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REVIEW ARTICLE

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Artificial intelligence in infrastructure construction: A critical review

Abstract Artificial intelligence (AI) has emerged as a promising technological solution for addressing critical infrastructure construction challenges, such as elevated accident rates, suboptimal productivity, and persistent labor shortages. This review aims to thoroughly analyze the contemporary landscape of AI applications in the infrastructure construction sector. We conducted both quantitative and qualitative analyses based on 594 and 91 selected papers, respectively. The results reveal that the primary focus of current AI research in this field centers on safety monitoring and control, as well as process management. Key technologies such as machine learning, computer vision, and natural language processing are prominent, with significant attention given to the development of smart construction sites. Our review also highlights several areas for future research, including broadening the scope of AI applications, exploring the potential of diverse AI technologies, and improving AI applications through standardized data sets and generative AI models. These directions are promising for further advancements in infrastructure construction, offering potential solutions to its significant challenges.

Keywords infrastructure construction, artificial intelligence, literature review, quantitative analysis, qualitative analysis

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1 Introduction

Infrastructure development is a crucial component of the national economy, but it faces significant challenges such as high accident rates, low productivity, and a shortage of skilled labor. To address these issues, the industry has increasingly turned to advanced data analytics, algorithms, and computing technologies. Among these advancements, artificial intelligence (AI) has emerged as a key frontier. AI is generally defined as the ability of a system to accurately interpret external data, learn from it, and adapt flexibly to achieve specific objectives (Kaplan and Haenlein, 2019). The core concept behind most AI algorithms involves creating intelligent machines and programs that can learn and solve problems, similar to humans. AI algorithms, such as artificial neural networks, genetic algorithms, and fuzzy logic, have the capability to address complex problems, map complex relationships, and predict results (Cheng et al., 2009), making them widely adopted in the sector.

This growing trend has led to a surge in research examining how AI can enhance the efficiency of safety assessment, progress monitoring, equipment supervision, and various other aspects of infrastructure development. For example, Ajayi et al. (2020) developed deep learning models to predict potential health and safety risks in power infrastructure projects. Similarly, Lei et al. (2019) proposed a data-driven convolutional neural network (CNN) algorithm that utilizes multiscanned point clouds to accurately monitor construction progress. Additionally, Zhou et al. (2019) developed an integrated deep learning model specifically designed to predict the positioning of shield machines. These studies collectively demonstrate that AI surpasses traditional analytical approaches in addressing complex engineering problems (Zhang and Lu, 2021).

With the growing interest and advancements in AI applications in the construction field, it is crucial to thoroughly examine the current state of affairs and pinpoint areas for further study. Numerous review studies have explored AI applications in the construction industry. Darko et al. (2020), for example, conducted a scientometric analysis to visualize major research trends, while Pan and Zhang (2021) explored the characteristics of keywords, journals, and clusters associated with AI research in construction. Furthermore, Abioye et al. (2021) critically reviewed the literature on AI applications in areas such as activity monitoring, risk management, and resource optimization. Recent scholarly endeavors include quantitative analysis by Chen and Ying (2022), who scrutinized 587 articles to discern the principal developmental trajectories of AI technologies in construction, and investigations by Dumrak and Zarghami (2023) into the role of AI in lean construction management. However, these studies either focused on specific use cases or provided a general overview of research progress without offering an in-depth analysis. Consequently, there is a significant gap in contextual analysis concerning the latest advancements and emerging trends in AI applications within the infrastructure construction sector.

Therefore, the objective of this study is to address this gap and provide a comprehensive review of AI applications in infrastructure construction from both quantitative and qualitative perspectives. This review will accomplish three main objectives. First, we investigate the current status of AI research in infrastructure construction. Second, connections between AI applications and the management and operational requirements of infrastructure construction should be established, with a focus on the latest technological achievements. Finally, potential research opportunities for further advancements are identified. Thus, this study will contribute to a more in-depth analysis of how AI can revolutionize infrastructure construction practices.

After the introduction, Section 2 outlines the overall review methods. Section 3 elaborates on the patterns found in the literature through quantitative analysis. Section 4 highlights the key research achievements through qualitative analysis. Section 5 discusses several topics for future research. The final section concludes this study.

2 Research methods

As shown in Fig. 1, this review is conducted in three steps.

The first step involves retrieving relevant literature from the Web of Science (WoS) database, which supports significant research across various academic domains (Rodríguez-López et al., 2020). The search keywords should include terms related to AI as well as infrastructure. AI is a sophisticated technology that includes subfields such as machine learning, knowledge-based systems, computer vision, and robotics (Abioye et al., 2021). Infrastructure construction typically includes transportation systems (e.g., roads, bridges, railways, and airports), utilities (e.g., sewage systems and electrical grids), communication networks (e.g., telecommunication and internet infrastructure), and other public facilities. Therefore, the keywords are defined as follows:

- "artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision" OR "robot" OR "natural language processing"; AND
- "infrastructure construction" OR "civil engineering" OR "infrastructure project."

This review focuses exclusively on the literature from the last decade, specifically from 2013 to 2023, to highlight recent research advances. Furthermore, this scope is limited to research papers, excluding other types, such as conference papers and textbooks. Only English papers were included to ensure uniform analysis. The initial search resulted in 1200 papers. One author of this study screened the title and abstract of all retrieved papers to remove irrelevant ones based on two criteria: (1) the study should focus on the construction stage of infrastructure projects, and (2) the study should provide sufficient technical details on how AI has been used to improve infrastructure construction. The screening results were then double-checked by the second author to avoid bias. Through this selection process, 594 papers were eventually chosen for the subsequent literature analyses. It is important to note that most of the reviewed studies aim to provide general AI-based solutions for infrastructure construction rather than focusing on a specific type of infrastructure project.

In the second step, VOSviewer, a widely used bibliometric analysis tool, is used to quantitatively assess knowledge structures and their evolving patterns within this research domain. In addition to visualizing the bibliographic coupling and co-authorship relationships, VOSviewer utilizes the terms appearing in the titles, abstracts, and keywords of the 594 included papers to generate the keyword co-occurrence network. Generic terms such as "civil engineering," "construction site," and "AI," which contribute minimally to the analysis of detailed knowledge structures, are omitted during this process.

In the third step, the keyword co-occurrence network is utilized to direct the categorization of retrieved studies into distinct classifications, each representing specific AI applications in infrastructure construction. Within each category, papers were selected based on their citation counts, and care was taken to avoid any potential redundancy during the selection process. As a result, a comprehensive compilation of key literature was collected, forming the foundation for an extensive analytical endeavor.

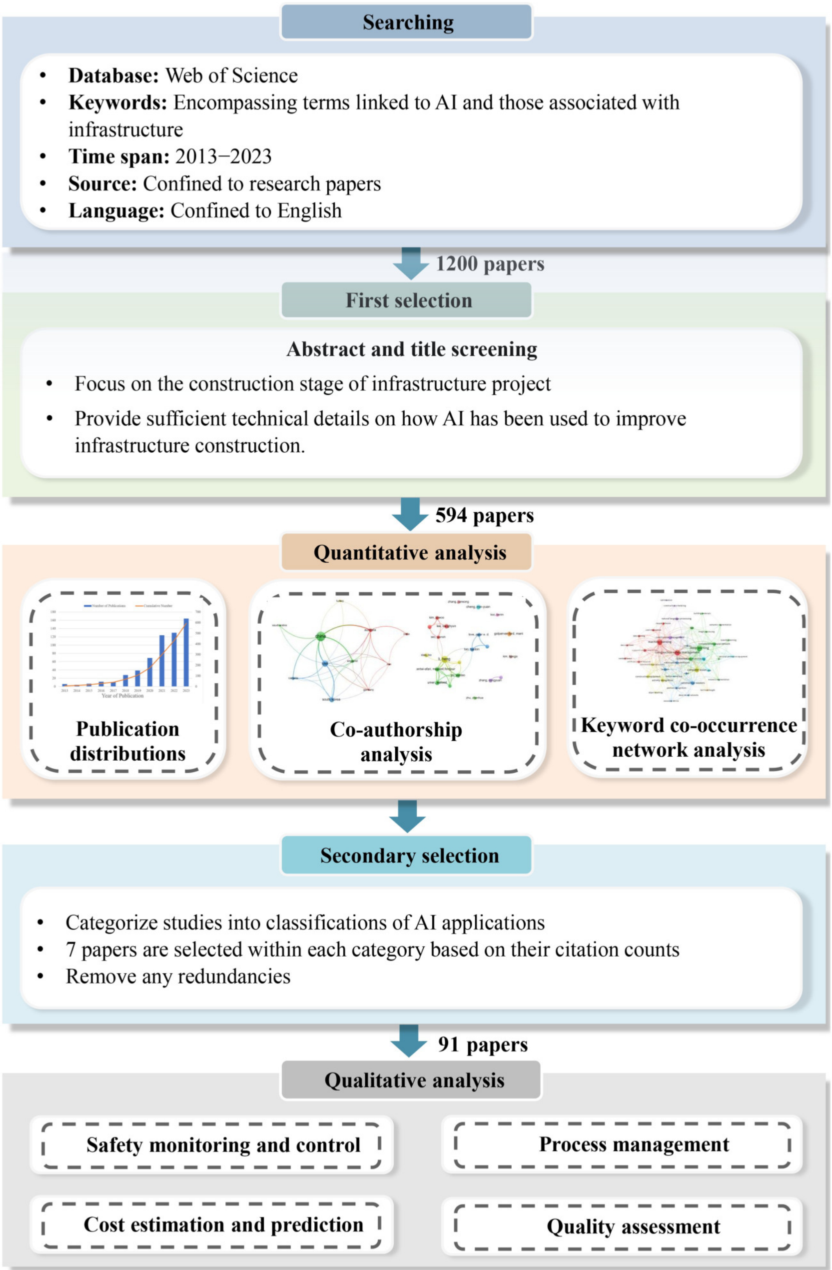

Fig. 1 Overall research workflow.

3 Quantitative analysis

3.1 Publication distributions

Figure 2 illustrates the distribution of the 594 retrieved papers from 2013 to 2023. Between 2013 and 2017, there was a gradual increase in annual publications, but the overall number of articles remained consistently below 20 papers per year. However, from 2018 to 2023, the quantity of research articles experienced substantial and rapid growth, surpassing 100 papers per year in 2021. This upward trend signifies a significant amount of AI research in infrastructure construction, highlighting the importance of exploring how AI can revolutionize practices in this field.

The papers retrieved in this study are sourced from a diverse pool of 155 different journals. The top 10 journals collectively contributed 334 papers, accounting for more than 55% of the total literature surveyed. Among these prominent journals, “Automation in Construction” contributed 122 indexed papers, representing more than 20% of the total indexed papers. Moreover, the 594 papers in this study had collectively received a total of 12, 614 citations, with 11,215 being non-self citations. On average, each article is cited 21.24 times, highlighting the significant impact of the research.

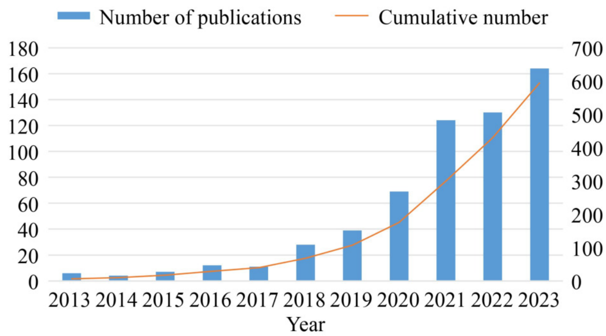

Fig. 2 Distribution of retrieved papers between 2013 and 2023.

3.2 Co-authorship analysis

Collaboration among scholars from different countries and academic institutions is essential for advancing research disciplines. We employed the "co-authorship" function within the VOSviewer software, with "countries" serving as the basis for analysis. To ensure both the quality and readability of the constructed network, the value of the "minimum number of documents of a source" parameter was set to 13 through a series of trial-and-error iterations (Wuni et al., 2019). Figure 3 clearly demonstrates that China, the United States, and Australia are at the forefront of AI research in infrastructure construction. However, the number of citations and total link strength among papers authored by researchers from Republic of Korea, Canada, and India are relatively modest, indicating a low level of collaboration among researchers from these countries.

To construct a researcher co-authorship network using VOSviewer, we set the "minimum number of published articles" parameter to 6. Of the 1733 researchers analyzed, only 22 met this threshold. Figure 4 provides insights into the connections among the most active researchers and

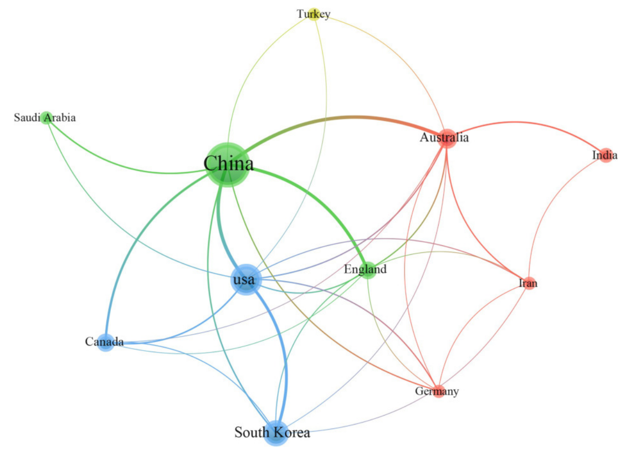

Fig. 3 Co-authorship networks among countries.

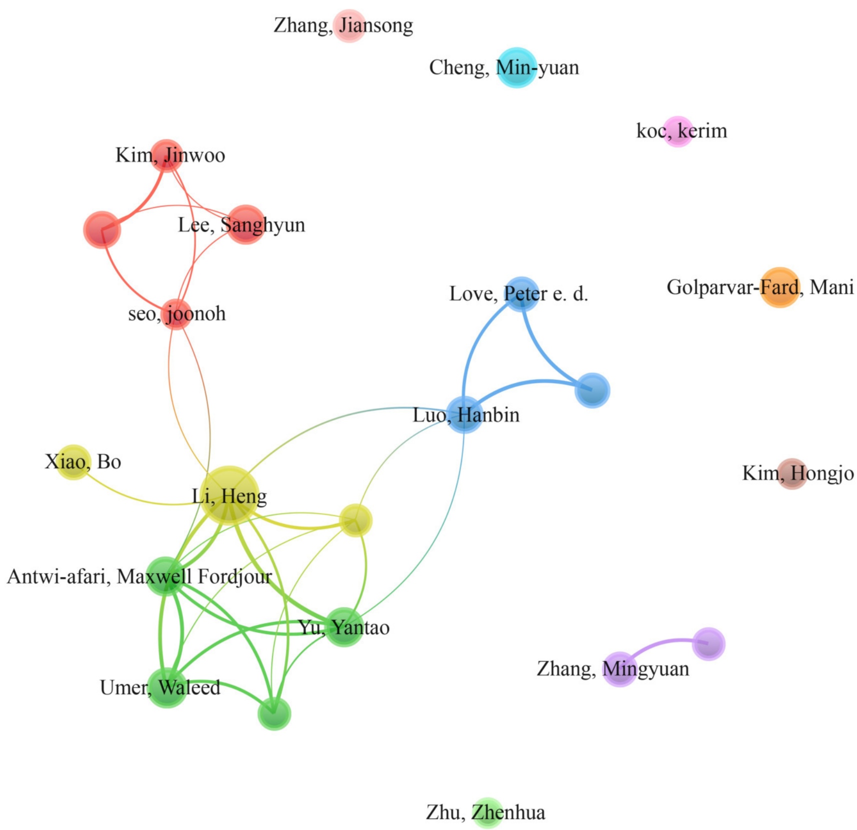

Fig. 4 Co-authorship networks among researchers.

the top 11 research clusters. The interconnectedness of the blue, yellow, red, and green clusters indicates a strong and active collaborative network among these researchers. Notably, 6 out of the 11 clusters were composed of a single researcher, indicating a lack of direct collaboration with other influential figures in the network. Additionally, there are 5 clusters with 2 to 4 researchers, suggesting a moderate level of collaboration.

3.3 Keyword co-occurrence network analysis

The co-occurrence network of keywords serves to uncover the primary themes and focal points within a specific research domain. This is accomplished by conducting a co-occurrence analysis on keywords extracted from the entire relevant literature and exploring the associations between research topics and methodologies (Hussein and Zayed, 2021). The "minimum occurrence count of keywords" parameter was set to 5, and general keywords such as "AI," "construction," and "civil engineering" were excluded. This filtering process resulted in a network of 43 keywords. In Fig. 5, each node represents a keyword, with its size reflecting the frequency of appearance in the titles, abstracts, and keywords of the included papers. The thickness of the curved lines connecting two keywords indicates the frequency of their co-occurrence.

These 43 keywords can be classified into two distinct groups: "application" and "methodology." This review primarily focuses its analysis on the keywords within the "application" category. An examination of these keywords reveals that they mainly revolve around four central themes: safety, schedule, cost, and quality. Notably, the total link strengths of the keywords related to safety, schedule, cost, and quality are 672, 470, 191, and 154, respectively. Consequently, within the domain of AI in infrastructure construction, scholarly attention is primarily devoted to construction safety, closely followed by construction scheduling. In contrast, the themes of cost and quality receive comparatively less attention.

4 Qualitative analysis

In addition to providing a comprehensive overview of research progress in AI in infrastructure construction through quantitative analysis, this review also presents a qualitative examination of the selected literature, which offers profound insights into the latest advancements. The papers within each thematic category were sorted in descending order based on their citation counts, and a total of 91 papers were chosen for detailed analysis. Among these papers, 42 focused on safety monitoring and control, 37 addressed process management, 7 concentrated on cost estimation and prediction, and 5 centered on quality assessment (Fig. 6).

4.1 Safety monitoring and control

Research on safety monitoring and control primarily

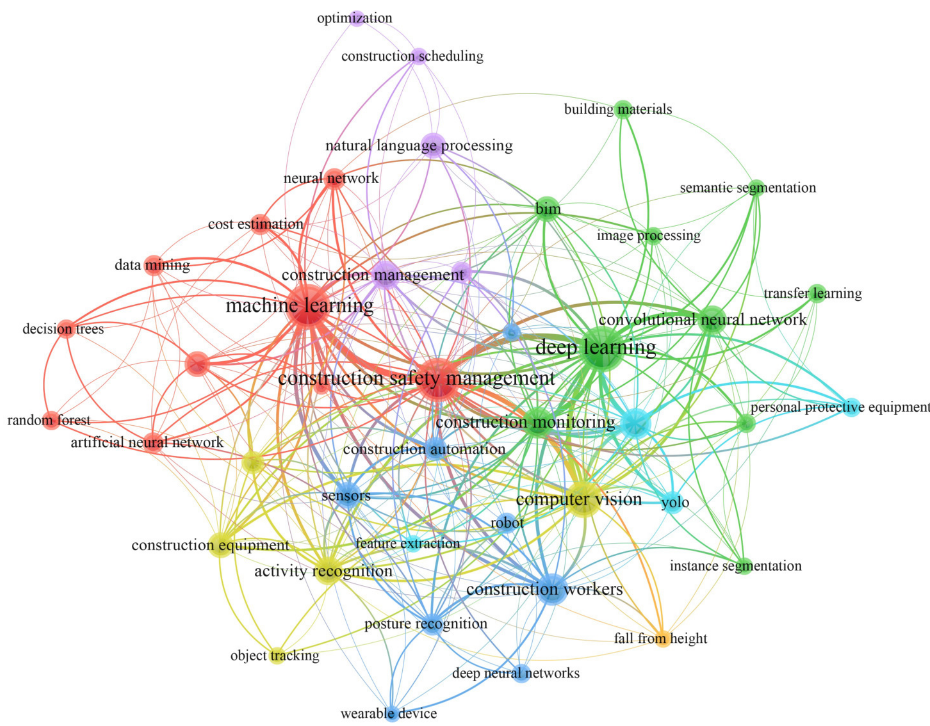

Fig. 5 Keyword co-occurrence network.

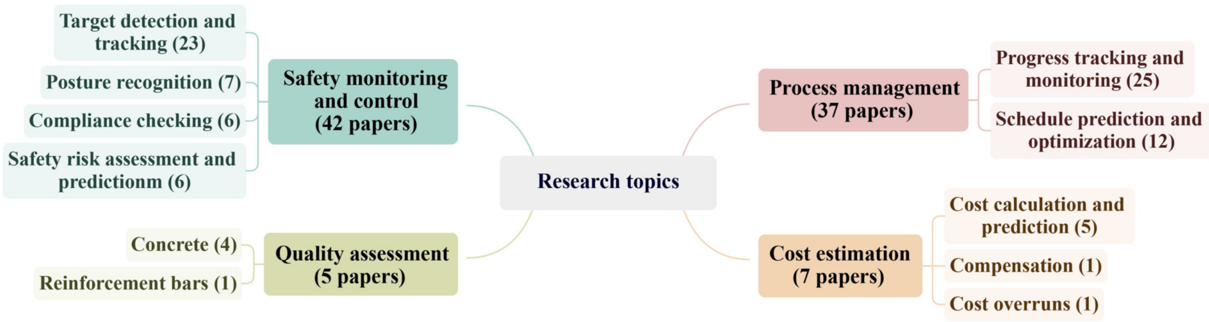

Fig. 6 Research topics of the 91 papers.

focuses on various aspects, including target detection and tracking, activity recognition, posture recognition, compliance checking, and safety risk assessment and prediction. Figure 7 illustrates the workflow of commonly used machine learning or computer vision techniques employed in this field. In current solutions, two categories of sensors are commonly used for data acquisition, in addition to data originating from text or BIM. The first category involves the use of sensors such as accelerometers, gyroscopes, and inertial measurement units (IMUs) to capture physical or motion-related features. The second category employs cameras to record videos, with image processing and computer vision techniques typically utilized for analyzing video data. However, compared to unimodal perception and reasoning, the application of multimodal perception and reasoning is relatively limited.

4.1.1 Target detection and tracking

Target detection and tracking play a crucial role in identifying unsafe interactions among workers, machinery, and danger zones. Prior to target detection, image processing must be performed, including noise reduction, image enhancement, resizing, and image segmentation (Ding et al., 2018). Subsequently, target detection has been conducted using algorithms such as YOLO (Cheng et al., 2022), CNNs (Ding et al., 2018), Faster R-CNNs (Kim and Chi, 2019), HOG features (Azar, 2016), and tailored algorithms (Fang et al., 2018b). Among these algorithms, YOLO ensures faster processing speed and is suitable for real-time applications, while Faster R-CNN allows for more precise target detection.

The advancement of machine learning algorithms has enabled the achievement of high accuracy in worker and machine detection (Memarzadeh et al., 2013; Fang et al., 2018b). Object detection algorithms, which typically have larger dimensions and simple shapes, are particularly effective for construction machinery. However, worker detection poses challenges such as different backgrounds, occlusions, and posture changes. Fang et al. (2019) employed Mask R-CNN to detect workers crossing structural supports during construction, achieving a recall rate of 90% and precision rate of 75% for overlapping. Son et al. (2019) utilized Fast R-CNN and ResNet-152 to detect workers in various postures against complex backgrounds, achieving an accuracy rate of 94.3%. Furthermore, detection and tracking are often used in combination. For example, Angah and Chen (2020) applied a gradient-based approach coupled with feature-based comparison, alongside the integration of Mask R-CNN, to track workers across sequential image frames. Their method yielded an MOTA of 81.8%. In another study, Xiao and Kang (2021) employed YOLOv3 for detection, associating the detection results of consecutive frames to derive tracking results. This approach facilitated a processing speed of 20.8 frames/second, accompanied by a MOTA of 93.2% and a MOTP of 86.5%.

Moreover, research on the detection and tracking of personal protective equipment (PPE) is crucial for enhancing safety at construction sites. Several studies have been conducted in this area, including studies on the detection of safety belts (Fang et al., 2018a), safety helmets (Huang et al., 2021), safety hooks (Choo et al., 2023), safety fences (Kolar et al., 2018), and safety vests (Delhi et al., 2020). The accuracy rates of these PPE detection methods generally exceed 90%. Wang et al. (2023) investigated the integration of electrodes and a microprocessor into safety helmets to capture electroencephalogram (EEG) signals. These signals were then processed using continuous wavelet transform (CWT) and a CNN model to identify workers' mental fatigue states. However, existing studies have focused mainly on easily noticeable PPE items, with limited attention directed toward smaller-sized PPE. In a recent study by Guo et al. (2023), Kinect 2.0 and a long short-term memory (LSTM) model were combined to assess the fastening of life-saving ropes, achieving an overall accuracy rate of 76.67%. This emphasizes the need for developing detection methods specifically tailored to smaller PPE items.

4.1.2 Posture recognition

The occupational health of workers can be compromised by the presence of awkward working postures and

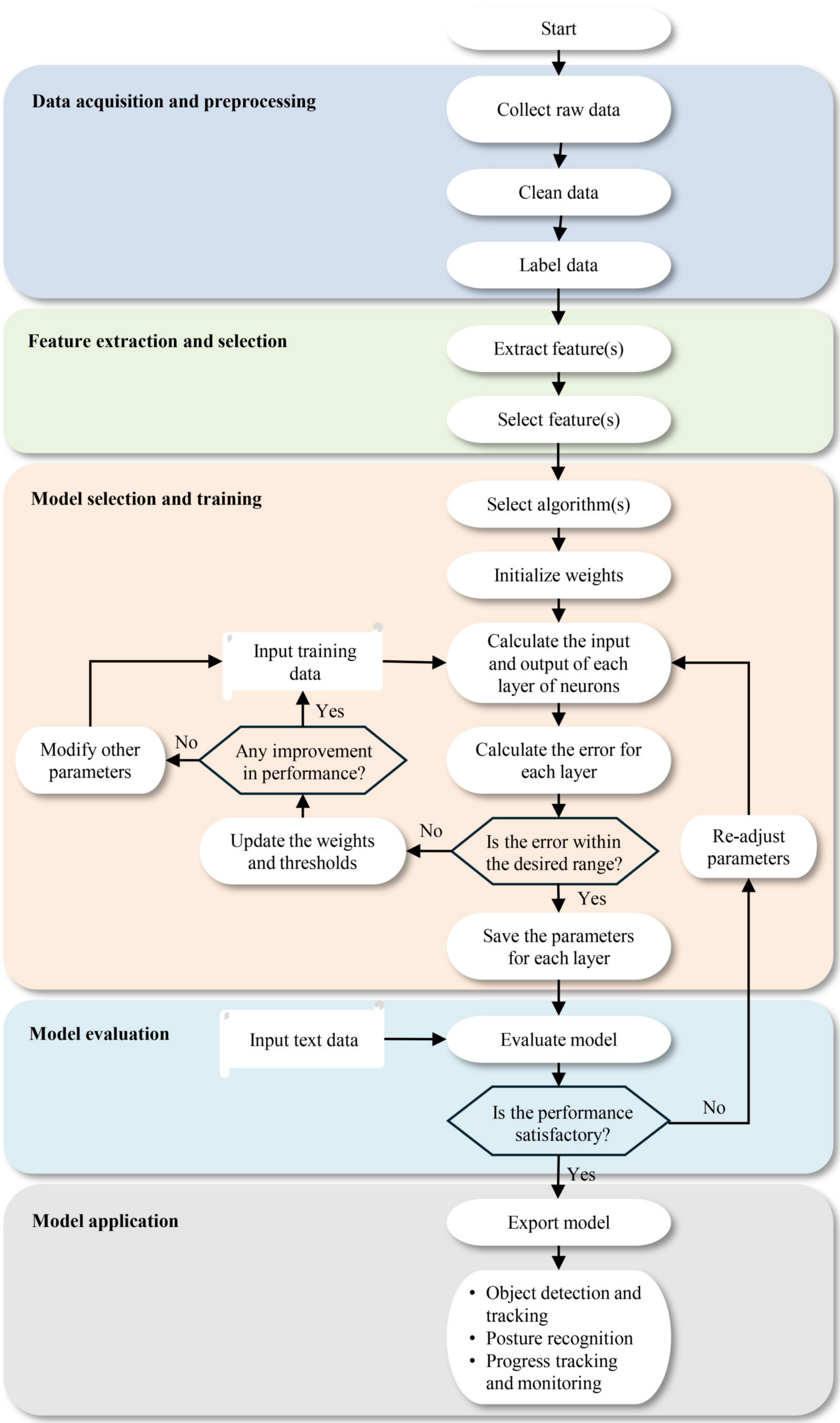

Fig. 7 General workflow of AI-based safety monitoring and control.

associated ergonomic risks. Recognizing these postures typically involves two primary methods. Some studies have focused on detecting workers' postures through the integration of sensors and machine learning techniques. For example, Zhao and Obonyo (2020) used IMUs on five different body parts of workers to collect motion data.

Based on these data, they utilized an integrated CNN and LSTM model to recognize the postures of construction workers. While this method yields high accuracy, it may affect worker operations because the sensors are attached to the body.

Alternatively, other studies used deep learning to extract the skeletal data of construction workers from videos. For instance, Yu et al. (2019) employed a stacked hourglass network to extract skeletal data and evaluated the ergonomic status of the human body using the Rapid Entire Body Assessment (REBA) method. The accuracy of this approach in posture extraction ranged from 70% to 96%. Although this method is convenient because it does not require additional equipment or sensors, its accuracy may be influenced by factors such as video quality and lighting conditions.

The heavy weight and operational complexity of construction equipment often lead to significant safety issues when transporting materials or interacting with objects at construction sites. Therefore, posture recognition in construction equipment is crucial for safety management. Excavators are often studied for pose recognition, with a focus on locating and identifying various components such as the boom (Soltani et al., 2017), the arm, and the bucket (Soltani et al., 2018), as well as estimating their poses. However, relying solely on partial posture recognition fails to provide a comprehensive understanding of the dynamic work area of construction equipment. This limitation significantly undermines safety accuracy within interaction zones. Other studies directly estimate the full-body poses of construction equipment, often using *k*-means clustering techniques for background subtraction and skeleton extraction. For example, Luo et al. (2020) directly estimated the full-body poses of equipment using various networks, such as the stacked hourglass network (HG), cascaded pyramid network (CPN), and an integrated model of these networks. The integrated model achieves a 93.43% accuracy rate for correct key points.

4.1.3 Compliance checking

To mitigate non-compliance risks in infrastructure construction, a multimodal perception and reasoning approach is employed for automated compliance checks, as illustrated in Fig. 8. The process begins with NLP-based text information extraction, followed by the integration of on-site data to ensure error-free and deviation-free construction. Zhang and El-Gohary (2015) proposed a rule-based semantic NLP method for extracting

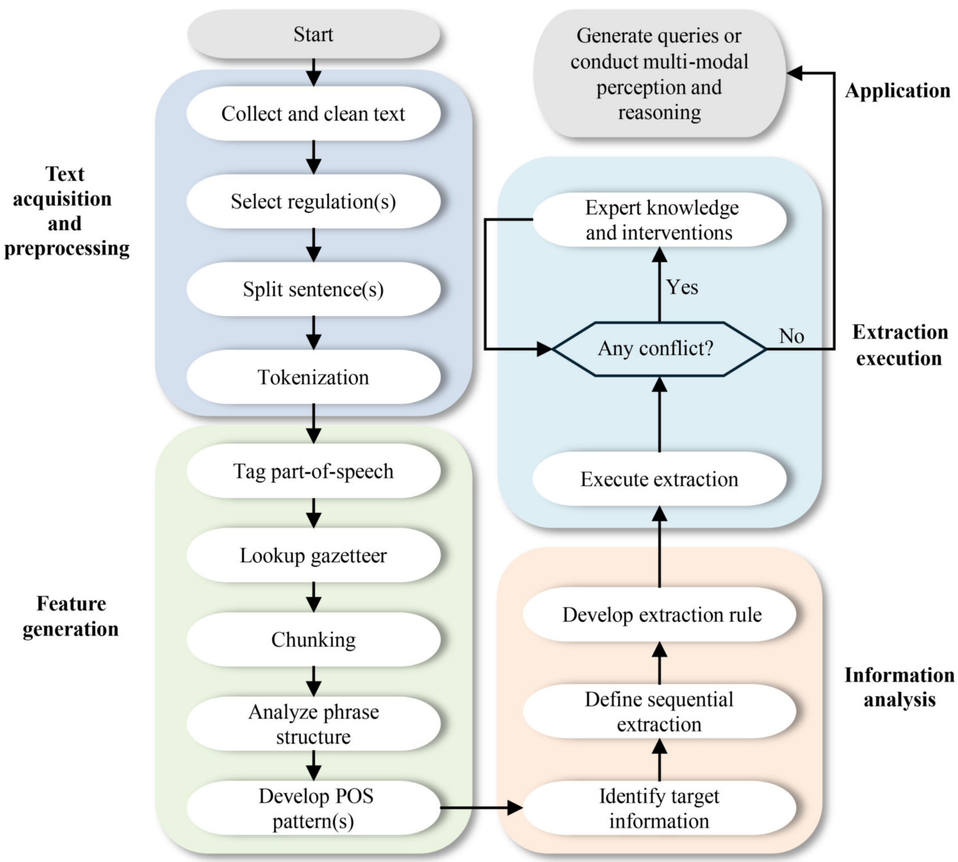

Fig. 8 General workflow of AI-based compliance checking.

information from code text files and then applied logical reasoning to ensure compliance. Ren and Zhang (2021) developed an information extraction method based on semantic rules to automatically extract construction execution steps from procedure documents, achieving an accuracy of 97.08% and a recall rate of 93.23%. The integration of ontology and on-site data acquisition with sensing technology enables automatic compliance checks for construction execution.

The combined information extraction method facilitates effective compliance checking for BIM data. Zhang and El-Gohary (2017) utilized EXPRESS-based technology to extract design information from BIM, while Guo et al. (2021) correlated extracted rule terms with keywords within BIM, automatically formulating SPARQL queries based on logical relationships. Similarly, Shen et al. (2022) employed ontology and NLP to establish a comprehensive security rule repository, enabling real-time risk assessment in routine construction activities. Additionally, Li et al. (2016) used NLP to convert textual descriptions of spatial structures into computationally interpretable spatial rules, achieving an average precision of 87.88% in spatial rule extraction tasks. They then utilized geographic information systems (GISs) for spatial reasoning to identify situations of non-compliance, thus mitigating risks associated with spatial configurations between utilities and their surroundings.

4.1.4 Safety risk assessment and prediction

Managers responsible for overseeing construction sites require real-time control over safety risks to proactively implement intervention measures. Some studies directly address fall risks, such as Piao et al. (2021), who utilized computer vision and dynamic Bayesian networks to classify fall probabilities into three levels. Indirect assessment of safety risks involves predicting the impact of accident factors, as demonstrated by Zermane et al. (2023), who used random forest (RF) to forecast risks related to site conditions, management, and other contributing factors. Moreover, construction workers frequently face noise risks at construction sites. Mostafavi and Cha (2023) proposed a deep learning-based feedforward model for proactive noise management.

In the assessment of risks related to human–machine collisions, important indicators to consider include proximity and crowdedness. To facilitate risk assessment, methods of knowledge representation and reasoning are utilized, allowing for the leveraging of expert knowledge and rules. Kim et al. (2016) utilized computer vision to estimate proximity and applied fuzzy reasoning to infer safety levels. Poh et al. (2018) utilized RF to predict the severity of safety indicators at construction sites. Their approach incorporated 6 project-related factors (e.g., project type, manpower) and 7 items from the contractor’s safety checklist (e.g., lifting operations, scaffolding conditions), enabling more effective intervention measures.

4.2 Process management

Studies in the field of infrastructure process management can be classified into two primary research directions: progress management and monitoring and schedule prediction and optimization.

4.2.1 Progress tracking and monitoring

The effective monitoring of infrastructure construction progress requires the accurate identification of individual activities carried out at construction sites, such as excavation, concrete leveling, brick laying (Bhokare et al., 2022), carpentry, and component assembly (Wang et al., 2021b). Dimitrov and Golparvar-Fard (2014) employed three support vector machine (SVM) models trained with appearance codebooks to recognize surface materials. Yuan et al. (2020) utilized supervised learning classifiers to process laser scanning data for material classification. Both methods aid in monitoring construction progress by identifying predominant surface materials. Golparvar-Fard et al. (2015) expanded on these efforts by developing a four-dimensional point cloud model for existing structures and using dynamic threshold comparisons to assess progress and automatically detect schedule deviations. This approach enables timely detection of potential delays in specific construction tasks, although it requires substantial investments to be applied across the entire project development continuum.

In contrast to directly tracking and monitoring construction progress, labor productivity serves as an indirect measure. Momade et al. (2022) developed predictive models using SVM and RF based on collected data on factors influencing labor productivity, achieving detection probabilities of over 90%. A critical aspect of evaluating labor productivity is the recognition of worker and equipment activities. Generally, a wider range of activity categories considered leads to higher recognition rates.

Some studies have employed sensors to collect data and then used traditional machine learning classifiers or deep learning models to analyze activities. Common machine learning classifiers include decision trees, logistic regression, SVMs, k-nearest neighbors, and other supervised learning classifiers, which require high-quality data sets. For example, Ryu et al. (2019) used wristbands with accelerometers to gather data on the hand activities of workers and achieved 88.1% accuracy in classifying subtasks in masonry construction using a multiclass SVM. LSTM is effective in capturing long-term temporal dependencies in continuous time series data, such as changes in workers' actions (Rashid and Louis, 2019). Kim and Cho (2020) collected predefined target motions using IMUs and successfully identified various construction activities with an accuracy rate of 94.73%. On the other hand, some studies have directly utilized computer vision for activity recognition through videos. Commonly used algorithms include LSTM (Chen and Demachi, 2021), optical flow (Bügler et al., 2017), and CNNs. For example, Luo et al. (2018a, 2018b) used two-stream CNNs and deep three-stream CNNs to capture worker activities in video sequences, achieving an average accuracy rate above 80%. Furthermore, Kim et al. (2019) utilized region-based fully convolutional networks (R-FCNs) for license plate detection and generating site visit logs, which can also be applied for productivity assessment.

Additionally, Cheng et al. (2017) integrated audio processing with SVM classification to identify equipment activities. After training an SVM model using audio amplitude features, Sabillon et al. (2020) estimated the cycle time of construction activities using a Bayesian statistical model, leading to the prediction of machinery productivity with low error rates (9.50% and 12.81%). This audio-based approach, in contrast to deep learning networks, eliminates the need for large-scale databases and demonstrates an extended capability to recognize various mechanical equipment activities.

4.2.2 Schedule prediction and optimization

Several studies have utilized machine learning to predict the progress, completion time, and potential delays in construction projects. The predominant methodologies in this field include RF and DT, with less emphasis on deep learning. For example, Ezzeddine et al. (2022) directly forecasted construction progress by monitoring planned and completed work quantities across all project tasks, resulting in a notable correlation of over 93% between actual and predicted values. Furthermore, researchers have expanded their efforts to anticipate delay risks from various influencing factors. Awada et al. (2021) achieved a remarkable accuracy of 91% in predicting the impact of project supervisor responses on concrete pouring, considering it a singular influencing factor. Gondia et al. (2020) identified 59 delay risk factors and used DT and naïve Bayes classifiers to predict project delay risks. Cheng et al. (2019) developed an NN-LSTM model to estimate completion time and demonstrated its superior reliability compared to conventional earned value management formulas. Additionally, Prieto et al. (2023) utilized ChatGPT to generate construction schedules, showing promising performance for simple use cases.

To mitigate project delay risks, certain studies have optimized construction site layout planning and improved resource scheduling efficiency through intelligent optimization algorithms. In resource scheduling optimization, Podolski (2016) successfully shortened the construction execution duration by employing a taboo search algorithm to optimize resource scheduling. Regarding layout optimization, Lien and Cheng (2014) used a particle swarm optimization algorithm to optimize tower crane placement. Similarly, Cheng and Chang (2019) utilized the symbiotic organisms search algorithm to optimize the layout of construction materials, reducing the total distance required for material transportation and accelerating project progress. Additionally, timely monitoring of public opinion is often essential for the successful delivery of major infrastructure projects. Jiang et al. (2016) employed web crawlers to gather relevant online comments and utilized two NLP techniques—sentiment analysis and topic modeling—to evaluate public sentiment toward the project.

4.3 Cost estimation and prediction

The primary objective of construction projects is to successfully complete each task within budgetary constraints, making cost management a crucial aspect (Juszczyk et al., 2019). Seven articles focused on the cost of infrastructure construction, specifically sports facilities and highway construction. By investigating the intricacies of cost-related issues, researchers explored methods to ensure quality and safety with limited financial resources.

Cheng and Hoang (2014) conducted a study on cost estimation in infrastructure construction using least squares SVM for both point and interval estimations. Through fine-tuning the differential evolution algorithm, they were able to achieve a mean absolute percentage error (MAPE) of 3.5% for point estimation. In recent years, there has been an integration of NLP and neural networks in cost estimation methodologies. Akanbi and Zhang (2021) proposed an algorithm that extracts design information and matches it with unit price information stored in a database, thereby enhancing cost estimation. Similarly, Juszczyk et al. (2019) utilized an ensemble of multiple neural networks for cost estimation, yielding MAPE errors ranging from 2.73% to 3.91%. Given that infrastructure construction costs are influenced by various factors, such as manpower, materials, and equipment, relying solely on point cost estimation may be inadequate for supporting cost management. Therefore, a combination of methods is essential for providing a comprehensive estimation of cost intervals. For example, Mir et al. (2021) addressed the impact of material price fluctuations on cost deviations by adopting an optimal upper and lower bound estimation approach. This allowed for the direct training of artificial neural networks to generate material price intervals and indirectly predict construction costs.

Moving beyond cost estimation, Alshboul et al. (2022) utilized multiple linear regression to forecast breach compensation in infrastructure construction projects. Karakas et al. (2013) employed swarm intelligence simulation to simulate the cost-sharing process between contractors and clients in various scenarios. These studies aim to empower decision-makers to better manage financial risks and achieve a balance of interests in infrastructure construction.

4.4 Quality assessment

There are five research papers focused on issues related to the quality of infrastructure construction. These papers specifically highlight the assessment of concrete quality, covering topics such as concrete crack detection, concrete erosion identification, and the prediction of concrete mechanical performance. Various deep learning methods have been proposed to aid in the quality inspection of concrete in civil infrastructure.

Dung and Anh (2019) employed a deep FCN to detect concrete cracks, achieving an impressive average precision rate of approximately 90%. Cui et al. (2021) utilized an improved YOLOv3 model to identify concrete corrosion and spalling, achieving remarkable accuracy and precision levels exceeding 95%, although the mean average precision (mAP) was 75%. Compared with other mainstream object detection algorithms, such as Fast-R-CNN, SSD, and YOLOv3, their method demonstrated superior accuracy in identifying concrete erosion damage. Yao et al. (2021) simplified the depth and complexity of the overall network structure by using an enhanced YOLOv4, resulting in improved crack detection speed and an mAP of 94.09% for real-time concrete crack detection. Additionally, Ashrafian et al. (2020) employed regression models such as RF, the M5 rule model tree, the M5 prime model tree, and CHAID to predict the mechanical properties of rolled concrete pavement. Their findings indicate that RF performs the best in predicting compressive strength, tensile strength, and flexural strength. These research efforts collectively demonstrate the rapid evolution of concrete quality inspection toward faster and more precise methods.

In addition to concrete, some scholars have conducted research on reinforcement bars. Improper placement of reinforcement bars in structures can significantly reduce their load-bearing capacity, leading to severe consequences. However, manual quality inspection of reinforcement bars is a time-consuming and error-prone process. Kardovskyi and Moon (2021) employed commonly used object detection algorithms such as Mask R-CNN and stereo vision to measure the quantity, spacing, and length of reinforcement bars. Their results demonstrate that the model can accurately estimate the quantity, with maximum relative errors for spacing and length being 3% and 8%, respectively.

5 Open questions for further investigation

5.1 Expanding AI application areas

Currently, research in the field of AI applications in infrastructure construction has focused mainly on safety and progress. However, it is crucial to expand this research to include cost, quality, and other critical factors. Traditional cost management methods, which often rely on point estimations, are insufficient to addressing the uncertainties and risks inherent in real-world construction projects. Therefore, a thorough exploration of interval estimation is necessary to improve the precision and reliability of cost estimates.

Moreover, existing research tends to prioritize material properties during the design phase, with limited consideration given to their relevance during construction. It is important to recognize the potential for AI to play a significant role in monitoring material properties, including tensile and compressive strength, allowing for real-time adjustments in response to unforeseen issues that may arise during construction activities.

In comparison to the four identified application areas, research on enhancing the environmental performance of infrastructure construction is noticeably lacking. The use of AI technologies to assess and regulate environmental factors such as noise levels, pollution, and waste disposal during the construction phase represents a significant avenue for further investigation. These AI-based measures not only address environmental concerns but also effectively manage health issues resulting from worker exposure to dust, toxic substances, and high noise levels.

5.2 Exploring the applications of different AI technologies

This review revealed that machine learning and computer vision are widely applied in infrastructure construction. However, there is untapped potential for further exploration of other AI technologies, particularly robotics.

The construction industry has entered a new era driven by advancements in construction robotics, including masonry robots, rebar-tying robots, 3D printing, exoskeletons, and drones (Cai et al., 2019). Within this context, the emphasis should be on enhancing the capabilities of robots to enable precise control and path planning in complex construction environments. This requires the development of proactive exploration and learning strategies to improve stability in robot behavior. Additionally, the collaboration between humans and machines has significant potential for advancing AI applications. Currently, research in worker-centric human–machine collaboration focuses on using brain activity data from wearable EEG devices to anticipate workers' responses to hazardous situations and adjust alarm thresholds accordingly (Zhou and Liao, 2023). Looking forward, there is a need to further integrate methods of human–machine collaboration, especially in high-risk scenarios such as lifting operations and work at height. This integration would leverage the combined insights of humans and machines, facilitating optimal group decision-making processes and thus enhancing overall efficiency while reducing safety risks.

However, it is crucial to recognize that implementing AI may present unique challenges, particularly in relation to data security. Researchers must prioritize data security and take measures to address security issues associated with engineering data. Solutions should be explored to ensure the protection of sensitive data, and the potential impact of such data on the effectiveness of model applications should be considered. As privacy protection technologies continue to evolve, applications increasingly require the concealment of sensitive facial information. Wang et al. (2021a) conducted a study on the recognition of safety helmets under facial blur conditions, highlighting the growing significance of AI in managing sensitive data in construction projects and the importance of proactive measures to effectively address these issues.

5.3 Enhancing applications through standardized data sets, domain knowledge integration, and generative AI models

In the field of infrastructure construction, AI algorithms are currently customized to address specific engineering tasks. However, their effectiveness relies heavily on high-quality training data. These data include project-related information, monitoring data, construction drawings, and various documents that are crucial for commonly used AI algorithms. Unfortunately, challenges related to data confidentiality and commercial sensitivities often make it difficult to acquire specific domain data sets in the infrastructure construction sector. As a result, many researchers are forced to create their own data sets, which involves a time-consuming process of data collection, cleaning, annotation, and evaluation. Therefore, it is crucial to enhance data set synthesis and data sharing by combining data sets from different projects and sources.

In addition to standardized data sets, incorporating domain knowledge into AI algorithms provides a viable solution for addressing issues arising from limited or poor-quality data. This integrated knowledge can be divided into three categories: relational knowledge, logical knowledge, and scientific knowledge (Zhou and Liao, 2023). The main challenge lies in encoding knowledge and executing it efficiently (Gupta and Sheng, 2020). Specific approaches, such as using semantic-based regularization, can be employed to integrate prior knowledge into the underlying deep learning framework (Diligenti et al., 2017). Physical laws can be embedded as constraints into neural networks, allowing traditional convolutional neural networks to be effectively trained to predict unlabeled object data (Stewart and Ermon, 2017). This integration holds promise for developing predictive models that optimize resource utilization and assess risks at construction sites.

Although specialized models are valuable, they also have inherent limitations, such as high complexity, limited generalizability, and significant maintenance costs. In contrast, generative AI models are gaining attention for their ability to train without specific optimization or tuning for specific tasks. These models acquire knowledge through exposure to large-scale data sets and broad learning. They facilitate the assimilation of probability distributions from provided training data and generate new data samples based on acquired knowledge. In the field of infrastructure construction, ChatGPT, as a generative AI model, can provide innovative solutions for resource planning and optimization. In addition to the work by Prieto et al. (2023), You et al. (2023) utilized ChatGPT for construction sequencing planning with the aim of minimizing manual intervention and streamlining the planning process. Generative AI can also contribute to compliance checks, construction equipment fault diagnosis, progress monitoring, and other domains.

6 Conclusions

In recent years, the emergence of AI has had a significant impact on the construction industry. AI offers distinct advantages in efficiently processing complex data sets and navigating dynamic challenges characterized by high levels of uncertainty, making it a stark contrast to traditional manual methods. This study conducted a comprehensive investigation of AI applications in infrastructure construction utilizing both quantitative and qualitative analytical methods.

This research employed quantitative methods to examine 594 scholarly papers, yielding valuable insights into the evolving trends of AI applications in infrastructure construction. Based on this analysis, several overarching themes were identified, systematically categorizing AI applications into four distinct subdomains: safety monitoring and control, process management, cost estimation and prediction, and quality assessment. The study also provided detailed explanations of the complex AI applications within each subdomain.

The significance of this review lies in its synthesis and discussion of the latest research contributions in the field. Additionally, it identifies pertinent research questions for future studies, such as expanding AI application domains, exploring diverse AI applications, and enhancing AI applications through the integration of standardized data sets and generative AI models. By addressing these areas, the aim is to inspire and provide direction for future research endeavors, thereby facilitating the ongoing evolution of AI in infrastructure construction.

Competing Interests The authors declare that they have no competing interests.

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