and needs for AI integration in construction management. The main contributions of this paper are its practical exploration of AI applications in construction management, its human-centered approach to AI adoption, and the introduction of a novel research framework to guide industry practitioners in AI integration.

Keywords: Construction management, Artificial intelligence, Construction 4.0, Research framework, Scoping review

1 Introduction

The field of construction management within the architecture, engineering, and construction (AEC) sector is characterized by inherent challenges and intricacies, covering an extensive array of construction-centric tasks and procedures that are closely linked with human elements and collaborations, and involving various participants from the outset of planning and design to the conclusion of construction and delivery [1]. The construction sector, encompassing real estate, infrastructure, and industrial facilities, represents the most significant industry in the global economy, contributing 13% to the world's GDP, and is anticipated to experience a 3% growth rate between 2018 and 2035, as per a 2020 analysis by the McKinsey Global Institute [2].

However, the complex nature of construction projects, coupled with the significant amount of manual labor on site, means that improper and poor management of any aspect often results in significant losses [3]. Fatal injury rates are also higher than the average for all other industries due to its labor-intensive nature and poor safety management during construction processes, making it one of the most dangerous industries [4]. Besides, only 31% of projects stayed within 10% of their budget, and a mere 25% adhered to the initial timeline from 2012 to 2014 [5]. Concurrently, the construction sector is progressing towards digitalization and smart technologies, aligning with the Industry 4.0 paradigm. Construction 4.0 signifies the incorporation and utilization of the tools and technologies from Industry 4.0 within the construction domain [6]. Consequently, there is a pressing need for conventional construction management practices to innovate and adapt to match the rapid progress in Construction 4.0, particularly in the realm of artificial intelligence (AI).

As a field within the broader realm of technology, AI empowers machines to interpret and adapt to data inputs similarly to human capabilities, thereby bolstering their abilities in perception, knowledge structuring, logical deduction, issue resolution, and strategic formulation [1]. Although AI has been well received in the AEC industry, current research in this area is still in its infancy. Previous work has mostly focused on review-related studies. While they have made valuable contributions, but they have had certain limitations. The existing literature on AI in Construction 4.0 often spans too wide a timeframe and lacks focus, as seen in studies by Xu et al. [7], Akinlolu et al. [8], and Abioye et al. [9]. These reviews encompassed articles from 1960 to 2020, which may not be relevant given the emergence of Construction 4.0 after Industry 4.0 in 2013. Additionally, the scope of analysis in these studies is either too broad or too narrow, lacking specialized

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research on construction management within the context of Construction 4.0 [10]. Elmousalamin [11] employed mixed methods to assess AI applications in parametric construction cost estimation, emphasizing cutting-edge technologies. Akinosho et al. [12] conducted a thorough review of deep learning in construction, evaluating its potential in structural integrity monitoring and site safety. They highlighted the need for further research in site planning, operational management, and health and safety. Literature reviews often concentrate on individual AI technologies like deep learning or on specific construction management areas, such as safety or cost, creating a void for comprehensive reviews on AI's broad application in construction management.

To fill this gap, this research intends to capture the development and application of AI in the field of construction management in the context of Construction 4.0, with a broader coverage within the existing literature. The underlying objectives are to identify the current landscape of AI applications in construction management and to develop a research framework for AI applications in construction management based on the identified research gaps and future directions. A scoping review was chosen to examine the articles in the field, resulting in a broad exploration of the limited literature and providing a foundation for future and more focused research [13]. This review makes the following contributions.

- Synthesize the fragmented research on AI in construction management and provide a unified perspective on current applications and future potential.
- Present a roadmap for researchers and practitioners to navigate the complex landscape of AI-driven innovation in construction projects.

The structure of this paper is organized as follows. Section 2 explains the relevant background. Section 3 explains the scoping review methodology. Section 4 analyzes the results of the review. Section 5 describes the proposed research framework. Section 6 concludes with the findings, contributions, and limitations.

2 AI in the AEC Industry

AI, as a key new technology, plays an essential role in the AEC industry [14]. It empowers machines with the abilities to reason, learn, acquire knowledge, communicate, perceive, plan, and manipulate objects, thereby addressing complex and ambiguous problems [15]. AI's benefits have piqued considerable interest in the AEC sector, with existing research shedding light on its potential. Aziz et al. [16] introduced a hybrid model that fuses the critical path method with a multi-objective genetic algorithm for optimizing large-scale construction projects through AI. This approach aims to create an Intelligent Critical Path Method System to improve project quality while cutting down on time and expenses, as confirmed by real-world case studies. Zabin et al. [17] analyzed the synergy of building information modelling (BIM) and AI in construction engineering through a literature review, outlining the prevalent uses of machine learning in BIM and identifying areas for further research. Saka et al. [18] explored the state of conversational AI in AEC, discussing current progress, challenges, and opportunities based on focus group insights and suggesting future research paths. The combination of AI with BIM is particularly advantageous, automating tasks, improving decision-making, and enhancing project results. This AI-enhanced BIM is emerging as a key area within the AEC industry.

From the academic point of view, AI has seen extensive utilization within the realm of construction engineering and project administration, as evidenced by numerous review articles that assess its current landscape, potential, and prospective hurdles. While previous reviews have often focused on the innovation or application within one or a few areas of construction management, this paper broadens the scope. It provides a comprehensive investigation into all key domains of construction management practices where AI can be integrated, thereby addressing a significant gap in the literature [9].

3 Scoping Review

A scoping review is a methodology for clarity of definition, methods, and reporting. The scoping review method was chosen because it could ensure a broad and inclusive perspective based on this emerging body of literature [19]. A scoping review begins with the formulation of a research question. Given that AI is a subfield of computer science dedicated to the exploration and advancement of principles, techniques, and technologies aimed at mimicking, amplifying, and improving upon human cognitive abilities, our analysis aims to address a comprehensive question that covers the multifaceted influence of AI on construction management operations, the obstacles it encounters, and the prospective directions for advancement. The central inquiry of this study is, "How extensive, broad, and intrinsic is the function of AI within the construction industry?"

This inquiry also delineated the distinct interconnections between artificial intelligence (AI), deep learning, representation learning, and machine learning prior to advancing the search strategy. To illustrate, machine learning is a specialized area within AI that facilitates forecasting or decision-making by discerning patterns from data, drawing on historical experience. Deep learning, a subset of machine learning, emulates the neural pathways of the human brain through the creation of layered artificial neural networks designed to handle and resolve intricate issues. Prominent models within deep learning encompass Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory Networks (LSTMs). The interplay between AI, deep learning, and machine learning [12] is depicted in Figure 1.

Besides, previous literature describes project management in different ways, and these descriptions include different contents. Many scholars believe that construction project management and constraint management are consistent, but there is a distinction between construction project management and construction management [20]. The former focuses on all the activities necessary to achieve the goals of a construction project, while the latter is mainly concerned with on-site construction activities, excluding the planning of production processes and site installation. Even the meaning of 'construction management' varies among scholars. Baduge et al. [21] emphasize that overseeing a construction project encompasses activities such as project planning, coordination, financial management, and oversight. The Construction Management Association of America (ACCA) provides its own definition [22]: «*Construction management is a specialized service that employs efficient management methods throughout the lifecycle of a project, from its initiation to its conclusion. The goal is to regulate the project's timeline, financial expenditure, and standard of quality*.» This review focuses on discussing the construction management of cost, time, quality, safety, and other aspects, as defined by ACCA. These other aspects would primarily consider the impact of Construction Industry 4.0, including intelligent construction management [3] and construction waste management [23], among others.

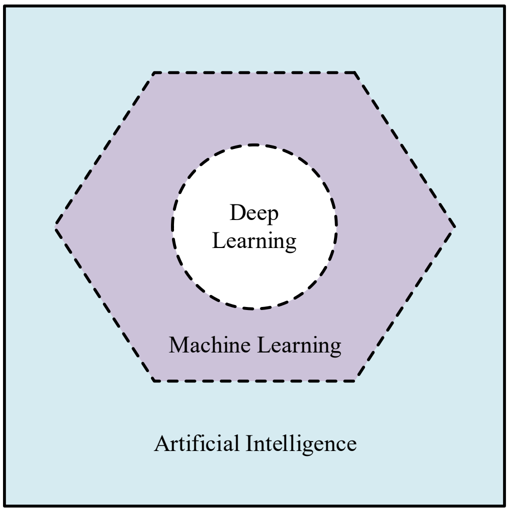

Figure 1. Relationship of AI, machine learning and deep learning

The scoping review's pivotal step was formulating a comprehensive search strategy and extracting data from the limited literature, using relevant AI and construction management keywords across databases like Web of Science, Scopus, and Google Scholar, without a time limit. After a two-step screening process, 60 articles were selected for detailed analysis, providing insights into the current state of AI applications in construction management. This was followed by a two-step screening process to identify articles that fit the research criteria: first, reviewing titles and abstracts, and second, conducting a full-text review of the articles that passed the initial screening. This rigorous approach resulted in 60 articles being selected for the detailed analysis.

4 AI in Construction Management

4.1 Cost Management

Cost management, also known as cost control, tracks the actual expenses of a construction project and compares them with the budget [24]. In terms of the chronological sequence of the construction project, cost control can be divided into pre-construction cost control, construction cost control, and post-construction cost control [25]. Traditionally, construction cost management is a process that relies heavily on the experience of experts, and ineffective cost management can cause numerous problems, such as cost overruns. To improve the cost management, AI technologies have been applied.

The application of some AI in various stages of project cost control is shown in Figure 2.

4.1.1 AI Assisted Pre-Construction Cost Control

Pre-construction cost control is the construction project budget, which occurs in the initial stage of cost management and can only be estimated [26]. Overestimation or underestimation of costs can lead to discrepancies between future budgets and actual expenditures, which emphasizes the need to improve the accuracy of construction project cost estimation as much as possible [27]. Tong et al. [28] developed a highway construction budget prediction model by mixing gray relational analysis and least absolute shrinkage and selection operator (GRA-LASSO). They identified eight key cost drivers and demonstrated through case verification that GRA-LASSO outperforms ordinary least-squares regression (OLS) and LASSO alone in terms of error estimation and model accuracy. Al-Tawal et al. [29] constructed and validated an Artificial Neural Network (ANN) model, utilizing cost and design information from 104 Jordanian projects. Their research demonstrated that ANNs are adept at resolving cost estimation challenges during the initial phases of architectural design, with the model achieving an average accuracy of 98% in the detailed design stage, 98% in the schematic stage, and 97% in the conceptual stage. In a separate study, Dang-Trinh et al. [30] employed a variety of machine learning algorithms, such as support vector machine (SVM), ANN, generalized linear model (GLM), decision trees (DT), Chi-Square automatic interaction detector (CHAID), and deep learning neural networks (DLNN), on real-world data from southern Vietnam. Their analysis revealed that DLNN models outperformed others, with a combination of ANN and GLM models also showing strong performance.

4.1.2 AI Assisted Construction Cost Control

During the construction phase, Odeyinka et al. [31] discovered that traditional cash flow prediction methods during bidding often misaligned with actual outcomes due to construction risks. They mitigated this by creating a model using cost flow and ANN backpropagation algorithms, based on data from 96 UK projects, to better predict construction risks' impact on cash flow. Besides, Babar et al. [32] enhanced Earned Value Management (EVM) by developing a Risk Performance Index (RPI) that includes additional performance indicators beyond schedule and cost. This model, validated through case studies, provided more accurate estimates and offered stakeholders a superior tool for project monitoring and decision-making, accounting for health, safety, and quality aspects often overlooked by traditional EVM.

4.1.3 AI Assisted Post-Construction Cost Control

This phase mainly focuses on the estimate at completion and the final construction cost. Caron et al. [26] proposed a Bayesian analysis model within the earned value management framework to calculate confidence intervals for cost and schedule estimates at project completion using collected data and qualitative expert knowledge. The model was tested on an oil and gas project. Kamoona et al., [33] proposed a robust intelligent prediction model for the estimate at completion using DLNN and SVM models. They analyzed two input optimization algorithms, genetic algorithm and brute force algorithm, and found that the estimate at completion results obtained with genetic algorithm input were more reliable and robust. Alsugair et al. [34] developed a final construction cost prediction model based on the owner's initial owner cost estimate and compared an ANN model with two linear regression models using data from 34 Saudi Arabian projects and found that the ANN model achieved a smaller mean absolute percentage error. Al-Gahtani et al. [35] developed a model to predict the final construction cost values based on ANNs using characteristic parameters from 135 construction projects in Saudi Arabia, including contract cost, contract duration, and project sector, at the early stage of a project.

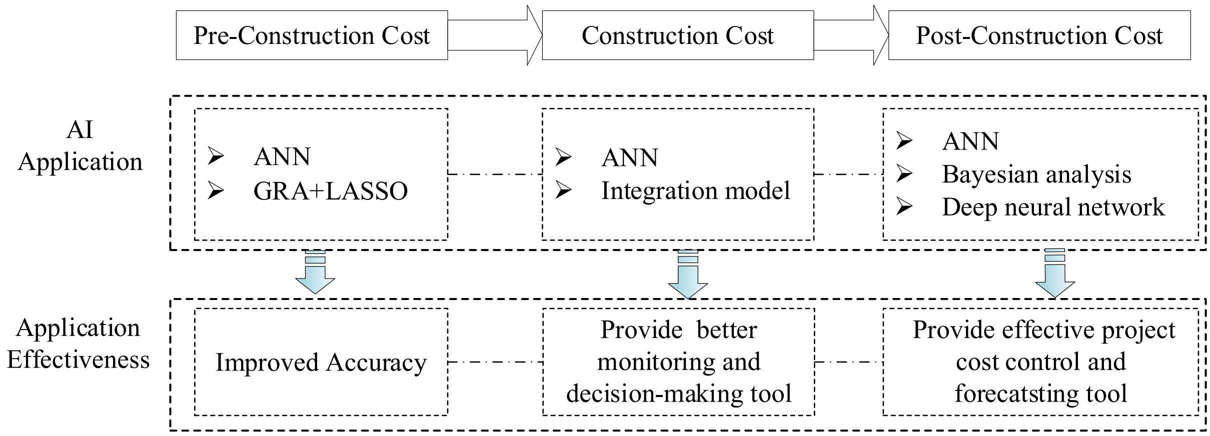

Figure 2. AI application in cost management

4.2 Time Management

Time management is a critical component that involves planning, organizing, and controlling the timely completion of all construction project activities. Completing a project on time is a key factor in determining whether a construction company makes a profit or a loss on a given project. Typically, construction contracts contain both penalty and incentive clauses; penalties are imposed for missed deadlines, while incentives are provided for early completion. As a result, construction managers devote considerable effort to ensuring that time is meticulously controlled throughout the entire duration of a construction project. Developing a schedule for a construction project and monitoring and controlling it during construction are critical to effective time management [36]. In a standard construction schedule, all work is broken down into various Work Breakdown Structure (WBS) components and specific activities, which are then delegated to appropriate subcontractors. In real-world construction scenarios, task scheduling becomes complex because sequencing requirements are influenced by multiple factors, including labor, materials, and the construction process itself. Although much research has focused on automated construction scheduling over the past three decades, most construction projects still rely on manual scheduling workflows [37].

4.2.1 AI Confirming Key Parameters

Construction projects are usually planned using traditional scheduling techniques such as the Program Evaluation and Review Technique (PERT), Critical Path Method (CPM), and Precedence Diagramming Method (PDM). Regardless of the method chosen, the parameters for the activities in the construction schedule are based on their likelihood of occurrence and anticipated completion time. These parameters are challenging to ascertain and introduce uncertainty into construction schedule management. Pregina and Kannan [38] suggested combining the Graphical Evaluation and Review Technique (GERT) with Fuzzy Logic to create a Fuzzy-based GERT (FGERT) approach for scheduling construction projects (Figure 3). Uncertainty in activity durations is handled by fuzzy operations. Compared to CPM, FGERT adds a parameter—the probability of activity occurrence—to the nodes in the flowchart or network, resulting in multiple completion times and their corresponding probabilities instead of a single construction projection completion time.

4.2.2 AI Assisted Optimization Schedule

Construction constraints fall into two categories: precedence constraints and resource constraints. Precedence constraints specify the order in which activities must be performed to ensure that certain tasks are completed before others begin. Yao et al. [39] used a deep reinforcement learning model with a valid action sampling mechanism, integrating a graph convolutional network for feature extraction and incorporating a reward shaping mechanism, to optimize schedules. The reward shaping function considers the precedent constraints and allows the agents to explore the possible actions, ultimately improving the effectiveness. Resource constraints refer to limitations on the availability or capacity of resources required to complete project activities. These resources can include materials, equipment, budget, and labor. Resource constraints are a common problem that should be considered in the schedule management of prefabricated construction projects. Yu used the double-code network diagram with the radial basis function fuzzy logic neural network algorithm to optimize the construction resource schedule for prefabricated construction projects [40].

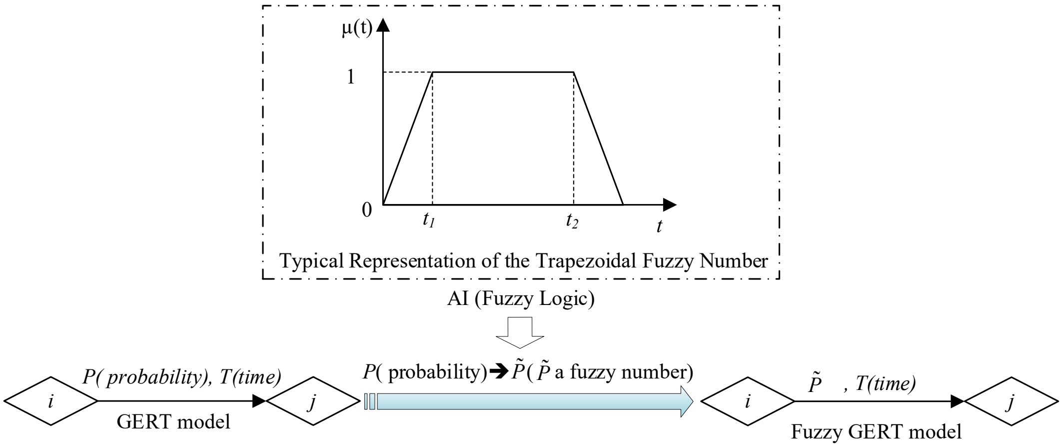

Figure 3. Representation of equivalate networks for the GERT Network

4.3 Quality Management

In construction projects, quality is defined by the specifications that are part of the construction documents [36]. The quality of construction materials and workmanship has the most direct impact on the overall quality of a construction project. Quality defects, such as cracks, rebar exposure, and wall deformations, occur from time to time [41]. Traditionally, quality defect inspection is performed by visual observation, tape measurement, and the use of a total station. The reliance on manual labor and individual's knowledge, experience, and responsibility leads to problems such as low efficiency and poor reliability [42]. Therefore, AI technology will continue to provide technical support in this regard, and some applications are shown in Figure 4.

Steel bar quality is a key issue in construction quality management, such as rebar exposure and unstable steel bar joints. Raoofi et al. [43] presented a framework reliant on deep learning that employs a mean-based categorization of a series of images for the purpose of detecting omitted welds in the assembly process of steel joists. This system is composed of multiple components designed to identify, monitor, and categorize the intersections of the joists. It incorporates post-classification techniques to filter out unreliable forecasts from the conclusive categorization. A vision inspection system using an extreme learning machine with a Gaussian mixture model-based dense estimation scheme to handle unbalanced samples has been developed for real-time solder joint defect detection [44]. Cuypers et al. [45] adapted three deep learning frameworks useful for construction quality management for rebar cover detection. The models encompass the loosely supervised IRNet, the semi-supervised method of cross-consistency training, and the fully supervised DeepLabv3+ architecture. Research indicates that the fully supervised approach of DeepLabv3+, even with a limited number of training instances, demands reduced pre-processing and is quicker to train, rendering it a more favorable option.

Cracking is a common problem in concrete construction projects. Crack detection is important for construction quality management, and a large number of intelligent crack detection methods have been developed in the past two decades [42]. Cha et al. [46] presented an image-based technique employing a CNN for identifying cracks in concrete structures. This method was evaluated using photographs of cracks captured under diverse settings, such as varying image dimensions, lighting conditions, and the presence of shadows. The findings indicated that these varying factors had no significant impact on the effectiveness of the technique. Dorafshan and Azari [47] developed one-dimensional (1D) and two-dimensional (2D) CNNs to detect cracks in concrete structures. They also proposed a method that combines a deep learning model with edge detectors to reduce residual noise. The method was trained and tested on impact echo (IE) data, and found that the 1D CNN generated the most accurate defect maps and successfully detected sound, debonded, and defective areas. Xu et al. [48] introduced a swift CNN approach to detect and pinpoint various seismic damages in compromised reinforced concrete columns through imagery. The image collections were assembled from on-site photography and augmented using an enhancement technique. Beckman et al. [49] developed a technique for identifying damage in concrete layers and assessed how the proximity of the specimen to the sensor impacts the precision of the detection.

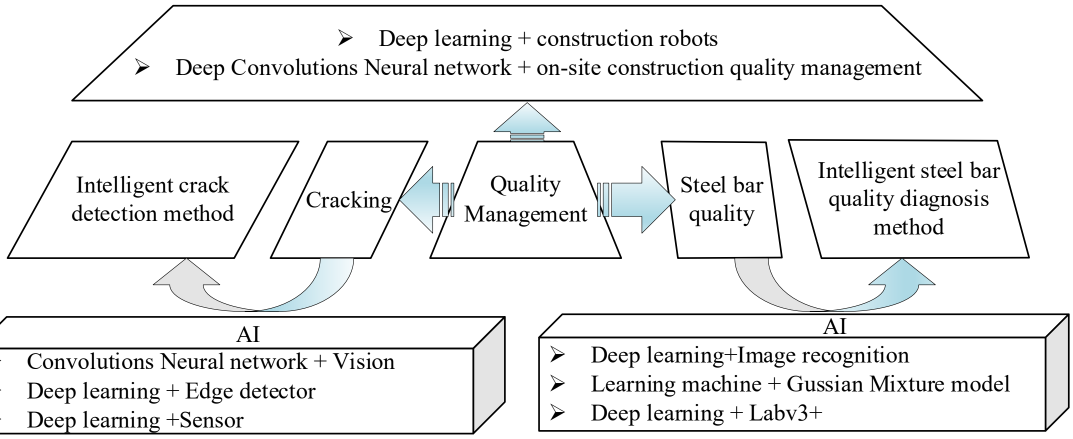

Figure 4. Quality management with AI

Beyond these studies, Wu et al. [50] put forth a tripartite federated learning model that enables the collective training of deep learning algorithms without the need to exchange local data among construction automatons. Sun and Gu [51] compiled datasets for construction materials, including concrete, brick, metal, wood, and stone, by gathering visual representations of these substances. They further employed various deep CNN architectures, such as visual geometry group (VGG) network and residual network (ResNet), to ascertain the datasets' reliability and efficacy for managing construction site quality.

4.4 Health and Safety Management

Safety and well-being oversight is a central task within the international construction management domain. Construction is frequently regarded as one of the most hazardous sectors. In the United States, the construction sector saw 1,061 worker deaths in 2019, representing 20% of all worker fatalities that year [52]. In China, between 2012 and 2019, there were 4,100 safety incidents in residential and urban construction sectors, leading to 5,011 fatalities. In the UK, the fatal injury rate in the construction industry was 1.74 per 100,000 workers in 2019, a figure almost quadruple that of the average across all sectors. The primary causes of mortality in construction—falls, being hit by objects, electrocution, and entrapment between objects—constituted approximately 60% of all construction-related deaths for that year [53]. Conventional approaches to safety and health management in construction heavily depend on manual processes, such as inspections by safety supervisors, which are resource-intensive and time-consuming, hindering the achievement of thorough safety surveillance.

AI can improve construction safety measures, reduce safety risks, and monitor job site safety. For health and safety management, as show in Figure 5, AI can improve worker safety training, manage the use of personal protective equipment, monitor construction safety equipment, ensure site safety compliance, and prevent falls.

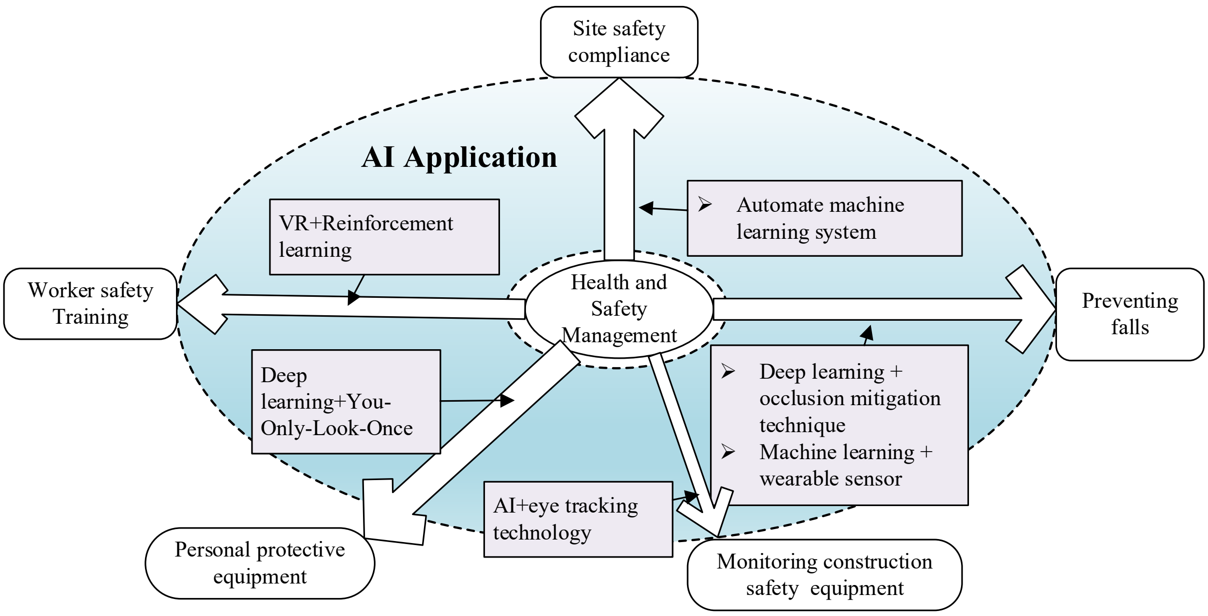

Figure 5. Health and safety management with AI

4.4.1 Worker Safety Training

Occupational safety is paramount in the construction sector, necessitating comprehensive training before workers begin on-site tasks. Research has demonstrated that thorough safety instruction significantly boosts safety outcomes. Shi et al. [54] introduced a multi-participant virtual reality (VR) system combined with reinforcement learning to assess training efficacy. Their findings suggest that presenting individuals with information has beneficial effects, motivating them to adhere to the modeled actions and sustain safe practices during emergencies. Extracting knowledge from past accident reports is beneficial for education in safety training. Baker et al. [55] established a term frequency-inverse document frequency representation method using natural language processing, CNNs, and hierarchical attention networks, to find the valid injury precursors for past accident report text. Qiao et al. [56] used Python to automatically classify construction accident narratives and evaluated 10 ordinary learning and 5 deep learning methods, to extract the key features from past accident reports.

4.4.2 Managing Personal Protective Equipment (PPE)

Nath et al. [53] introduced three deep learning frameworks grounded in the You-Only-Look-Once (YOLO) design for assessing workers' PPE. The initial method leveraged machine learning algorithms, including neural networks and decision trees, to identify workers and various PPE items (e.g., helmets, high-visibility jackets). The second method employed a single CNN to identify workers and confirm their PPE. The third method, an extension of the first, first identifies workers in the input imagery, extracts these images, and then employs CNN-based classification to categorize them. The findings indicated that the second method outperformed the others, whereas the first method was the most computationally efficient. Hayat and Morgado [57] also used the You-Only-Look-Once algorithm to propose a real-time automatic safety helmet detection system for construction sites. The experimental results showed that the system achieved an accuracy as high as 92.44% and is suitable for low light conditions.

4.4.3 Monitoring Construction Safety Equipment

Construction equipment (including machinery and vehicles) is the main force in construction projects. However, many accidents can occur due to blind spots in the operator's line of sight or workers approaching the construction equipment [58]. AI can help construction supervisors or equipment operators comply with existing safety protocols [58]. Mental fatigue is another cause of construction accidents. To solve this problem, Li et al. [59] proposed a novel method using wearable eye-tracking technology to identify and classify multi-level mental fatigue in construction equipment operators, which is validated through an experiment with six participants performing a simulated excavator operation. The study used Toeplitz Inverse Covariance-Based Clustering (TICC) to identify three levels of mental fatigue, extracted four eye movement feature sets, and found that SVM can be the most effective classification algorithm, achieving accuracies between 79.5% and 85.0% across various scenarios and subject biases and demonstrating the feasibility in real-world construction settings.

4.4.4 Preventing Falls

In order to prevent falls caused by inadequate supervision of personal protective equipment, Fang et al. [60] proposed an automated inspection method for the use of personal protective equipment in aerial work scenarios. A deep learning-based occlusion mitigation technique was tested under various conditions, demonstrating its reliability and robustness in inspecting fall prevention measures and facilitating safety supervision. In addition, an automated system [61] was developed using wearable sensors and machine learning algorithms to identify work at height and safety hook attachment status, employing atmospheric pressure, acceleration, and gyroscopic signals. Through field trials with 20 construction workers and leave-one-subject-out cross-validation, the system achieved 96% accuracy in identifying work at height and 86% in detecting safety hook attachment, thereby addressing knowledge gaps and enhancing safety management by minimizing falls.

4.4.5 Ensuring Site Safety Compliance

Construction sites present complex conditions and require improved management. Mei et al. [52] developed a computer vision-based intrusion detection method for static hazardous areas in construction, and used YOLO V5 to formulate intrusion judgment rules that consider worker posture and orientation, achieving precision and recall rates of 96.05% and 90.05%, respectively, thereby addressing the limitations of manual monitoring and improving site safety. Togan et al. [62] developed an automated machine learning system to select the most accurate accident severity predictors for construction professionals with limited data science expertise, using real-world accident data and automated machine learning approaches such as Auto-Sklearn, Auto-Keras, and customized Auto Machine Learning, which provide higher scalability, accuracy, and actionable insights.

4.5 Others Management Areas

With the development of the construction industry, the issue of construction and demolition waste (CDW) is becoming more prominent and cannot be overlooked. In the US, the volume of CDW reached over 600 million tons in 2018, while in the UK, CDW accounted for a staggering 67% of total waste in 2023. In China, statistics from 2020 show that CDW amounted to 3 billion tons [23]. To minimize human intervention in the sorting process, Lin et al. [63] developed an efficient method for sorting CDW using a deep learning approach combined with knowledge transfer. Zhao et al. [64] proposed to identify construction and demolition waste by detecting changes through deep learning. The method was evaluated on three specific forms of construction and CDW—demolition debris, landfills, and large landfills—and the results showed that the overall accuracy of CDW detection reached 91.67%, indicating that it was the most accurate among the methods tested. The research of construction management has also been conducted on intelligent construction management evaluation [3], cyber risk management and other related areas.

5 Research framework and Discussion

Figure 6 illustrates a research framework for AI in construction management in the dynamic era of Construction 4.0, specifically for its current evolution and future needs in the AEC industry. This framework addresses key areas such as time management, where AI techniques optimize schedules and predict potential delays. The latest approach of Automated Stacking Cranes (ASCs) bridges the gap between virtual and real environments [65], helping to solve the scheduling problem. Cost management benefits from deep learning algorithms to manage costs and identify inefficiencies [18]. AI algorithms enhance automated data collection and analysis for optimized resource allocation and cost savings. They also bolster quality control through vision technologies and autonomous monitoring, such as detecting abnormal sounds indicating quality issues. AI systems prioritize safety by identifying hazards and preventing accidents with Augmented Reality (AR). They analyze data from various sources to spot unsafe practices and conditions. The research framework aims to integrate these technologies to optimize project outcomes, enhance safety, ensure data transparency, and improve construction management efficiency and accuracy.

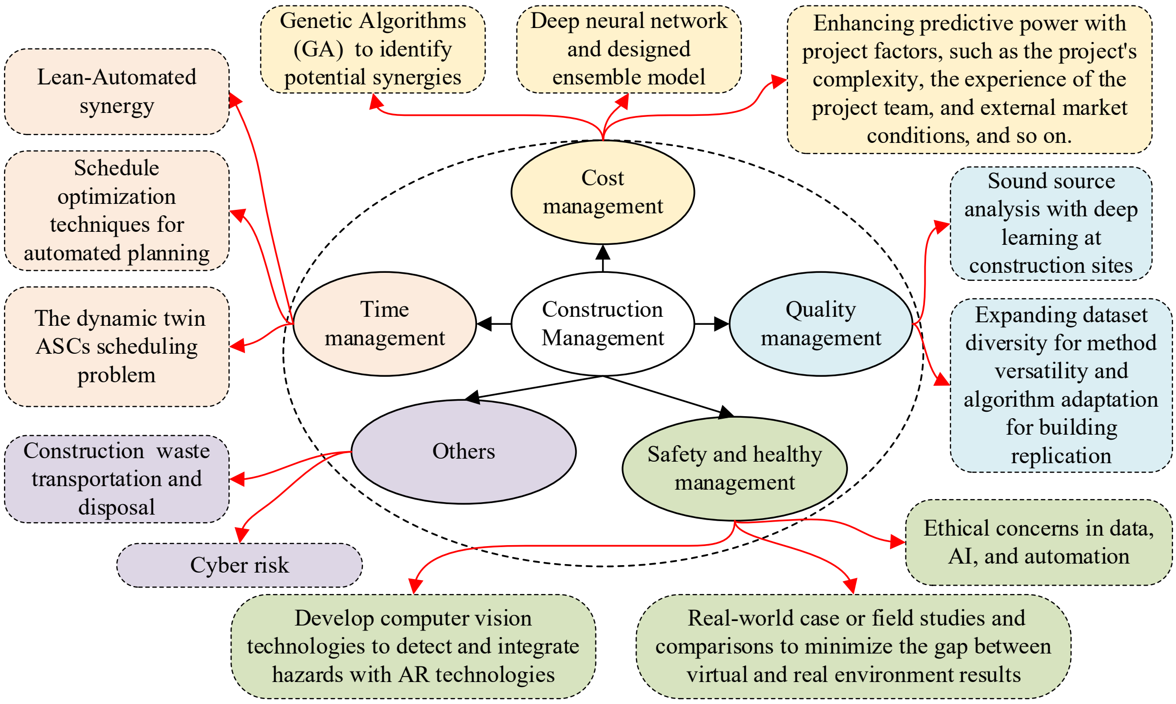

Figure 6. Research framework for AI in construction management

Several studies have delved into AI's role in construction practices, yet there is an imperative for a holistic research framework to steer future studies and applications within the realm of Construction 4.0. Firstly, a notable deficiency lies in the minimal application of AI methodologies like genetic algorithms and DLNNs in practical construction endeavors. Integrating these technologies with project-specific factors could significantly enhance forecasting accuracy and streamline resource allocation, necessitating additional investigation into their scalability and flexibility. Secondly, scholarly efforts must confront tangible issues such as data acquisition, data integrity, and the assimilation of AI within current workflows. The construction sector, characterized by its intricacy and dynamism, produces substantial data across a construction project's lifespan [14]. On one hand, data sourced from various channels, including visual imagery, textual information, audio recordings, and video footage, present disparities in format and structural composition. On the other hand, data are often difficult to access due to data structure, missing data, noise, and the cost of data collection and preprocessing [18]. Therefore, good data is a prerequisite for the effectiveness of AI. Fourth, ethical and social considerations must be addressed to ensure that the use of AI promotes fairness, transparency, and accountability while minimizing negative impacts on workers, the environment, and society [66]. Finally, the future of AI in Construction 4.0 requires a more holistic and integrated approach. This requires collaborations among researchers, practitioners, and policymakers to develop innovative AI solutions that address the unique challenges of construction projects, particularly from the perspectives of project lifecycle and sustainability as echoed in the recent studies in this field. By fostering interdisciplinary research and leveraging the expertise of diverse stakeholders, the construction industry can realize the full potential of AI to transform construction management and drive sustainable development.

6 Conclusions

By analyzing the selected 60 articles, this paper provided a scoping review to meticulously examine the current landscape, identify key areas when AI is applied in construction management, and develop a research framework to highlight the current development of AI in construction management including their challenges and opportunities.

In particular, this paper made three major research contributions. First, it focused on the practical implications of AI in construction management by going beyond theoretical discussions to examine real cases and their outcomes. It provided valuable insights into how AI can be effectively implemented to address specific industry challenges. For example, AI-powered robotics will perform tedious, complex, or dangerous tasks, reducing human error and improving site safety. The integration of AI with robotics promises to automate routine tasks, freeing up human resources for more strategic and creative tasks. AI can also optimize scheduling, streamline communication, and automate processes. Second, this paper emphasizes the human element in AI adoption, recognizing that the successful integration is as much about people and processes as it is about the technology itself. This human-centered perspective is critical to fostering a culture of innovation and ensuring that AI solutions are not only technically sound but also socially acceptable and operationally efficient. Finally, this paper has introduced a novel research framework for advancing AI in construction management. This framework provides a structured way for organizations to assess their current AI capabilities and plan for future advancements. By highlighting AI in five management areas, this paper not only contributed to the academic discourse, but also served as a practical guide for industry practitioners seeking to navigate the complex terrain of AI adoption in construction management.

The research has limitations. First, while the review provides an extensive analysis of AI in construction management, it may not cover all specific areas or technologies, with a focus on early stages and less on operations and maintenance. Second, the analysis is based on 60 articles, which might not represent the full spectrum of research quality, impact, or context, possibly due to regional or language biases in the database. Lastly, construction management's scope is broader than the areas examined, suggesting a need for a lifecycle perspective in future research to explore AI's application from inception to completion and beyond.

Acknowledgements

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