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Review

Roles of artificial intelligence in construction engineering and management: A critical review and future trends

Yue Pan, Limao Zhang *

School of Civil and Environmental Engineering, Nanyang Technological University, 50 Nanyang Avenue, Singapore 639798, Singapore

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ABSTRACT

With the extensive adoption of artificial intelligence (AI), construction engineering and management (CEM) is experiencing a rapid digital transformation. Since AI-based solutions in CEM has become the current research focus, it needs to be comprehensively understood. In this regard, this paper presents a systematic review under both scientometric and qualitative analysis to present the current state of AI adoption in the context of CEM and discuss its future research trends. To begin with, a scientometric review is performed to explore the characteristics of keywords, journals, and clusters based on 4,473 journal articles published in 1997–2020. It is found that there has been an explosion of relevant papers especially in the past 10 years along with the change in keyword popularity from expert systems to building information modeling (BIM), digital twins, and others. Then, a brief understanding of CEM is provided, which can be benefited from the emerging trend of AI in terms of automation, risk mitigation, high efficiency, digitalization, and computer vision. Special concerns have been put on six hot research topics that amply the advantage of AI in CEM, including (1) knowledge representation and reasoning, (2) information fusion, (3) computer vision, (4) natural language processing, (5) intelligence optimization, and (6) process mining. The goal of these topics is to model, predict, and optimize issues in a data-driven manner throughout the whole lifecycle of the actual complex project. To further narrow the gap between AI and CEM, six key directions of future researches, such as smart robotics, cloud virtual and augmented reality (cloud VR/AR), Artificial Intelligence of Things (AIoT), digital twins, 4D printing, and blockchains, are highlighted to constantly facilitate the automation and intelligence in CEM.

1. Introduction

The construction engineering and management (CEM) inside the scope of the architecture, engineering, and construction (AEC) industry is fraught with its own problems and complications, which covers a set of construction-related activities and processes along with human factors and interactions [97]. Construction, as a large sector of the economy, plays prominent roles in driving economic growth and long-term national development [76]. According to a survey from McKinsey Global Institute in 2017, the global construction industry makes up around 13% of the world's Gross Domestic Product (GDP) and this number is projected to rise to 15% in 2020. Meanwhile, construction projects create a broad range of job opportunities for 7% of the world's working population. Despite its economic importance, an obvious issue is poor labor productivity during the construction procedure, negatively leading to the waste of manpower, material resources, and financial resources. Since construction activities contribute a lot to our society economically, it makes the most sense to take proper construction management for the purpose of improving product performance. If the construction productivity is enhanced by as much as 50% to 60% or higher, it is estimated to bring an additional $1.6 trillion into the industry's value each year and further boost the global GDP [20].

Construction with inherent complexity is regarded as one of the most dangerous industries, which is greatly susceptible to a variety of unpredictable factors, such as participants in different roles, the changeable environment in large uncertainty, struck-by-equipment hazard, and others [172,199]. Therefore, the construction industry tends to cause a small scale of fatal accidents with higher frequency than other domains, which is even responsible for 30-40% of fatalities worldwide [251]. For example, accidents on construction sites have killed more than 26,000 workers in the United States during 1989 – 2013 [243]. There were in total 782 fatal construction accidents in Europe in 2014, and the rate of casualties was about 13 per 100,000 workers [213]. According to Korea's Ministry of Employment and Labor annual report from 2012 to

* Corresponding Author.
E-mail addresses: pany0010@e.ntu.edu.sg (Y. Pan), limao.zhang@ntu.edu.sg (L. Zhang).

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2015, the mortality rate of Korea's construction industry remained the highest among other economic sectors [98]. Construction in China has been regarded as one of the riskiest industries, where the number of fatal accidents exceeds many developed countries without a significant downward trend [234]. Numerous researches have revealed that safety issues are tied up with hazardous working conditions and the lack of supervision, emphasizing the necessity of construction management for safety guarantee and accident prevention [120]. Through identifying, evaluating, and reacting to the potential risk in dynamic and hazardous construction environments at an early stage, it is expected to eliminate safety hazards and then achieve a sustainable reduction in fatalities in the construction industry.

In the context of "Industry 4.0", CEM is going through constant innovations towards digitalization and intelligence, in order to realize a considerable boost in automation, productivity, and reliability. That is to say, the construction industry is reshaping itself along the whole construction value chain, including the planning, construction, operation, and maintenance (O&M). For the purpose of launching the real digital strategies in CEM, artificial intelligence (AI) acts as the backbone to change the way a construction project performs. As a branch of computer science, AI drives computers to sense and learn inputs like human-being for perception, knowledge representation, reasoning, problem-solving, and planning, which can deal with complicated and ill-defined problems in an intentional, intelligent, and adaptive manner. The investment in AI is undergoing rapid growth, in which machine learning particularly accounts for a major proportion to learn sufficiently robust data from multiple sources and then act on the insights of data to make smart decisions adaptively. According to a report from Accenture company [168], AI is already altering every walk of life, which heralds dramatic potential to boost labor efficiency by 40% and double annual economic growth rates in 2035. To make AI live up to expectations, more and more companies are actively investing in various AI technologies, which put AI into a sharper focus and extend its application scope [46]. When AI talents continue to mature, it is believed that AI methods will become the next digital frontier to easily transform massive data into useful knowledge, leading to a high degree of automation and intelligence in both industry and commerce. Although a considerable amount of engineering data increases unprecedently in the construction project, the adoption of AI techniques still lags behind the process in other industries. Therefore, there is immense interest in implementing a variety of AI methods in the CEM domain to seize the valuable opportunity of digital evolution for better performance and profitability.

Due to the remarkable growth of AI applications in civil engineering, some reviews about this topic have been published. However, most of them only highlight the value of AI on a specific sub-area, such as structural engineering [175], building information modeling (BIM) [252], automated construction manufacturing [86], computer vision [66], and others. That is to say, they only offer a narrowed perspective rather than a general view of AI implementation within CEM. In the meanwhile, they largely depend on the manual review and appraisal, possibly leading to biased findings [87]. Moreover, Darko et al. [50] conducted a review on AI in the AEC industry using scientometric analysis, in order to raise the awareness of AI in AEC. But it does not provide a comprehensive introduction of AI techniques and practical AI applications in CEM. Only two future research directions, namely the robotic automation and convolutional neural networks, are identified, which are not sufficient. Yan et al. [219] reviewed the literature specifically concentrating on data mining in the construction industry. However, data mining is a subset of AI to automatically process data and retrieve useful insights. Many promising techniques beyond data mining also deserve some attention, which are capable of providing value-added services in CEM, such as the performance prediction and optimization, process mining, visual analytics, energy management, and others [22].

To tackle these existing limitations of current reviews, we aim to present a broader and more systemic review to capture the evolution and application of AI in the domain of CEM incorporating both the scientometric analysis and qualitative analysis. To sum up, the main objective of this review is to: (1) search the academic publications within the topic and perform scientometric analysis (Section 2); (2) summarize the activities and characteristics of CEM and highlight the benefits of AI in CEM (Section 3);(3) report several hot research topics of the state-of-the-art AI techniques for CEM improvement (Section 4); and (4)identify the signposts for the future researches for digitalizing CEM (Section 5).

2. Analysis of publications

In the beginning, relevant papers within the domain of CEM are retrieved to prepare our database for review. The following three criteria are adopted to guide the search of peer-reviewed papers: (1) Web of Science (WOS), Scopus, American Society of Civil Engineers (ASCE) Library, Wiley Online Library, and IEEE library are defined as the adopted academic databases for selecting targeted publications. (2) Selected keywords focus on the main concepts of this review, which can be simply divided into two aspects: one is about the AI along with its critical branches, and the other is about CEM. To make the search more effective, we also refer to some previous review papers [50,92] to identify specific keywords. These two kinds of keywords are then combined by Boolean operations. In short, a search is performed on relevant studies following the rule below: ("artificial intelligence" OR "AI" OR "computational intelligence") AND ("civil engineering" OR "construction engineering" OR "construction industry" OR "construction management" OR "construction project"). (3) Many existing reviews have built a profile of relevant publications over the last two decades, which are proved suitable to comprehend the development changes and developments within the targeted topic [92,136]. Accordingly, we set the search period from 1997 to 2020 for a meaningful investigation based on the reason below. Since 2002, due to the growth of data and computational power, the research interests gradually turn to machine learning and deep learning at a higher level of intelligence for various purposes in the construction industry. Before 2002, researches mainly concentrate on the expert system, which is the early AI-enabled method to mimic human behavior and knowledge for decision making. It is known that these works before 2002 are relatively simple and intuitive, and thus we don't have to consider them all. For controlling the number of papers, the main articles for 5 years before 2002 are retrieved as representatives. In brief, there are three more restrictions to determine the scope of publication research, including published year (1997 – 2020), document type ("Article", "Review"), and language ("English"). As a result, a total of 4,473 papers mostly related to the study area are chosen and stored in our database, which are discussed as follow.

(1) The annual number of relevant publications shows an upward trend during 1997–2020, indicating that the use of emerging AI in the construction industry is becoming a hot topic at present. It

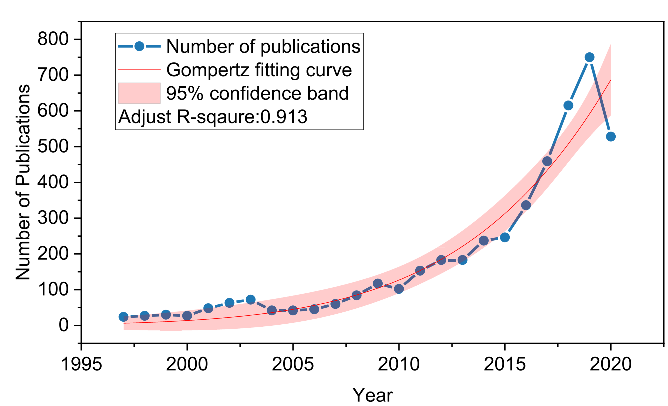

Fig. 1. Amount of publications for AI applications in CEM during 1997 – 2020.

is clear in Fig. 1 that the number of relevant publications increases rapidly year by year in the past 23 years. Around 84.78% of papers are published from 2010 onward, which means the popularity of AI-based CEM boosts especially after 2010. It should be noted that the last number 528 is only the papers published in the first six months of 2020, which has surpassed the annual publications during 1997–2018. A Gompertz function is used to fit the data well under an adjusted R-square of 0.913, which is visualized by the red line in Fig. 1 along with a 95% confidence band. When the fitted function works, it is estimated that the number of relevant publications can increase to over 700 at the end of 2020. That is to say, AI solutions in the field of CEM are gaining more and more attention under the expectation of bringing digital innovation in construction.

(2) Journals, which public more relevant papers about CEM, are more likely to be cited by other papers on similar topics. Fig. 2 visualizes the top 10 journals that provide the most number of related papers and the top 10 journals owning the most-cited papers in our prepared datasets. All the 12 journals in Fig. 2 have an impact score larger than 3.0 in the year 2020, and thus their importance can be validated. In other words, these journals contribute more to studies on the topic of AI-based CEM. As can be seen, the majority of journals owning more than 400 publications on the targeted topic are *Journal of Computing in Civil Engineering*, *Automation in Construction*, *Journal of Construction Engineering and Management*, and *Computer-Aided Civil and Infrastructure Engineering*, which take up approximately 39.48% of papers in our dataset. Also, papers from these top 4 journals are more influential, which can be cited more frequently by other selected papers. Although the number of related publications from *Journal of Cleaner Production* and *Safety Science* ranks at the 8^{th} and 9^{th} place, these two journals are not in the list of top 10 most-cited journals. Instead, *Neurocomputing* and *IEEE Transaction on Neural Networks and Learning Systems* can provide main sources of references for citations. These two journals mainly focus on a collection of new computational models and algorithms from the theory level, which can be applied in engineering practice to realize their application values.

(3) With the help of a Java-based scientific visualization tool named CiteSpace, the co-occurrence keyword analysis is performed to output knowledge maps. Keywords are the core words or phrases to capture the essence of papers, which are depicted in Fig. 3 by nodes and co-occurrence links. The size of font and node directly proportionates to the number of publications containing a certain keyword. It is clear that the top 5 keywords in the highest frequency of occurrence are "artificial intelligence", "neural network", "construction management", "model", and "machine learning". Apart from frequency, a metric termed centrality can also be calculated to measure the role of nodes in the knowledge network [121]. It turns out that these five most-frequent keywords also have a comparatively high value of centrality (0.51, 0.18, 0.38, 0.3, and 0.39, respectively), which are also likely to exert more influence on other nodes. To better understand a bunch of keywords, we can simply divide them into two parts. One is about the method, such as "artificial intelligence", "neural network", "machine learning", "fuzzy logic", and "algorithm". The other is about the purpose, such as "construction management", "design", "prediction", "optimization", and "classification".

(4) Cluster analysis is conducted by CiteSpace to discover underlying topics and research front from a large collection of papers. Since the network of keywords in Fig. 3 has a large modularity Q (0.775), it suggests that this network can be reasonably divided into several clusters for further investigation. Fig. 4 visualizes the 11 identified clusters. For a clearer understanding, Table 1 splits these discovered clusters into two groups: one concerns the method, and the other concerns the leading application areas. The silhouette scores of all clusters are larger than 0.859, indicating the great homogeneity in each cluster. In other words, the robustness and significance of the clustering results are verified. Labels derived from the log-likelihood tests (LLR) are assigned to clusters to characterize the cluster's nature. For example, the cluster named expert system (#0) is in the largest size. That is because the expert system has been proposed early since the 1970s and developed for a long time, resulting in the earliest average year of publications (2010) among 11 clusters. The current research trend of the expert system is to integrate higher-level intelligence (i.e., machine learning and deep learning) into it, allowing for automatic adjustment of the knowledge base to inform more reliable decisions [152]. By contrast, the mean year of second-largest cluster #1 is 2019, indicating that the recent hot issues have turned to the topic of digital

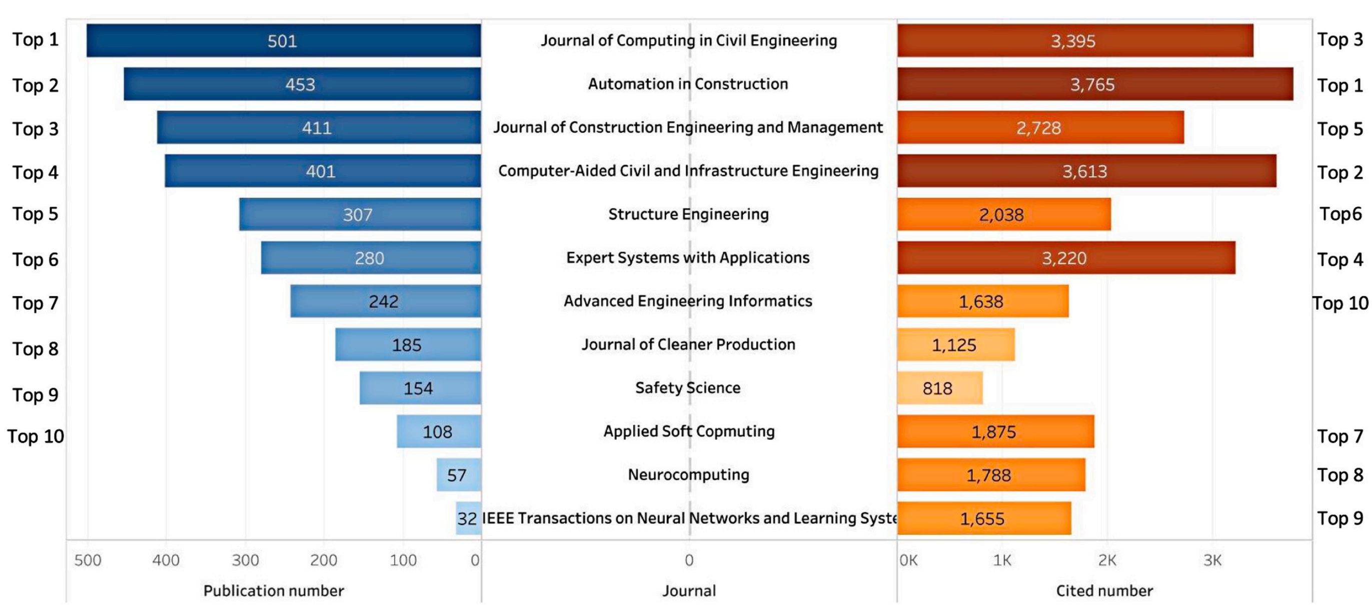

Fig. 2. Top 10 journals in terms of paper number and cited number.

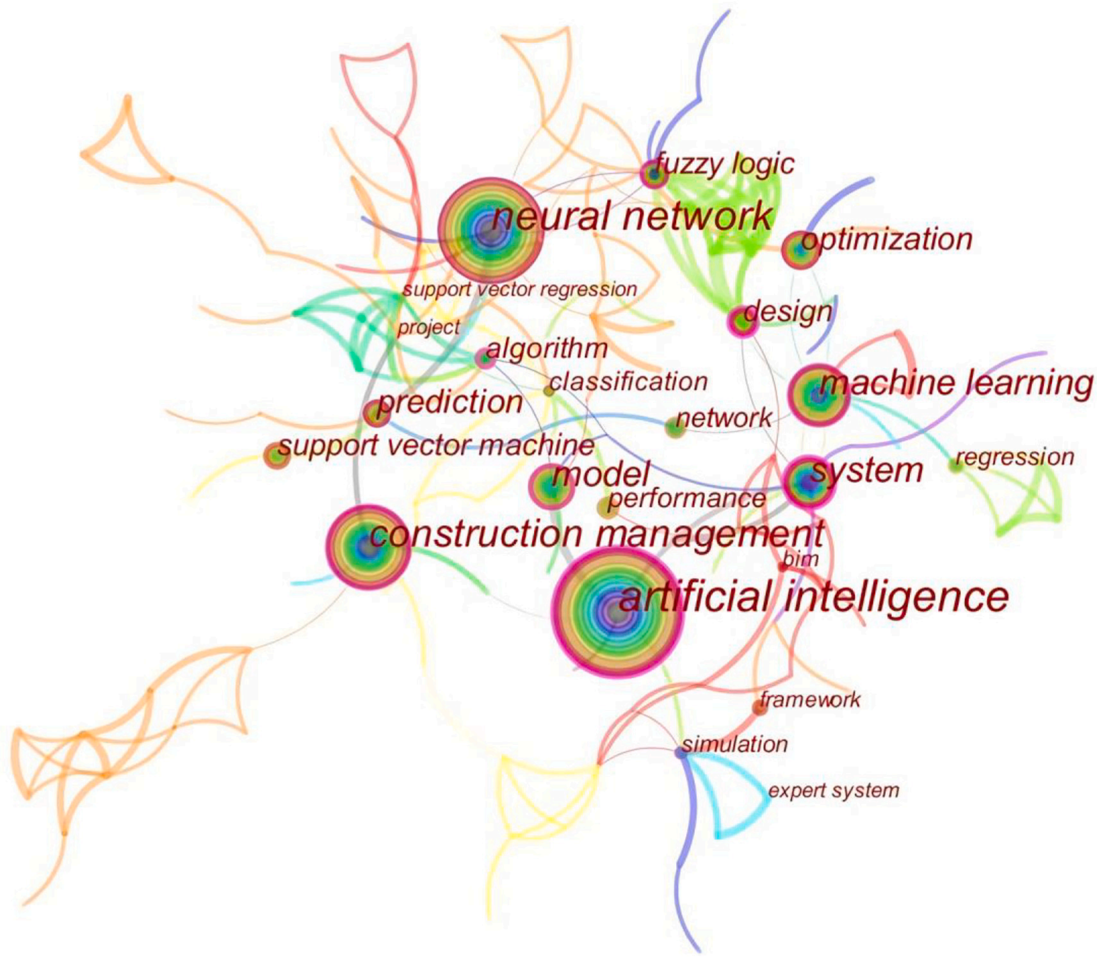

Fig. 3. Keywords of the selected papers visualized in a network.

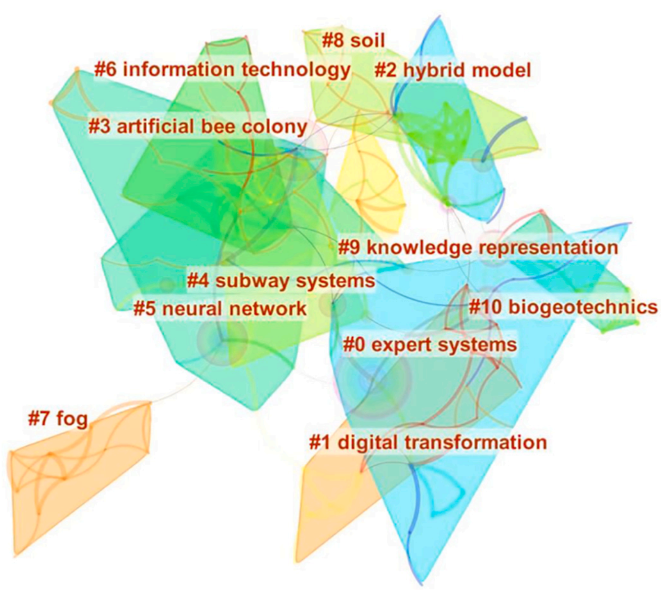

Fig. 4. Cluster map of keywords.

transformation. Ongoing efforts have been made to implement more advanced digital solutions in the real construction project, such as BIM, IoT, digital twins, and others, which are part of the growing trend in driving CEM towards digitalization, automation, and productivity.

3. Understanding of CEM

Through reviewing the relevant and latest publications, we summarize the related activities and characteristics of CEM to provide an in-depth understanding of the construction industry. It should be noted that large volumes of heterogeneous data are collected at every stage of the project especially with the advent of the BIM and wireless sensor network (WSN) to make CEM a data-intensive field. Hence, it is reasonable to perform various AI techniques to take full advantage of such data in a range of ways, which have the potential to effectively tackle the characteristics of CEM during the total project life cycle. To sum up, several benefits from AI are highlighted, which are proven to significantly advance the field of CEM.

3.1. Activities in CEM

CEM can be split into two parts: one is construction engineering, and the other is construction management. Construction engineering can be defined as a completed process including designing, scheduling, budgeting, building itself. Appropriate management over the lifetime of a project is a necessity for all sorts of construction projects, aiming to guide the project to success under the control of time, cost, scope, quality, and collaboration. Project managers coordinate closely with other participants to draw up plans, schema, timelines, costs, personnel arrangements, and others for construction management. They monitor

Table 1
Summary of the identified clusters.

Type	Cluster ID	Cluster topic	Size	Silhouette	Mean year	Alternative label (LLR)
Method	0	Expert system	19	0.896	2010	Multicriteria decision making, profiling, agreement option, decision support systems, computer programming
	2	Hybrid model	14	0.978	2013	Computational intelligence, machine learning, hybrid method, multivariate regression, fuzzy logic
	3	Artificial bee colony	13	0.949	2016	Optimization, swarm intelligence optimization, genetic algorithm, structural design, sustainability
	5	Neural network	11	0.859	2012	Neural networks, artificial neural network, fuzzy neural networks, differential evolution, crack detection
	9	Knowledge representation	9	0.888	2018	Software prototyping, intelligent agents, product individual characteristics identification, probabilistic methods, fuzzy logic
Application/ Purpose	1	Digital transformation	14	0.972	2019	Bim, industry foundation classes (ifc), big data, internet of things (iot), digital twin
	4	Subway systems	12	0.892	2016	Condition assessment, health monitoring, image processing, system identification, construction safety
	6	Information technology	11	0.876	2014	Construction cost management, control variable, communications & control systems, safety, data mining
	7	Fog	10	0.974	2019	Smart contract, smart oracle, blockchain, cloud, storage
	8	Soil	9	0.972	2017	Artificial ground freezing, water demand, hydrology, sustainable development goals, environmental science
	10	Biogeotechnics	8	1	2015	Hazardous waste disposal, groundwater potential mapping, thermal conductivity, electrical conductivity, electrical conductivity probe

the entire progress of work and concentrate on all aspects of the project (i.e., labor, capital, time, equipment, material, risk), and then give back corresponding instructions to lower the possibility of delays, budget overruns, high risks, and great conflicts. In short, the main activities in CEM can be classified into three major phases as follows.

(1) Planning: Before the start of physical construction, it is of necessity to create detailed plans for the project development concerning resources, schedule, budget, dependencies, and others. The well-prepared plans need to be fitted to a reasonable time scale and workflow, which assist in reducing cost, duration, and irrational process in the practical project. For instance, the schematic design can be drawn to fully describe the building systems. Scheduling can chronologically distribute multiple activities, and then assign dates, workers, and resources to a certain activity. Cost estimation is the process of predicting the required funds and resources for conducting a project within a defined scope. In short, the main task in the planning phase is the project plan formulation to rationally streamline the construction process, which can also serve as a reference to monitor the actual process and direct it to be finished punctually within the estimated budget

(2) Construction: This is a phase of executing the physical construction, and thus the plan made at the previous phase is expected to pay off. Construction workers and project managers are the major participants involving in the construction phase. For construction workers, they are the manual labor to perform the on-site tasks, including layout marking, excavation, foundation work, column casting, wall construction, lintel, roofing, plastering, fixing of doors, windows, electrical and plumbing works, tiles laying, painting, and others. Skilled workers are also needed to operate sophisticated machine tools. Regarding project managers, they oversee the actual construction process regarding the scope, budget, and schedule, and then compare the observations to the defined planning. If an inconsistency is detected, the corresponding action can be enacted to bring the process back into conformance or adjust plans to copy with changes. Moreover, managers are responsible for recognizing the exposure of risk and the associated impact on the performance, schedule, or budget of projects. For better quality control. these identified risks need to be analyzed in both the qualitative and quantitative view, and thus timely responses can be created to proactively address the potential issues.

(3) Operation and Maintenance (O&M): When construction is completed, the project will enter a new phase called O&M. It is known that O&M takes most of the time within the lifecycle, leading to a large amount of cost accounting for around 60% of the total project budget [74]. The goal of O&M is to operate and maintain a constructed facility to not only meet the anticipated functions over its lifecycle but also ensure the safety and comfort of users. More specifically, operation means the provision of day-to-day services to operate and control the facility in an efficient, economical, and reliable manner, while maintenance aims to minimize the possibility of system failure from two aspects. For one thing, time-based preventive maintenance detects the potential risks and adjusts the ongoing operation prior to unexpected events. For another, corrective maintenance implemented after the occurrence of problems strives to repair the problematic parts and get them back on the normal status as quickly as possible. Besides, recent attention in O&M has focused on sustainability. The execution of O&M must obey some energy regulations and standards to make the facility run long-termly, safely, and energy-savingly, and eventually improve users' satisfaction.

3.2. Characteristic of CEM

Since a construction project is unique, temporary, and progressive in nature for producing the desired objective, CEM can be considered as a process to handle a series of interrelated tasks over a fixed time period within certain limitations. According to the relevant papers retrieved in Section 2, the key characteristics of CEM are outlined from the following five points.

(1) Uniqueness: Due to the differences rooting in client requirements, project size, conditions, influences, and constraints, construction projects are varied from one another to enhance the difficulty of project management. Thus, it is unreasonable to simply replicate the scheduling, design scheme, budget, and logistics of an existing project to a new one. In addition, individuals with differing roles, including designers, engineers, suppliers, contractors, managers, and other service providers, are temporarily organized in a project. It means that each project is carried out by a unique team, and each team has its own characteristics regarding the participants' skills, knowledge, experience, communication, and collaboration. It is noteworthy that a highly customizable solution is deemed as a necessity to ensure the reliability and efficiency of the project that is very technical and characteristically unique.

(2) Labor intensive: Typically, a huge amount of manual labor will engage in a construction project, who can offer great quantities of physical effort for project implementation, timely completion, and quality assurance. It is estimated that the proportion of labor costs can

take up over 30% of the total project budget, indicating that intensive labor is a critical component in construction. For improving the performance and productivity of construction projects, there is fast growth in the demand for skilled and semi-skilled workers with rich expertise and proficient skills, and thus many efforts are needed to provide professional training. Meanwhile, another trend to release the burden from manpower costs is that unskilled workers are being replaced by automatic machines. It is envisaged that the collaboration of knowledgeable labor forces and machines is capable of driving the project forward more easily, efficiently, and safely.

(3) Dynamics: Although a project has been clearly defined from the beginning to the end, the actual execution of the project is unable to always stick to the plan. Inevitable changes or adjustments caused by various reasons will occur dynamically throughout the whole lifecycle of the project. For instance, the project alternatives need to be reformulated due to some human factors (i.e., clients' dissatisfaction, designers' and engineers' mistakes, financial problems from contractors) and unforeseen conditions (i.e., undesired delay, bad weather, complex geologic environment, additional demands of labor, equipment, and material). Besides, when any additions or reductions are applied to the project scope, the scheduling and budget should be updated accordingly to adapt to the changing circumstances. To assure the success of a construction project, managers need to flexibly identify changes and perform effective controls.

(4) Complexity: The complexity of construction projects can arise from two aspects, namely the task and participant. For one thing, construction tasks are heavy, diverse, and interconnected, which can possibly meet conflicting scheduling or performance problems. To make the operation process running smoothly, a variety of factors, such as security, environment, weather, workers, time limit, and others, should be taken into full consideration. Additionally, although the advanced technology (i.e., BIM and IoT) and new materials are adopted for more sustainable development, they are prone to contribute toward a higher degree of complexity. For another, workers with varying backgrounds, cognitive levels, and business interests will play different roles in the project, who communicate and share information with each other for a common goal. This kind of multi-disciplinary collaboration will inevitably result in intricate interactions in individuals and tasks.

(5) Uncertainty: Uncertainties are unknown before they occur, which can be regarded as unavoidable threats to raise the risk of project failure. Notably, a high level of uncertainty is inherent in complicated construction projects, which is closely related to various factors. For instance, before the site construction, scheduling and cost need to be estimated reasonably under great uncertainty. The improper estimation will impede the progress of the project. As for the architecture design, some questions about it remain to be answered, such as whether the design can pass audits, whether clients are satisfied with the design, and others. In the construction phase, a great deal of unknown uncertainty comes from the ground conditions, soil-structure interaction, weather conditions, building material properties, design changes, reliability of suppliers, and others. If these uncertainties are detected and measured in an early stage, potential risks can be mitigated to increase the likelihood of a successful construction project.

3.3. Benefits of AI in CEM

Although AI stands out as transformational technology to potentially bring about unprecedented changes in our work and life, its application in CEM with the nature of uniqueness, labor-intensive, dynamic, complexity, and uncertainty is still in its infancy. In the immediate future, the construction industry is projected to increase more focus and investment in AI. That is to say, a variety of AI methods will be utilized to well handle the rapid growth of data generation in CEM through training suitable models. It is believed that AI can deliver promises on prediction, optimization, and decision making, in order to assist the traditional construction industry to catch up with the fast pace of automation and digitalization. The substantial benefits of AI in CEM are outlined below.

(1) Automation: AI drives the process of project management more technically automatable and objective. It is proved that AI-based solutions contribute to overcoming distinct disadvantages from conventional construction management relying on manual observation and operation, which is more prone to bias and confounding. For instance, machine learning algorithms are applied to intelligently learn the mass of accumulated data for hidden knowledge discovery, which are also integrated into project management software to facilitate automatic data analysis and decision making. The insights gained from such advanced analytics help managers to better understand the construction project, formalize tacit knowledge from project experiences and rapidly spot the project concerns in a data-driven manner [89]. As for the on-site construction monitoring, drones and sensors are utilized to automatically record data and take images/videos about the construction status, environment, and progress, in order to offer a more comprehensive picture of the site through various project stages without human interaction. That is to say, evidence caught by such techniques can replace the traditional manual observation, which tends to be time-consuming, tedious, and error-prone.

(2) Risk mitigation: AI can monitor, recognize, evaluate, and predict potential risk in terms of safety, quality, efficiency, and cost across teams and work areas even under high uncertainty, which has been predominantly adopted for risk identification, assessment, and prioritization [3]. That is to say, various AI methods, like probabilistic models, fuzzy theory, machine learning, neural networks, and others, have been applied to learn data collected from the construction site to capture interdependencies of causes and accidents, measure the probability of failure occurrence, evaluate the severity of the risk from both the qualitative and quantitative view. They can effectively address the limitations of traditional risk analysis, such as the vagueness and vulnerability from specialist experience and subjective judgment. As a result, the AI-based risk analysis can provide assistive and predictive insights on critical issues, which help project managers to quickly prioritize possible risks and determine proactive actions instead of reactions for risk mitigation, such as to streamline operations on the job site, adjust staff arrangement, and keep projects on time and budget. In other words, AI presents valuable opportunities to realize early troubleshooting to prevent undesirable failure and accidents in the complex workflow. Additionally, robots can take charge of unsafe activities to minimize the number of humans working in dangerous environments.

(3) High efficiency: Another important use of AI techniques is in optimization problems, aiming to make the construction project run more smoothly and efficiently. For instance, process mining is a new AI-enabled approach to generate valuable insights into the complicated construction procedure, such as to track key workflows, predict deviations, detect invisible bottlenecks, extract collaboration patterns, and others [198]. Such discovered knowledge is critical to project success, which can guide the optimization of the construction execution process. It is expected to avoid unnecessary steps, reworks and conflicts, potential delays, and poor cooperation. In turn, tactical decisions can be made for trouble-shooting at an early stage, driving the improvement of operational efficiency. It is also effective in preventing costly correction at the remaining stage. Different types of optimization algorithms are also a powerful tool for drawing up more plausible construction plans under the optimal tradeoff among time, cost, and quality [17]. Moreover, AI-powered robots have been directly adopted on the construction site to take over the repetitive and routine construction tasks, such as bricklaying, welding, tiling, and others. They can work continuously without taking a break at almost the same rate and quality, indicating that the proper use of smart machinery will ensure efficiency, productivity, and even profitability.

(4) Digitalization: It should be noted that BIM has played the leading role in digitalizing the construction industry, which has gone far more than the 3D modeling to provide a pool of information concerning the

full project lifecycle [90]. To further facilitate the digitalization of information in intelligent CEM, BIM can be reasonably considered as a digital backbone to work with AI. For BIM, it provides a platform for not only collecting large data about all aspects of the project, but also sharing, exchanging, and analyzing data in real-time to achieve in-time communication and collaboration among various participants. For the AI techniques, they deeply explore massive amounts of data from BIM to automate and improve the construction process. The integration of BIM and AI can move the paper-based work towards online management. For one thing, it can deliver the most efficient and effective information to keep continuous updating of the ongoing project. For another, it can take advantage of BIM data to make real-time analysis, and thus immediate reactions can be performed to streamline the complicated workflow, shorten operation time, cut costs, reduce risk, optimize staff arrangement, and others.

(5) Computer vision: The automated and robust computer vision techniques have gradually taken the place of the laborious and unreliable visual inspection in civil infrastructure condition assessment. Current advances in computer vision techniques lie in the deep learning methods to automatically process, analyze, and understand data in images or videos through end-to-end learning. Towards the goal of intelligent management in the construction project, computer vision is mainly used to perform visual tasks for two main purposes named inspection and monitoring, which can potentially promote the understanding of complex construction tasks or structural conditions comprehensively, rapidly, and reliably [179]. To be more specific, inspection applications perform automated damage detection, structural component recognition, unsafe behavior, and condition identification. Monitoring applications is a non-contact method to capture a quantitative understanding of the infrastructure status, such as to estimate strain, displacement, cracks' length, and width. To sum up, the vision-based methods in CEM are comparatively cost-effective, simple, efficient, and accurate, which can robustly translate image data into actional information for structural health evaluation and construction safety assurance.

4. Research topics of AI in CEM

Various AI techniques have been developed to make machines mimic human cognitive processes in terms of learning, reasoning, and self-correcting. According to [138], the developed AI techniques are categorized into four major groups, namely the expert system, fuzzy logic, machine learning, and optimization algorithm. To be more specific, an expert system is a straightforward and understandable method towards intelligent decision making, which contains possible expert knowledge and reasoning to address complicated problems. Fuzzy logic deals with input data in vagueness, uncertainty, impreciseness, and incompleteness through converting them into computer understandable forms, and then responses are made based on a set of fuzzy rules. Machine learning is a great step of AI to teach machines how to discover patterns hidden in large data and realize data-driven predictions on future tasks. As machine learning evolves, deep learning and reinforcement learning as the new trends have been developed at a higher level. Optimization algorithm aims to locally or globally search the optimal results from a set of available alternatives. In addition, process mining is still a young discipline to bridge the gap between process management and data science. Although process mining takes full advantage of event logs with the aim of monitoring, diagnosing, analyzing, and improving the actual process, it has not yet received enough attention. Herein, we also consider the process mining techniques as an important branch of AI.

It is known that the application domains of AI could be very wide. Relying on the five important AI approaches mentioned above, we put emphasis on six hot research topics of AI in CEM, as summarized in Fig. 5. Different AI approaches have been carried out in these research topics for different purposes, such as to detect and mitigate risk, to understand the nature of the project for better planning and adjustment. What's more, these topics are highly associated with the five discovered keyword clusters belonging to AI methods in Table 1. For example, the topic of knowledge representation and reasoning is related to clusters of expert system and knowledge representation; the topics of information fusion, computer vision, and neural language processing are connected with clusters of the hybrid model and neural network; the topic of intelligent optimization is relevant to the cluster of artificial bee colony; the topic of process mining is linked to clusters of knowledge representation and hybrid model. In each research topic, we list at most five representative papers for each supporting area in tables under the selection standard that they are highly cited by other researchers or they are published in recent ten years or they are from the leading research groups. These publications serve as evidence to verify that the use of these popular AI approaches in CEM is not just a theoretical subject. The introduction of six hot research topics is detailed below.

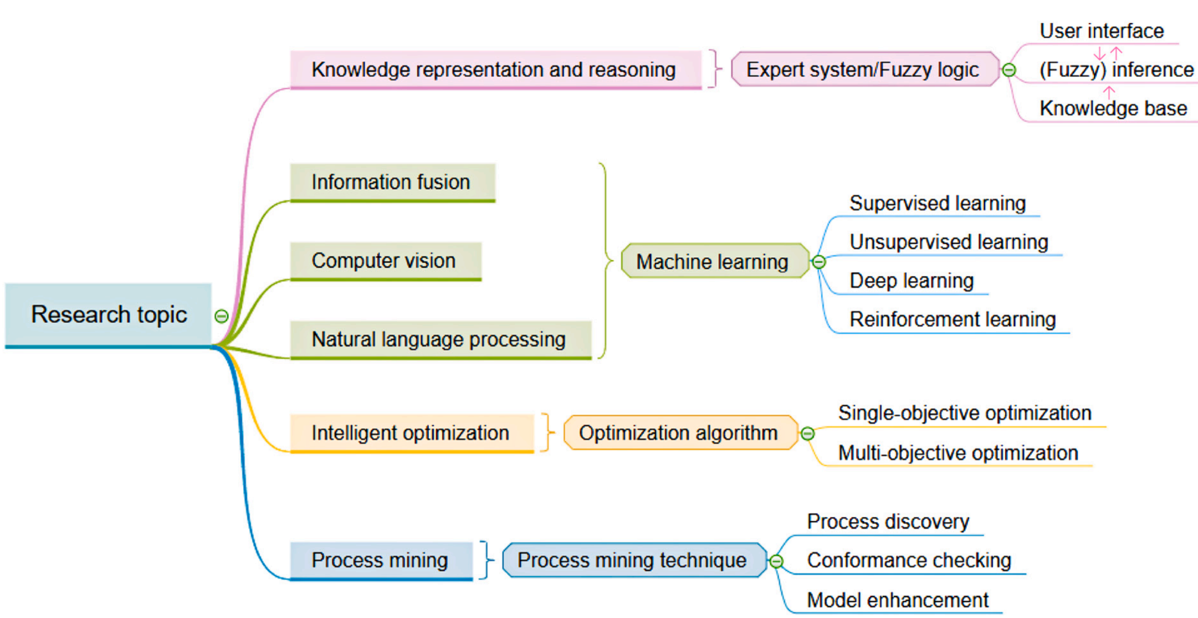

Fig. 5. Summary of main research topics and their corresponding AI approaches.

4.1. Knowledge representation and reasoning

Knowledge representation and reasoning are the early forms of AI, which adopt a symbolic representation of domain knowledge and predefined rules to build the knowledge-based system instead of complex algorithms or statistics. Computers can, therefore, rationally understand the available knowledge, facts, and beliefs from the real world, and then make use of them to draw valid conclusions and facilitate logic inference in a transparent and efficient manner. Table 2 summarizes some relevant studies in the field of CEM. Particularly, structural equation modeling (SEM) and Bayesian network are two simple and useful tools to establish measurement models for knowledge representation. To be specific, SEM introduced in the 1980s adopts the schematic diagram to describe the complicated casual relationships among multiple variables, which can also estimate associated coefficients concurrently [216]. One of the important applications in SEM is construction safety management from different angles, which is commonly integrated with exploratory factor analysis (EFA). For instance, Zaira and Hadikusumo [224] performed SEM to recognize the most impactful intervention-related safety practices for the improvement of workers' safety behavior. Liu et al. [126] combined SEM and EFA to determine the predominant risk factors and guide the safety control in the complex metro construction project. Zhang et al. [236] developed an SEM-based method to identify changeable roles of safety leadership during different phases of a construction project, which helped to better allocate duty on safety management among stakeholders.

As for the Bayesian network, it is a probabilistic graphical model with nodes as variables and links as causality. The typical approach for constructing a proper Bayesian network structure depends on either a large amount of historical data or the knowledge of engineers/experts. Apart from modeling the causal relations among attributes of uncertainty and risk, the Bayesian network can act as a powerful decision-making tool using the Bayesian inference [158]. On the one side, the forward propagation can forecast the probability distribution of the risk event under the combination of relevant factors. On the other side, the backward propagation can output the posterior probability distribution of each factor in a certain condition of the risk event. It has been widely used in modeling, analyzing, and predicting the construction project risk in terms of structural health, complicated construction environment, operation quality, contract, scheduling, cost, and others, allowing for identifying critical factors and making better decisions to minimize failure probability. For example, Wu et al. [214] performed predictive, sensitivity, and diagnostic analysis in a dynamic Bayesian network, aiming to provide corresponding preventive strategies before undesirable events occur. Leu and Chang [114] developed a Bayesian-network-based safety risk assessment to calculate probabilities of safety risks and examine causes of accidents at steel building construction projects, in order to reduce the risk of the object fall, collapse, and electrocution. Yet et al. [222] presented a Bayesian Network modeling framework to analyze risk scenarios and budget policies, which helped managers in project selection, planning, and control.

Besides, there are also many other mature approaches for reasoning purposes. For clarity, we classify some important methods demonstrating border applications in CEM into three types as follows. The first one is probability-based reasoning, which refers to probability theory with logic to indicate the uncertainty in knowledge. The fault tree analysis (FTA) and the Bayesian network are two representatives for probabilistic risk analysis and failure evaluation. The second one is rule-based reasoning, which deploys a set of rules in the "if <conditions>, then <conclusion>" format along with logical connectives, such as AND, OR, NOT, and others. As a typical method in this category, fuzzy logic is particularly useful in modeling qualitative data elicited from expert opinion and allowing reasoning with ambiguous information, which generally follows the three steps of "fuzzifying" inputs by membership functions, integrating knowledge and making inferences by fuzzy set logic, and "defuzzifying" these inferences for a final decision [93]. It has been found that to integrate fuzzy logic with the Bayesian network or analytic hierarchy process (AHP) has shown complementary strengths in risk assessment or multi-criteria selection especially when the problems are characterized by subjective uncertainty, ambiguity, and vagueness [70]. The last one is the fuzzy cognitive map (FCM) learned from data or developed by expert opinions. Under the combination of the fuzzy logic and cognitive map, this kind of fuzzy graph structure interprets complex relationships and allows systematic causal propagation, which can provide immediate understanding and identification of root causes of a risk event even under complicated, uncertain, and subjective conditions [211]. Also, the hybrid FCM with other methods, like SEM, Bayesian network, have been developed to drive the modeling process faster and determine more accurate parameters, which has been extensively used for risk analysis, decision making, and project complexity analysis [131]. Remarkably, although the above-mentioned methods are easy to implement, they tend to suffer from the high computational cost in large-scale spatial and temporal datasets.

Table 2
Some studies for knowledge representation and reasoning.

Method	Purpose	Studies
SEM	Construction safety management	[126,162,224,236,239]
	Project complexity understanding	[130]
	Optimization of construction collaboration	[217]
Bayesian network	Risk analysis and prediction in construction projects	[96,114,153,214,222]
FTA	Risk analysis and prediction in construction projects	[41,88,91,151,184]
Fuzzy Bayesian	Risk analysis and prediction in construction projects	[1,134,153,192,208,241]
Fuzzy AHP	Risk analysis and prediction in construction projects	[1,117,134,148,192]
	Multicriteria selection of construction site, contractor, supplier	[21,94,165,167]
FCM	Risk analysis and prediction in construction projects	[37,237]
	Change analysis in construction projects for better planning	[102,181]

4.2. Information fusion

A notion of the smart CEM is to use various sensors installed in civil infrastructures for data acquisition. Since this type of collected data contains a large amount of hidden knowledge, information fusion is necessarily performed to combine such data from multiple sources for better detection, inference, and characterization. In turn, promising results of an overall evaluation can be generated to ensure the efficiency, reliability, and sustainability of the project. The techniques of information fusion have been extensively utilized in multisensory environments with the following advantages. Firstly, the heterogeneous data gathered by multiple sensors are usually influenced by measurement error, sensor accuracy, environmental factors, inevitably leading to a high degree of uncertainty in practical projects. Through aggregating multiple evidence, additional informative and rich data can be generated to better tackle uncertain problems and reduce data ambiguity. Secondly, it has been found that fusing observed information can reach a higher accuracy of a classification decision than considering each sensor independently. Moreover, data fusion supports wider spatial and temporal coverage, which helps decision-makers to more clearly comprehend the observed situation and achieve more convincing predictions.

Notably, information fusion is a powerful tool especially for risk perception in construction projects. It intends to perform a credible assessment of the overall structural safety based on the integration of information from different sensors at different locations. In general, there are three levels of information fusion, namely the data level, feature level, and decision level [30]. At the data level, the information fusion process directly utilizes raw data in the form of signal refinement as inputs, such as structure vibration velocity and acceleration. It can not only offer more accurate data than the individual source, but also provide a preliminary understanding of the observed situation. At the feature level, characteristics of features are retrieved from the raw data, which are then fused into a single concatenated feature vector. These extracted features can be fed into machine learning models for further analysis. At the decision level, decisions from different data sources are integrated under specific combination rules, in order to generate more robust and accurate evaluation along with more specific inferences about the risk status. Table 3 lists some relevant works about information fusion. It can be seen that two main methods are widely used for information fusion, namely Dempster-Shafer (D-S) evidence theory and machine learning.

The D-S evidence theory is a mathematical method to combine multi-sensory information under incompleteness, inconsistency, and imprecision. As an extension of the probability theory, it adopts the basic probability assignment (BPA) function, belief (Bel) function, and plausibility (Pl) function to quantify evidence and its uncertainty. That is to say, D-S evidence theory is able to integrate beliefs from multiple sensors. One of its significant applications is structural health monitoring, which can synthesize multi-source evidence in an extremely high degree of conflict to support risk perception and assessment for single structure elements or complicated structural systems. Guo et al. [83] has verified the effectiveness of D-S evidence theory in detecting and locating even slight damage in beams and plates under noisy environments. Moreover, D-S evidence theory has been integrated into other AI techniques, such as Bayesian network [153], fuzzy theory [238], cloud model [242], and genetic algorithms [80], to achieve more satisfactory performance. Also, it should be noted that D-S evidence theory has obvious advantages over the Bayesian model: one is that it needs no prior probability, and the other is that it can well handle incomplete data.

Although D-S evidence theory is simple, it may lack accuracy and flexibility to formulate non-linear relationships in complicated problems with huge data. Currently, various machine learning algorithms have been increasingly applied in the forecasting analysis, which can learn large data from different sources and then focus on predicting new inputs [4]. In particular, the ensemble model, support vector machine (SVM), and artificial neural network (ANN) are more often used, whose performances have been compared with each other in the intelligent diagnosis of machine structure [85]. Specifically, ensemble learning methods, such as random forest, adaptive boosting, extreme gradient boosting, and others, combine decisions from multiple weak models and reach the final results by voting. SVM builds optimal hyperplanes in higher-dimensional space to search for a global solution. ANN is inspired by biological neural networks with interconnected neurons to imitate human learning processes. Similarly, machine learning embodies its great value in structural health monitoring for different purposes, such as structural damage identification and diagnosis, structure strength prediction, system reliability, and durability assessment, infrastructure maintenance, and others. Its effectiveness and robustness have been proved in a variety of civil structures, including the beam, slab, steel frame, building, dam, bridge, metro tunnel, tower, and others [175]. Moreover, some efforts have been made to develop hybrid models by integrating D-S evidence theory into machine learning algorithms, aiming to make better use of multi-sensory information and obtain higher accuracy [161,250]. Apart from structural engineering, machine learning also acts as a practical method in predicting building energy consumption, which offers data-driven guidance to formulate long-term strategies for energy planning, management, and conservation [9]. Since a lot of smart energy meters and sensors have installed in buildings to monitor their energy consumption during the O&M phase, sufficient data concerning various factors (i.e., electricity, lighting, cooling, and heating load, temperature, humanity, etc.) is available to be explored by machine learning algorithms for reaching a full understanding of building performance.

Table 3
Some studies for information fusion.

Method	Purpose	Studies
D-S evident theory	Structural health monitoring	[80,83,65,238,242]
	Fire detection and alarm	[55,215,225]
Ensemble model	Structural health monitoring	[47,56,195,223,244,247]
	Building energy consumption prediction	[13,157,194,209,210]
SVM	Structural health monitoring	[48,161,171,233,250]
	Building energy consumption prediction	[34,60,150,178,246]
ANN	Structural health monitoring	[49,79,82,146,163]
	Fire detection and alarm	[81,122,173,176]
	Building energy consumption prediction	[23,33,64,95,107,115,118,140,177,186]
Reinforcement learning	Infrastructure maintenance	[139,212,220]
	Building energy management	[106,124,125`,129,143]

4.3. Computer vision

There has been a surge of interest in the emerging topic of computer vision in construction-related projects over the last few years. Typically, computer vision takes effect in conjunction with acquisition equipment, like camera, unmanned aerial vehicles (UAVs), LiDAR, and others, to offer non-contact and remote solutions for project monitoring, and then these captured image data can be converted into actional information in a reliable, fast, and cost-effective manner [189]. Technologies aided by computer vision mainly contribute to the automatic and robust vision-based inspection, which gradually take the place of the error-prone, time-consuming, laborious, and dangerous manual observation by people. In the end, the current state of unsafe conditions or behavior in the infrastructure or construction site can be easily identified and assessed, which in turn suggests solutions to mitigate the possible hazards ahead of time [136].

Table 4 lists some studies of computer vision in CEM. It is clear that the practical goals of computer vision in CEM mainly lie in structural health monitoring and construction site monitoring. For one thing, computer vision supports the automated process of detecting and assessing the defects and damage (i.e., crack, spalling, corrosion, holes, joint damage, etc.) exiting on various types of civil infrastructure, including buildings, bridges, tunnels, roads, sewer pipes, and others, aiming to ensure the safety and serviceability of the structure systems [108]. It is helpful not only in the routine inspection for construction quality control or infrastructure maintenance, but also in the post-disaster inspection to lay a solid foundation for recovery and

Table 4
Some studies for computer vision.

Method	Purpose	Studies
CNN-based	Structural health monitoring	[16,31,36,147,226]
	Construction site monitoring	[35,54,,132]
R-CNN-based	Structural health monitoring	[32,39,53,103,218]
	Construction site monitoring	[,67,68,,187]
YOLO	Structural health monitoring	[227]
	Construction site monitoring	[104,145]
FCN-based	Structural health monitoring	[59,119,154,202,218]
GAN	Structural health monitoring	[73,135]
Point cloud-based	Construction project management	[19,182,183,197,204]

reconstruction in the afflicted district. For another, computer vision is performed for field observation, which can automatically track, recognize, predict, and assess construction resources on site, such as workers, materials, equipment, and others. Based on the continuous and automatic monitoring of unsafe conditions and behavior, safety-related information can be extracted from 2D digital images and videos to evaluate potential risk in ongoing works and site conditions timely and precisely from three views: scene, location, and action [179]. For example, Fang et al. [69] summarized the successful application areas of computer vision in detecting improper usage of personal protective equipment (PPE), exposure of hazard area, risk of falling, failure of following the safety procedure and planned workflow. Generally speaking, computer vision can provide problem-solving directions in minimizing risks before their occurrence, which greatly improves the field-based occupational safety and health during the construction procedure.

Currently, deep learning has become the mainstream method in computer vision instead of the traditional statistical models, which has a stronger ability in capturing the contextual information from images to achieve state-of-the-art results. Deep learning-based methods are mainly responsible for three tasks, namely the image classification, object detection, semantic segmentation. To be more specific, image classification is to understand an entire image as a whole by assigning a certain label to it. The classification task is often conducted by the most popular architecture named convolutional neural networks (CNNs) with three important types of neural layers, which are the convolutional layers for generating feature maps, pooling layers for reducing the spatial dimensions of inputs, and fully connected layers for creating 1D feature vector to make the classification. More advanced models have been developed based on CNN as their backbone architecture, such as AlexNet, VGGNet, ResNet, and others. Object detection aims to both identify and locate one or more unsafety conditions in an image, which can draw the bounding box around each object of interest and give it a proper label. For this purpose, the region-based convolutional neural network (R-CNN) is the basic algorithm to combine rectangular region proposals and convolutional neural network features. Some variations, like Fast R-CNN, Faster R-CNN, Mask R-CNN, are also developed to improve the poor computational efficiency of R-CNN. Another family of object detection named you only look once (YOLO) also plays significant roles, which only relies on a single convolutional network trained end to end to predict the bounding box and the corresponding probability of the class label. The goal of semantic segmentation is to semantically understand the role of each pixel in the image, and thus each pixel is given a label to precisely identify the location and shape of damage. This task heavily depends on an extension of the classical CNN called fully convolutional networks (FCNs), which adopts the fully convolutional layer instead of the fully connected layer. FCN is proven useful in learning a mapping from pixels to pixels and making predictions on arbitrary-sized inputs. Moreover, it should be noted that insufficient training images are a common problem in the actual project. Generative adversarial network (GAN) propose in 2014 can be in charge of data augmentation to improve the model performance [230].

In addition, it should be noted that the 3D point cloud is another important type of image data in computer vision to capture the accurate as-is conditions of facilities with spatial information. Many point-based algorithms have been developed to specialize in manipulating complexity and variety of point cloud arising from varying density and irregular sampling, aiming to cluster and segment such point cloud data in an efficient and accurate manner. They have also been applied to the whole lifecycle of construction projects to automatically find the objects of interest and make an evaluation of the as-built status for intelligent project management. Through 3D model reconstruction, geometry quality inspection, construction progress tracking, and performance analysis, it is expected to improve project quality, productivity, and safety [205].

4.4. Natural language processing

Natural language processing (NLP), as an important subfield of AI, mainly drives computers to process, explore, and interpret language-related data in the form of text and words, resulting in human-like natural language comprehension. The traditional manual way of studying the free-text data is prone to leave a lot of valuable knowledge unexplored. For this concern, NLP is increasingly adopted to replace the tedious human oversight, which can make sense of the textual information in great volumes under less labor cost and fast speed. Since the construction industry is information-intensive, NLP has the potential to deeply investigate lots of text files accumulated in the domain of CEM for supporting the management of construction projects and engineering information. Noteworthily, a growing interest of NLP is appearing in the domain of CEM to improve construction safety, which intends to retrieve important information from the safety reports and make content analysis for better interpretability and less ambiguity.

Typically, safety reports are in the unstructured or semi-structured free-text data format, which documents undesired construction incidents along with detailed information, like events, time, location, causes, injuries, and others. With the help of NLP, valuable and regulatory information can be efficiently extracted from a high number of unstructured textual reports. Managers can, therefore, learn lessons from the incident precursors to achieve amelioration of construction safety control and assessment. For one thing, dangerous behavior and factors can be easily identified and classified at an early stage for the post-event analysis, and thus human intervention can be performed in time to lower the risk in construction sites and procedures. For another, it can also make convincing predictions on the potential hazards that are prone to occur in future events, such as workers' injury and fatality, equipment damage, abnormal process or conditions, and others. It allows managers to take proactive actions to prevent the re-occurrence of similar accidents.

In essence, the NLP-based risk analysis can be considered as a task of classifying causations leading to construction accidents and retrieving similar risk cases, which has been commonly realized by some popular machine learning algorithms. Marucci-Wellman et al. [137] carried out four machine learning algorithms, namely naïve Bayes, single word and bi-gram models, support vector machine, and logistic regression, to classify text of injury narratives from large administrative databases for injury surveillance and prevention, all of which could reach more than 30% accuracy compared to manual review. Besides, ontology is another useful method to conceptualize the terms, their conceptual dependencies, and the associated axioms. Since it relies on meaning and rules to automate the information extraction and content analysis, it has been proved effective in avoiding the relatively opaque nature of machine learning [193]. However, there are two obvious shortcomings in the machine learning and ontology-based models: one is that they tend to be inefficient due to the great human effort in preparing features and rules; the other is that their classification performance cannot always be ensured due to the weak generalization. As an alternative, some deep learning-based approaches have also been proposed for NLP, which can extract feature representations automatically and show promising improvements in capturing arguments and their underlying relationships from textual documents. For example, Zhong et al [245] designed a novel framework incorporating deep learning and text mining for the purpose of more than topic identification and hazard classification, which could also build word co-occurrence networks to reveal hazard patterns and track hazard dynamic evolution over time for accident prevention. Except for handling construction accident reports to ensure site safety, NLP techniques can also be conducted to convert other unstructured documents with different contents into understandable and actionable information for various goals, such as to automatically assign workforce, check the compliance of BIM-based building designs recorded by IFC schema with building codes, extract energy requirements from energy conservation codes, and others. Some studies about NLP applications are listed in Table 5.

4.5. Intelligent optimization

Intelligent optimization is a task of searching for the optimal solution to minimize or maximize an objective function subjected to a set of constraints. Typically, the optimization problem can be divided into two types: the simple version is the single objective optimization to identify a single optimal alternative; while the complex one is the multi-objective optimization to simultaneously optimize more than one objective function and then return a feasible set of decisions. It is known that the determination of the most optimal solution in engineering practice under high complexity, interdependency, and nonlinearity could be cumbersome and time-consuming. To ease such a process, various types of meta-heuristic optimization methods developed in the past several decades appear to be the prospective alternative. They can take less time in determining the acceptable near-optimal solutions, which are especially suitable in complex nondeterministic polynomial time-hard problems and multi-objective optimization problems through seeking the balance between intensification and diversification of the search space [77]. In particular, some meta-heuristic optimization methods, such as genetic algorithm (GA), simulated annealing (SA), particle swarm optimization (PSO), shuffled frog-leaping algorithm (SFLA), firefly algorithm (FA), differential evolution (DE), artificial bee colony (ABC), ant colony optimization (ACO), have been extensively used in the domain of CEM, which are proven to own merits of simple implementation, efficient computational time, robustness, and global optima selection. Hybrid models to integrate these methods have also been proposed to further improve the optimization performance.

In Table 6, the optimization techniques play critical roles in decision making across the entire lifecycle of a complicated construction project. Firstly, optimization is proven useful in addressing the issue of prioritizing tasks and allocate proper crews/resources under conflicts and limitations [61]. As summarized by [11], the optimization-based scheduling approach intends to maximize the labor stability, minimize the completion time and cost, balance workload, and analyze the dynamic demand over the course of the project. In other words, time-cost-quality trade-off in construction schedules can be well handled and quantified, contributing to the increased productivity, flexibility, quality, work continuity, and collaboration towards the smooth completion of the construction task. Secondly, optimization is a prospective alternative for the structural design problems, which can effectively deal with a series of design constraints to identify suitable truss size and shape, reinforcement layout, and others. In general, the main problem is raised to minimize structural mass or maximize load capacity subjecting to stress, displacement, and/or natural frequency constraints, aiming to design optimal structure with notable stiffness, ductility, reliability, and long service life [28]. From references listed in Table 6, it can be seen that several experiments have been applied successfully in both the basic truss and complex structural systems. Also, optimization can dynamically update the structural model considering uncertainty from material properties, structural geometry, and others, aiming to predict structural responses matching the reality well. Thirdly, the construction site layout planning also involves optimization. This topic can be interpreted as a decision-making process to determine the feasible location for a set of interrelated facilities under multiple constraints from the shape and boundary of the site and intricate interaction of various activities and workers, in order to meet design requirements, maximize design quality, and minimize design cost [123]. By tracking on-site vehicles and labor along with the demand and location of equipment and material, a dynamic layout model can be developed to further ensure the safety, productivity, and cost-efficiency of the construction process in real time. Noted that, the synergy of BIM and optimization becomes popular at present, which provides valuable opportunities for automatic generation, visualization, and simulation of the optimized solutions and layout scheme [10,201]. Lastly, the importance of optimization has been highlighted in identifying optimized solutions for developing cost-optimal and nearly-zero-energy buildings with less computational effort [84,174]. For long-term sustainability, problems need to take into account multiple criteria, variables, and constraints to improve the building energy consumption, greenhouse gas emissions, operation and retrofit cost, indoor thermal comfort, lighting and HVAC systems, renewable energy systems, and others, which can ultimately guide the energy renovation interventions and building upgrading.

Table 5
Some studies for NLP.

Method	Purpose	Studies
Machine learning model	Construction safety report analysis	[40,44,78,137,229]
	Staff arrangement	[142]
	Stakeholder opinion mining	[133]
Ontology-based model	Construction safety report analysis	[42,193,232,249]
	Energy requirements extraction from codes	[248]
Deep learning model	Construction safety report analysis	[,228,245]
	Integration with BIM for code checking	[188,231]

Table 6
Some studies for intelligent optimization.

Method	Purpose	Studies
Single-objective optimization	Construction project scheduling	[12,72,116,144]
	Structural design	[28,29,71,100,190]
Multi-objective optimization	Construction project scheduling	[8,61–63,105]
	Structural design	[18,43,75,164,166]
	Dynamic model updating	[170,180]
	Construction site layout planning	[2,101,111,149,201]
	Energy efficiency decision-making	[15,51,52,113,174]

4.6. Process mining

Process mining is relatively a young research discipline belonging to a sub-area of AI techniques. Since process mining is devoted to exploring event logs, it can be regarded as a connection between event logs and the operational process. As a result, it can provide transparent and fact-based insights from real event logs for better process monitoring and control. The research topic of process mining can be grouped into three major types, which are process discovery, process conformance, and process enhancement [198]. In other words, event logs can be learned to automatically create process models as a reflection of the actual process and calculate process metrics. Then, a wide range of analytical methods can be carried out in the discovered process model to detect possible problems (i.e., inefficiencies, bottlenecks, and other weaknesses) and capture characteristics of the organization in the process. Consequently, process mining assists managers to quickly point at the key parts of the process and inform data-driven decisions for strengthening operations and accelerating the process.

Some software products for process mining are available to efficiently convert event logs into process-related views and deliver insightful analytics, such as the ProM framework, Disco (Fluxicon), Celonis, ARIS Process Mining, Myivenio, and others. The first task of the software is to create a visual map to clearly describe the step-by-step process, which is followed by more advanced analysis in the model to realize functions of diagnosis, checking, exploration, prediction, recommendation, and others. With the help of software, process mining is not merely a theoretical subject, which has been put into industrial practice, such as healthcare, business, education, manufacturing, and others [57]. According to a recent survey, the top benefits of process mining techniques are associated with objectivity, accuracy, speed, and transparency [6]. It is worth noting that the starting point of process mining is the event log, a special data type containing process-specific information, including cases, activities, persons, and time, to capture flows of activities in the chronological order. Since the growing use of BIM applications can also generate great volumes of computer-generated event logs, it is reasonable to expand process mining to CEM for knowledge discovery and decision making.

To further maximize the strength of BIM event logs, some researches as outlined in Table 7 have performed process mining-based approaches to automatically discover critical processes in BIM-enabled projects, which can provide the basis for process analysis to explore participants' behavior and work process objectively. For example, Kouhestani and Nil-Bakht [110] retrieved the as-happened design process from log data based on process discovery algorithms, which was then deployed to build process models to strongly support managers in understanding and analyzing the BIM project execution. Hattab and Hamzeh et al. [7] built an agent-based model and social networks to simulate the way the communication and behaviors of design teams perform in a BIM-based design process, and then the established model was carefully examined for proactive design management. Commonly, there is hidden knowledge about productivity, bottlenecks, process deviations, social networks of actors behind such event log data. It means that the full potential of the BIM event log can be harnessed from the data layer. Some researchers have paid attention to knowledge discovery towards better management of the design phase. For example. Yarmohammadi et al.[221] and Zhang et al. [240] extracted implicit command execution patterns to evaluate design productivity. Pan et al. [155,159] utilized novel clustering algorithms to retrieve inherent insights into design behavior at both the individual and team level, in order to strategically plan the work schedule. Pan et al. [160] and Zhang et al. [235] built social networks to describe the collaborative design among designers, which could capture characteristics of the sociological network and designers' performance to further enhance cooperation. Pan and Zhang [156] built the long-short term memory neural network to learn design command sequences, resulting in accurate predictions about the three most possible incoming commands to guide the design process. In brief, all the promising analysis and results show that the exploration of complex processes in a data-driven and systematic manner offers unprecedented opportunities to understand the BIM-enabled projects. Based on measurement, diagnosis, prediction, and benchmark of productivity and collaboration from the log data, proper decisions can be expectedly informed to formulate suitable collaboration strategies and work arrangements toward a more efficient and sustainable modeling process.

5. Future research trends

In the future, CEM will continue to undergo rapid digital transformation. It is evident that more and more advanced technologies inspired by AI will be implemented and spread to the entire lifecycle of the project (i.e., design, construction, O&M). As outlined in Fig. 6, we focus on six important directions to further tackle a diversity of existing issues in laborious, complex, or even dangerous tasks within the CEM domain. For one thing, the first three topics, namely smart robotics, cloud VR/AR, and AIoT, are usable, efficient, and strongly linked to the built environment for safety enhancement and evaluation, operational performance improvement, and others [66,120,191]. At present, most of the relevant studies are still conceptually proposed. To accelerate extensive applications toward a growth phase, it is believed that the interest in these three topics will keep on the rise and become more acknowledged. Moreover, the new development is to connect them with BIM to constitute the more advanced systems for a higher level of automation, interoperability, and intelligence. For another, the last three research areas, namely the digital twins, 4D printing, and blockchain, are emerging topics from innovations of the manufacturing and financial industry. The possible hotspots in the near future are to extend the last three topics to the construction industry in the pursuit of the long-term sustainability of projects. Herein, we regard these six identified future directions of CEM as the key technological innovators to further embrace the innovation in construction. The tremendous potential of these future directions lies in paving a more affordable and effective way to relieve the burden on manual labor and facilitate smart construction management, as presented below.

(1) Smart robotics

Smart robotics have been progressing rapidly to drive a wide range of semi- or fully-autonomous construction applications. There are two broad types of robotics, namely the ground robots and aerial robots [14]. For instance, construction robots in different functions have been developed based on human requirements, which can automate some manual processes and take over repeatable tasks, such as brick-laying, mansory, prefabrication, model creation, rebar tying, demolition, and others. In other words, robots make it easy to transform low-level components (i.e., steel, wood, concrete, etc.) into high-level building blocks. Also, robots can be in charge of some high-risk tasks to protect workers from work-related injuries and accidents. Thus, there are several foreseeable benefits of such robots, including to address the labor shortage, to lower operation costs, to ensure overall quality, productivity, and safety. Regarding the aerial robots, unmanned aerial vehicles (UAV) carrying image acquisition systems (i.e., camera, laser scanner, go-pros) are typical representatives. They are the rising trend in land survey, site monitoring, and structure health monitoring, since they can make the procedure easier, safer, more efficient and affordable. Instead of the manual inspecting, UAVs fly over the construction site or even fly into the building structure to take high-resolution images, capture real-time videos, conduct laser scanning remotely, in order to maintain the safety of employees and detect structure defects (i.e., cracks, erosion, blister, spall, etc.). Moreover, machine learning can be deployed to train robots, and thus robots with talent can act more intelligently by learning from a simulation. An issue in the current state is that the adoption of smart robotics has not reached a large scale and the approaches of construction automation remain at the seed phase [24]. Therefore, continued effort needs to be put to enhance robot usage by equipping the robot systems with more powerful abilities and merging them into the built environment. As the robot technology becomes increasingly ubiquitous, robots will be used for performing more professional tasks in unstructured environments, which is expected to bring opportunities for future construction automation.

(2) Cloud virtual and augmented reality (cloud VR/AR)

The evolutionary path of VR/AR is towards the cloud. Based on the fifth-generation (5G) networks and edge cloud technologies, cloud VR/AR solutions have appeared to speed up VR/AR applications and improve users' experience. For one thing, VR/AR performs as the information visualization technology to realize more interactions between the physical and cyber worlds, where VR simulates the entire situation and AR integrates the information about the real entities with computer-

Table 7
Some studies for process mining.

Method	Purpose	Studies
Process discovery and diagnose	Build process models to describe the as-happened process and make the diagnosis to discover potential reasons for failure and delays	[7,45,109,110]
Pattern extraction	Retrieve the most frequent command sequences for productivity monitoring and evaluation	[155,159,221,240]
Social network analysis	Discover social networks in the design process to increase collaboration opportunities	[160,235]
Time-series analysis	Make intelligent design command predictions towards automation and intelligence of the design process	[156]

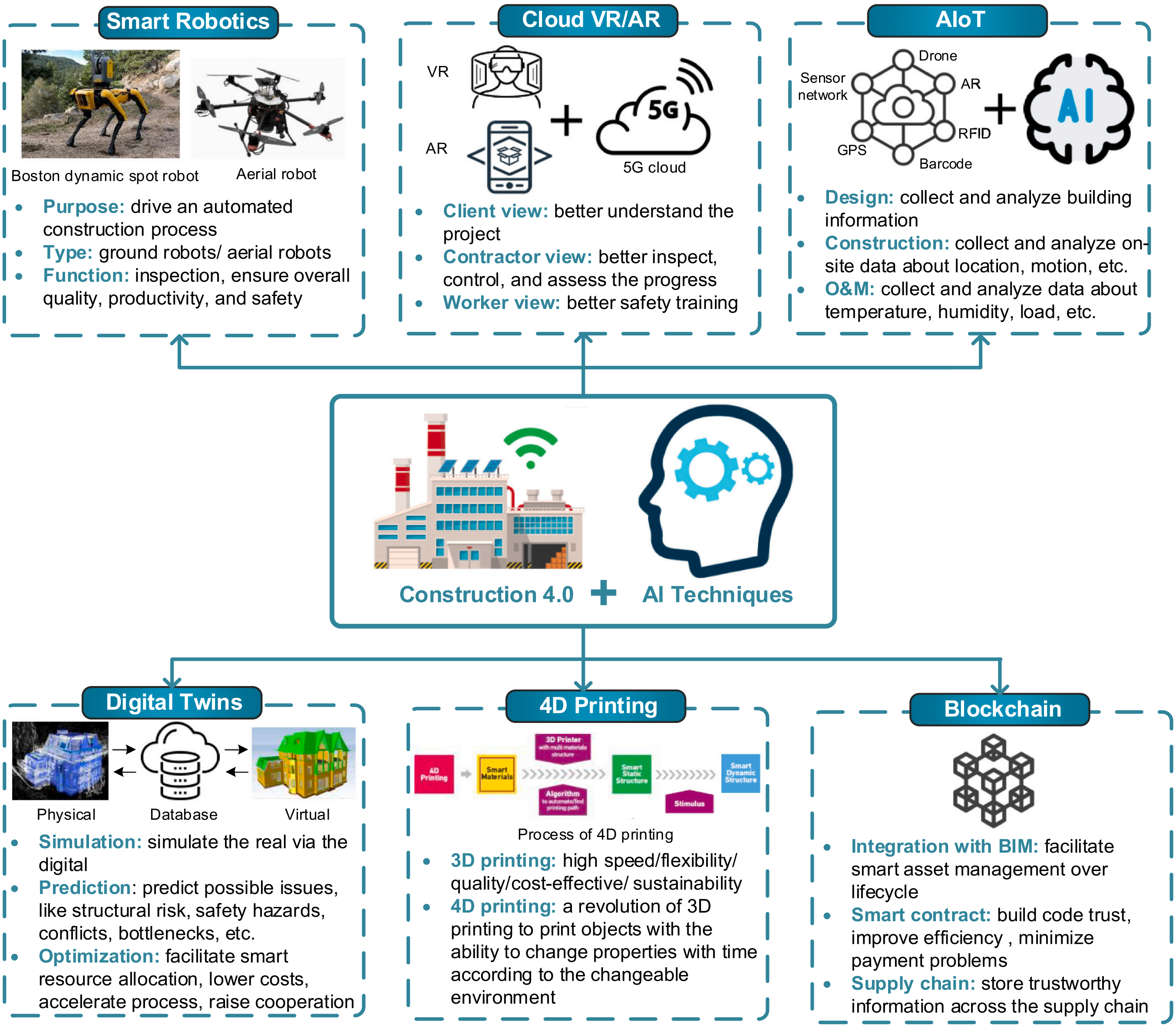

Fig. 6. Future directions of AI in CEM.

generated images. Due to the merit of providing an engaging and immersive environment, VR/AR has been tentatively applied to simulate hazardous construction scenarios, which helps managers to easily recognize underlying dangers and issues in the working environment and then formulate reasonable plans and measures ahead of accidents in a visual and interactive way [120]. Another common adoption of VR/AR emerged in recent years is construction engineering education and training [203]. Instead of courses taught by professionals, VR/AR technologies can well train workers on the basis of both visualization and experience in real time, aiming to strengthen workers' cognitive learning and safety consciousness and even raise overall productivity. For another, the 5G evolution is fast enough to stream VR and AR data from the cloud. That is the say, the significant advances of cloud VR/AR root in cloud computing and interactive quality networking, which can effectively strengthen the data processing capability from the local computer to the cloud and then make real-time perception along with responsive interactive feedback. As for the future work about construction safety instruction and evaluation, it is desired to design a cloud architecture of VR/AR under the integrated applications of virtualization, cloud computing, edge computing, AI techniques, network slicing, and others. As expected, it can rapidly process imagery data from different cloud VR/AR services for supporting a rapid and automatic process of as-built model generation, and thus the immersive and intuitive scene information can be revealed for risk evaluation. Moreover, another potential topic is to configure cloud VR/AR with BIM to further maximize the value of BIM. The integration of cloud VR/AR and BIM can visualize and immerse the physical context of the construction activities into the real environments, which is expected to bring various benefits, such as to make the complex interdependencies between tasks more explicit, to make people literally walk into buildings for a better understanding of the project, facilitate onsite assembly with fewer unnecessary mistakes, and others [206,207].

(3) Artificial Intelligence of Things (AIoT)

AIoT is the new-generation of IoT, which incorporates AI techniques into IoT infrastructure for more efficient IoT operation and data analysis. To be more specific, IoT can be defined as a network of interconnected physical devices, like sensors, drones, 3D laser scanner, wearable and mobile devices, radio frequency identification devices (RFID), which is attached to construction resources to collect real-time data about the operational status of the project. Many studies have focused on developing some smart IoT-based sensing systems to feasibly track the progress, monitor the worksite, which are expected to support continuous project improvement and accident prevention [99]. In the meantime, the huge amount of recorded data can be shared over a network, and then be analyzed deeply by various AI methods to offer actional insights for better supervision and decision making. In other words, AIoT solutions for the construction industry rely on real-time data transformation and instantaneous data analysis. Since AIoT is empowered by AI, its superiority over the traditional IoT lies in providing analysis and control functions for intelligent decision making. Through synthesizing and analyzing data collected via IoT infrastructure in unprecedented volumes and rates, it can automate the real-time decision making at an operational level to remotely control the construction worksite, optimize the project performance, and predict future conditions for the maintenance planning [38,127]. However, the practical use of AIoT is still in the startup phase, since this new technology still has some wrinkles to work out, like the edge computing issue, security issue, and others. Besides, a literature review reveals that the BIM-IoT integration is increasingly beneficial in several prevalent domains, like construction operation and monitoring, health and safety management, construction logistics and management, facility management [191]. That is to say, BIM offers an information delivery and management platform, while IoT provides a steady flow of time-series data. Accordingly, it can be envisioned that the synergy between AIoT and BIM under 5G wireless communication will become the hot spot in future works, which can considerably promote the efficiency of the data collection, data transmission, data processing based on cloud computing towards smart home, smart city, and smart construction industry [142].

(4) Digital twin

The digital twin is a realization of the cyber-physical system for visualization, modeling, simulation, analyzing, predicting, and optimizing. It incorporates three key components, namely the physical entity, virtual entity, and connection of data, to form a practical loop [141]. Typically, there are two ways of dynamic mapping in the digital twin [169]. On the one hand, inspection data is collected in the physical world, which is then transferred to the virtual world for further analysis. On the other hand, simulation, prediction, and optimization are performed in the virtual model by learning data from multiple sources, which can provide immediate solutions to guide the realistic process and make it adapt to the changeable environment. As evidence from literature [25], more attention has been paid to the inclusion of BIM, IoT, and data mining techniques into the digital twin, aiming to deliver smarter construction services. More specifically, BIM as a digital representation can be the start point of the digital twin, and the web-based integration of IoT gathers a large amount of data to enrich BIM. Both the as-built and as-designed models can be accessible in the digital twin, where information from these two parts can continuously exchange and synchronized. To maximize the strength of data, various data mining and AI techniques are leveraged to make digital twins generic across the board domains for automated monitoring of site progress, early detection of potential problems, optimization of construction logistics and scheduling, value chain management of the construction company, evaluation of structural health, and others. Due to industry trends, the research attempts on the development of digital twins will continue to increase. Except for the buildings and other infrastructure assets, the next point can focus on the practical use of digital twins under cloud computing and IoT-based services at the city level integrating heterogeneous subassets, like buildings, utilities, transportation infrastructure, and people [128]. Besides, VR simulation can be paired with the human-centered digital twin to model, monitor, and predict a person's cognitive status, which is expected to become a key component of the future infrastructure equipped with smart information and communication technology in smart cities [58].

(5) 4D printing

The emerging technology called 4D printing adds the fourth dimension from time into 3D printing, enabling the 3D printed objects to change their shape and behavior over time in response to external stimuli, like heat, light, temperature, and others. It is notable that 4D printing inherits all merits from 3D printing (also known as additive manufacturing). 3D printing relies on a computer-controlled machine guided by digital 3D models to produce objects layer-by-layer with some promising advancements as follows [112]. Firstly, the 3D printer can work automatically and efficiently with little human surveillance, which potentially shortens the project duration from weeks or months to a matter of hours or days. Secondly, the 3D printer is more flexible in creating curved walls and roofs and other unstandardized shapes. Due to the great geometric freedom, more sophisticated designs and structures can be easily built and customized with no restriction of the usual fabrication. Thirdly, the materials for 3D printing can be empowered with special features, such as great tensile strength, corrosion resistance, high-temperature resistance. This kind of optimized material with controlled mechanical behavior helps to raise the durability of buildings. Lastly, most materials used are recycled, organic, and eco-friendly, leading to great sustainability. The number of materials can be estimated accurately to avoid unnecessary waste and decrease material costs. Although there are more and more construction projects based on concrete, polymer, and metal additive manufacturing applications since 2012, many of them are not performed for commercial use [26]. To further promote the practical application of 3D printing, problems that need to be settled include to control structural safety, to conduct architectural paradigm shift, to develop a rational and digital design workflow. Notably, 3D printing is now moving towards 4D printing involving the time dimension and intelligent behavior. The big breakthrough of 4D printing over 3D printing is its intelligent behavior in transforming configurations for self-assembly, multi-functionality, and self-repair. 4D printing in construction is currently in its experimental stage, which has imposed some fresh challenges, such as the great demand for digitally savvy engineers, advanced computational analysis, new ideas in design and structure verification [27].

(6) Blockchain

A nascent technology called blockchain is a powerful shared global infrastructure, which is originally utilized for simplifying and securing transactions among parties [196]. Basically, the concept of blockchain can be explained as a verified chain with blocks of information, and each block embodies data associated with processes in a trusted environment. That is to say, history data along with modifications can be saved across a network and protected by cryptographic technology. Since the blockchain builds a distributed ledger, all users of the network can access the stored digital information concurrently. Once a block is entered and verified, no modification is allowed in the information. In the same way, blockchain in construction can aggregate the adaptable and scalable knowledge into a shared dashboard, and thus the project management systems can be converted into a more transparent and secure practice. As literature shows, the key opportunities of blockchain in CEM lie in the built environment for smart energy, cities, government, homes, transportations, and others, which are still insufficiently developed [185]. For example, blockchain can be served as a decentralized, transparent, and comprehensive database for the improvement of built asset sustainability, resulting in a more inclusive and reliable process for the project lifecycle assessment [185]. It can also be combined with BIM to collect large data from various stages of the project and share data securely among stakeholders, aiming to support life-cycle project management [200]. The BIM model can be updated timely when it receives the next block of information. Therefore, project delivery can become automated and streamlined, achieving improved productivity, trustworthiness, and cost. In addition, the creation of a smart contract written into code is another critical application of blockchain to enforce the expected behavior by itself and reduce payment fraud [5]. The process will only be executed when the corresponding criteria are satisfied, resulting in high accuracy, compliance, transparency, cost-effectiveness, and collaboration in activities, like payment, contract administration, and others.

6. Conclusions

Recent decades have seen the rapid development of digital technology and the growth of big data in the old construction industry. In particular, the adoption of AI has gained significant attention, which tries to equip machines with human-like intelligent behavior and reasoning. It is found that various AI techniques have created tremendous value in revolutionizing the construction industry, leading to a more reliable, automated, self-modifying, time-saving, and cost-effective process of CEM. In contrast to traditional computational methods and expert judgments, the promising AI is superior in dealing with complex and dynamic problems under great uncertainty and intensive data, which is more likely to return accurate and convincing results for tactical decision-making. The contributions of this review are: (1) To provide a basic understanding of CEM and reveal the potential value of AI in supporting and improving CEM. (2) To capture and discuss the state-of-the-art researches related to AI applications in CEM, which provide strong evidence to highlight the benefits of AI techniques in providing intelligent solutions by learning from previous data even with incompleteness and uncertainty in an automatic, efficient, and reliable manner. (3) To depict the evolution of research trends in the future, which help researchers to appreciate these prominent future works in AI-enabled CEM and seek further research opportunities for the more widespread leverage of AI in CEM.

Within the context of CEM, AI has been found to automate and accelerate the process of learning, reasoning, and perceiving from large data, which exhibits huge potential in tackling different engineering projects according to their own characteristics. That is to say, the AI-based solutions in construction projects are different from one another. As expected, strategic decisions that are suitable for a certain project will be informed without human intervention under complicated and uncertain environments. Besides, this kind of tactical decision making can possibly be adapted to the changeable conditions to optimize the project operation continuously for delivering smarter construction management throughout the full project lifecycle. Hence, it can be reasonably considered that the practical value of these relevant research topics lies in addressing challenges arising from characteristics of CEM, including uniqueness, labor-intensive, dynamics, complexity, and uncertainty. In general, AI makes sense of big data to yield deeper insights following three basic steps, including data acquisition and preprocessing, data mining based on appropriate models, and knowledge discovery and analysis. Different AI-related approaches can eventually achieve three major functions presented below, which are beneficial to CEM in terms of automation, risk mitigation, high efficiency, digitalization, and computer vision.

(1) Modeling and pattern detection: Modeling is a process of creating conceptual models in a standard, consistent, and predictable manner. Since modeling is the key prerequisite for further knowledge interpretation and reasoning to resolve complex construction problems, the quality and reliability of the established model will have a significant impact on analytical results. Various knowledge representation methods based on rules, logics, and schemas have been developed for building the research model in an understandable form for computers. Also, the model is supposed to incorporate rich information of the real project, including declarative, procedural, structural, meta, and heuristic knowledge. Another direct way of information extraction from data is patten detection, which can detect and retrieve critical patterns and regularities hidden in large data with ease and automaticity. In other words, pattern detection can simplify the complicated problem by decomposing it into small pieces and return outputs only based on characteristics of data itself, which has demonstrated application potential in process mining, computer vision, NLP, and others. For instance, process discovery algorithms can automatically define and map the end-to-end construction process into a clear process model in the digital representation, which can then act as a foundation for fact-based analysis to improve the process. Besides, pattern recognition is especially useful in extracting features from images or videos, which can automatically identify damage-like, crack-like, unsafety condition-like patterns for infrastructure condition assessment and construction safety assurance.

(2) Prediction: The AI-powered analytic based on machine learning is typically a prediction task, which learns from given sets of historical data to make precise predictions for new observations. Specifically, the supervised learning for classification or regression can assign the class label to data or predict future data value and trends. The purpose of unsupervised learning for clustering is to separate data points without labels into several meaningful clusters, and data in the same group owns similar traits. As for the construction industry, the prediction is also an important strategic task for project control instead of empirical methods. In particular, AI is expected to classify, quantify, and forecast potential risks related to project performance and their relevant impacts, in order to conduct reliable diagnosis and analysis ahead of time concerning broad aspects of the project performance, like planning, constructability, safety, productivity, and others. The predicted results can, therefore, serve as the baseline knowledge to guide proactive management, aiming to ensure the effectiveness and reliability of the project towards its goals. For instance, since undesired delays will inevitably lead to low efficiency, cost overruns, and other negative effects, the prediction of possible delays in the construction process can help in uncovering key factors related to bottlenecks and pursuing high-accuracy estimation in project duration. Under the comprehensive consideration of numerous factors along with their interrelationships, AI assists in precisely perceiving the safety risk of structure systems in advance even under uncertainty and dynamics.Accordingly, immediate actions can be taken to copy with the possible risk to reduce the likelihood of the risk event occurring.

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(3) Optimization: Optimization can be considered as a decision-making process for seeking and delivering practical sustainable solutions to the construction project. By maximizing the expected effects, optimization can make a process perfectly adhere to a set of criteria and constraints. Typically, popular meta-heuristic optimization algorithms, such as GA, SA, PSO, and others, have been widely applied for construction project planning, construction, and maintenance. They can constantly provide recommendations to not only minimize duration and cost but also maximize productivity and safety. For example, based on optimized project objectives, proper plans in terms of strategy, operation, and schedule can be formulated at the planning stage as an important premise for project success. At the phase of executing construction tasks in a complicated site, optimization assists in better allocating resources, arranging staff, determining layouts of facilities, and making corresponding adjustments in a reasonable and timely manner. Lastly, O&M optimization intends to both run the day-to-day operational tasks responsibly and perform maintenance measures suitably at optimal cost, which can keep the infrastructure in a satisfactory state. It also contributes to reducing waste and building energy consumption to support sustainability.

Declaration of competing interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property. We declare that they have no competing interests.

We confirm that the manuscript has been read and approved by all named authors.

We confirm that the order of authors listed in the manuscript has been approved by all named authors.

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