Heliyon 10 (2024) e26888

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Review article

Artificial intelligence and machine learning applications in the project lifecycle of the construction industry: A comprehensive review

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ARTICLE INFO

Keywords:
Artificial intelligence
Machine learning
Project lifecycle
Construction industry
Construction management
IoT

ABSTRACT

The construction industry faces many challenges, including schedule and cost overruns, productivity constraints, and workforce shortages. Compared to other sectors, it lags in digitalization in every project phase. Artificial Intelligence (AI) and Machine Learning (ML) have emerged as transformative technologies revolutionizing the construction sector. However, a discernible gap persists in systematically categorizing the applications of these technologies throughout the various phases of the construction project life cycle. In response to this gap, this research aims to present a thorough assessment of the deployment of AI and ML across diverse phases in construction projects, with the ultimate goal of furnishing valuable insights for the effective integration of these intelligent systems within the construction sector. A thorough literature review was performed to identify AI and ML applications in the building sector. After scrutinizing the literature, the applications of AI and ML were presented based on a construction project life cycle. A critical review of existing literature on AI and ML applications in the building industry showed that AI and ML applications are more frequent in the planning and construction stages. Moreover, the opportunities for AI and ML applications in other stages were discussed based on the life cycle categorization and presented in this study. The practical contribution of the study lies in providing valuable insights for the effective integration of intelligent systems within the construction sector. Academically, the research contributes by conducting a thorough literature review, categorizing AI and ML applications based on the construction project life cycle, and identifying opportunities for their deployment in different stages.

1. Introduction

Enhancing productivity within the building sector is crucial to addressing the present and upcoming demands of the industry effectively. Based on the latest estimates provided by the United Nations, the global population is projected to experience significant growth over the coming years. By 2030, it is expected to reach approximately 8.5 billion, followed by an increase to 9.7 billion by

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https://doi.org/10.1016/j.heliyon.2024.e26888
Received 27 August 2023; Received in revised form 15 February 2024; Accepted 21 February 2024
Available online 24 February 2024

2050. The projection suggests that the world's population may reach around 10.4 billion by 2100 [1]. The anticipated demand for infrastructure in the near future exceeds the capacity of the current construction sector to meet such requirements, thus highlighting its inadequacy in providing infrastructure at the desired pace. The present incapacity of the construction industry to fulfill the predicted infrastructure requirements in the near future can be attributed to its deficient adoption of digitalization and excessive dependence on manual approaches [2,3]. The construction industry's challenges are often linked to inadequate technological expertise and a low level of technology adoption. These issues have been associated with cost inefficiencies, project delays, subpar quality performance, uninformed decision-making, low productivity, and shortcomings in health and safety outcomes [4].

As a response to the slow performance growth in the construction sector, organizations are initiating the investigation and adoption of AI (Artificial Intelligence) to optimize procedures and drive productivity. This endeavor offers various advantages, such as mitigating cost overruns, enhancing site safety, improving project planning management efficiency, and fostering productivity growth at construction sites [5–7]. The utilization of AI technologies has facilitated the automation processes and conferred a competitive edge to these companies. AI plays a fundamental role as the cornerstone in implementing authentic digital strategies within the fields of engineering, construction, and management. As a discipline within computer science, AI empowers computers to emulate human-like capabilities in perceiving and learning inputs. These capabilities include knowledge representation, perception, problem-solving, reasoning, and planning. AI enables computers to tackle intricate and ambiguous problems intentionally, intelligently, and adaptively. Conversely, machine learning is recognized as the process of developing and implementing computer algorithms capable of acquiring knowledge from historical data or experience to construct models, exercise control, or make predictions through statistical methodologies [8].

Earlier, scholars and researchers have produced a body of literature that examines the utilization of AI and its subfields in addressing unique challenges specific to the construction industry. For example, machine learning techniques have been implemented in the construction sector for various purposes, such as estimating costs, monitoring health and safety, predicting risks, and enhancing supply chain and logistics processes, among other applications. Robotic technology has found practical applications in the construction sector, spanning various areas such as offsite assembly, site management, performance evaluation, and the efficient handling of

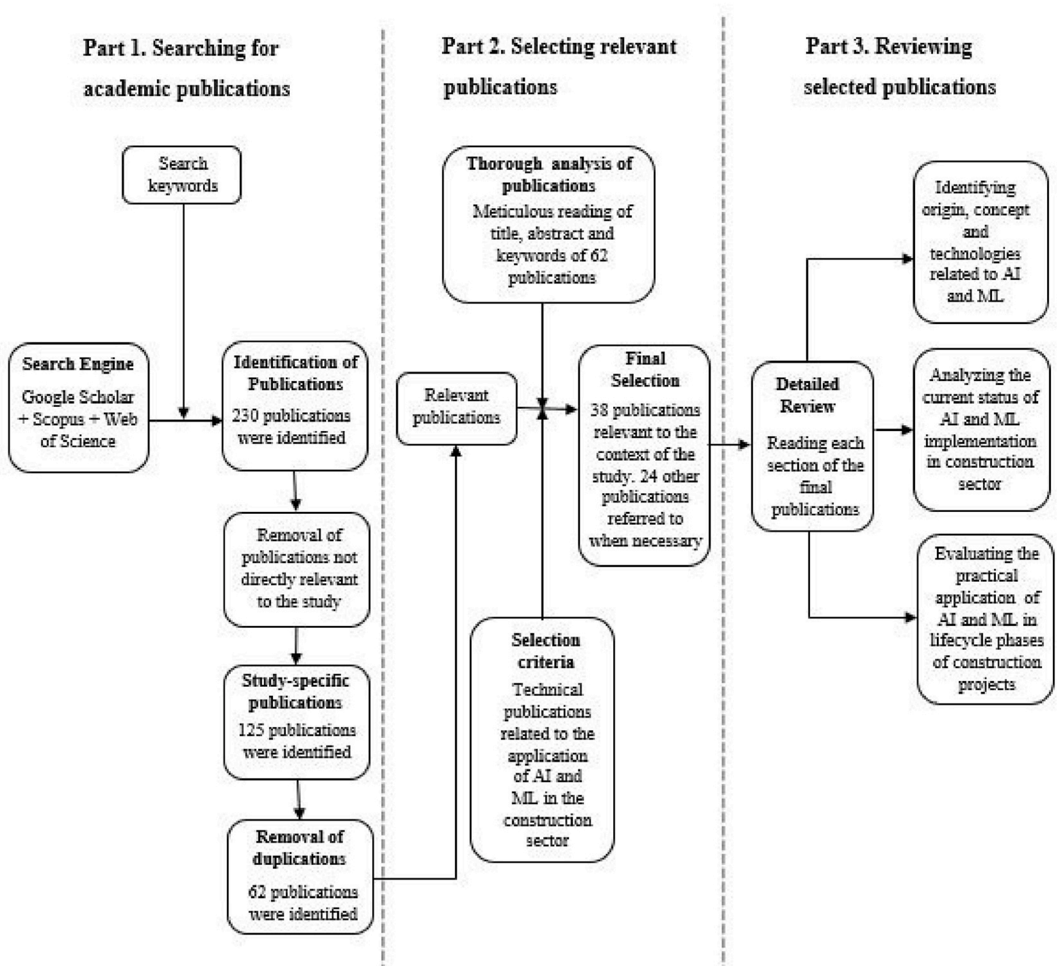

Fig. 1. Research methodology following the PRISMA guideline.

construction equipment and materials [9]. However, a notable research gap exists about the utilization of AI and ML in the construction lifecycle. To address this, the present study thoroughly examines existing literature, delving into the core principles and current state of AI and ML applications within the construction industry's unique context. The rationale behind crafting a review article in this field is rooted in addressing a recognized gap in the existing literature. Despite the transformative potential of AI and ML in the construction industry, there is a lack of systematic categorization of their applications throughout the various phases of the construction project life cycle. The intention is to conduct an in-depth analysis, drawing on the available literature, to explore the fundamental principles and the current landscape of AI and ML applications in the context of the construction sector. By providing a comprehensive assessment of their deployment across diverse project phases, the review aims to offer valuable insights into the effective integration of these intelligent systems within the construction sector. The primary objective of this research is to provide a comprehensive evaluation of how AI and ML are applied across various lifecycle phases in construction projects, ultimately aiming to provide valuable insights for the successful integration of these intelligent systems within the construction sector. There are three main resolutions were established to assist in accomplishing the aforementioned aim.

- Exploring the origin, conceptual framework, and technological dimensions of AI and ML applications.
- Assessing the adoption and application status of AI and ML in the construction industry from 2010 to 2022.
- Analysing the integration of AI and ML within specific phases of construction project lifecycles.

This study delves into the innovative possibilities of integrating AI and ML in various stages of a construction project's life cycle. The subsequent sections of this paper are structured as follows: Section 2 details the methodology adopted for conducting this research. Section 3 provides insights into the inception, principles, and technologies associated with utilizing AI and ML. Section 4 discusses the current landscape of AI and ML applications within the construction sector. Furthermore, Section 5 critically examines the diverse use cases of AI and ML throughout different life cycle stages of construction projects.

2. Research methodology

To select and evaluate a substantial amount of literature that falls within the predetermined scope of this research, a comprehensive review consisting of three parts was adopted. This includes an initial search of various databases for relevant literature, filtering out irrelevant results, and analyzing the remaining content. Fig. 1 illustrates the three-step process that was followed to conduct the research.

2.1. Searching for academic publications

To initiate the search for relevant literature, Google Scholar, Science Direct, Scopus, and Web of Science, which include a wide range of scientific publications, were utilized [10]. The authors conducted A thorough investigation using the "article title/abstract/keyword" in the aforementioned search engines, employing a search phrase comprised of two components. Keywords relating to "artificial intelligence," "machine learning," "automated planning and scheduling," "natural language processing," or "computer vision" made up the first section. The second section included terms such as "construction," "construction industry," "construction engineering," "construction management," or "construction engineering and management." To ensure a comprehensive review, the search was limited to 2010 to 2022, as the implementation of AI and ML in the construction sector remains nascent. In addition, the investigation was not restricted to any particular journals to prevent limiting the number of identified papers. As the most reliable and well-known sources of information, "article" or "review" was chosen as the document type [11]. The study began with an initial search on Google Scholar, which yielded 121 publications. To ensure a more comprehensive dataset, we extended our search to Scopus and Web of Science, identifying a total of 230 publications. After removing publications not directly relevant to the study, the collection comprised 125 publications, including journal and conference papers. Each publication underwent a rigorous assessment, focusing on its relevance to the construction sector, leading to the exclusion of articles that were unrelated to the topic.

The result of this phase of the study indicates that "Automation in Construction," "Journal of Construction Engineering and Management," "Engineering Applications of Artificial Intelligence," "International Journal of Construction Management," "Journal of Building Engineering," and "Advanced Engineering Informatics" exhibit a publication volume of three or more papers each. At this stage, the cumulative count of papers reached 62, originating from a diverse set of 33 academic journals and conference proceedings.

2.2. Selecting relevant publications

In the second part, an extensive evaluation was carried out on the 62 publications following the completion of part 1. The purpose of this stage was to determine the papers that were related to the specific topic of the study. We conducted a thorough analysis of the titles, abstracts, and keywords from 62 research papers to identify the pertinent ones. As a result, 38 papers that were deemed applicable to this study were identified through this in-depth study. The purpose behind excluding specific publications was to guarantee the inclusion of only those papers that focused on applications of AI and ML in construction project lifecycle stages. It was also focused on those papers that try to improve the traditional construction system in various phases of projects. The authors also remove those paper that stands for the same applications. Here, the most updated one is to choose which is better in terms of applicability, cost and efficiency. This type of selection will help project associates to sort out the application of the various construction phases very easily. Table 1 presents the numbers of initially selected publications and the pertinent papers included.

2.3. Reviewing selected publications

In this phase, an extensive content analysis was conducted to explore the genesis, core principles, and technological advancements of AI and ML. Moreover, the review focused on comprehending the existing state of AI and ML adoption in the construction industry and its real-world application across different stages of construction projects, as detailed in the selected articles. Fig. 2 illustrates the connectivity diagram of keywords prepared from the literature that deals with AI and ML applications. As stated in Fig. 2, a total of 36 keywords were found, and they are clustered into four separate groups according to their interconnectivity. The total link strength between all these words is 1232, and the most used words in these studies are “Machine learning,” “AI technology,” and “Construction industry.” These investigations also show that the words “Internet,” “Building,” “Infrastructure,” and “Review” are strongly correlated. All these have a combined link strength of 620. Furthermore, the history, ideas, and technology involved in the application of AI and ML are explained in Section 3 of this study. On the other hand, section 4 focuses on the current state of AI and ML applications in construction. The many uses of AI and ML are examined in Section 5 for all phases of the lifespan of building projects.

3. Origin, concept, and technological development of AI and ML

AI and ML are dynamic and inter-disciplinary fields at the intersection of computer science, cognitive science, and mathematics [12]. AI is the study and development of intelligent systems with human-like intelligence, reasoning, problem-solving, and decision-making capacities [13]. ML, a subfield of AI, concentrates on the formation of algorithms and models that facilitate the automatic acquisition of knowledge from data, thereby improving the performance of machines through experience [14]. The concept of creating machines that exhibit intelligence like humans originates in diverse domains, including philosophy, computer science, fiction, and advancements in electronics and engineering [15]. The introduction of Alan Turing's intelligence test marked a significant milestone in the field of AI as it went beyond conventional theological viewpoints and mathematical theories regarding the feasibility of intelligent machines [16]. After a span of sixty years, intelligent machines have exhibited superior performance compared to humans across multiple domains, notably in learning. This extraordinary accomplishment has become a reality by leveraging rapid

Table 1
Overview of initially chosen publications and publications pertinent to the study.

Journal	Number of initially selected publications	Number of relevant papers selected for detailed analysis
Automation in Construction	9	7
Journal of Construction Engineering and Management	6	3
Engineering Applications of Artificial Intelligence	5	3
International Journal of Construction Management	4	2
Journal of Building Engineering	3	1
Advanced Engineering Informatics	3	2
Engineering Applications of Artificial Intelligence	2	1
International Journal of Advanced Robotic Systems	2	2
Journal of Artificial Intelligence Research	2	2
Safety Science	2	2
IEEE	2	1
Frontiers in Public Health	2	1
Journal of Open Innovation: Technology, Market, and Complexity	1	1
Canadian Journal of Civil Engineering	1	1
Sustainability	1	1
Buildings	2	1
Journal of Intelligent & Robotic Systems	1	1
Energy and Buildings	1	0
Renewable and Sustainable Energy Reviews	1	0
The International Journal of Advanced Manufacturing Technology	1	1
International Journal of Managing Projects in Business	1	0
International Journal of Knowledge-Based Development	1	1
International Journal of Innovation Science	1	1
Journal of Open Innovation: Technology, Market and Complexity	1	0
IEEE Transactions on Industrial Informatics	1	1
Smart and Sustainable Built Environment	1	0
Construction Innovation	1	0
KSCE Journal of Civil Engineering	1	0
International Journal of Advanced Logistics	1	1
Building Research & Information	1	1
Engineering, Construction and Architectural Management	1	0
Assembly Automation	1	0
Journal of Civil Engineering and Management	1	0
Total	62	38

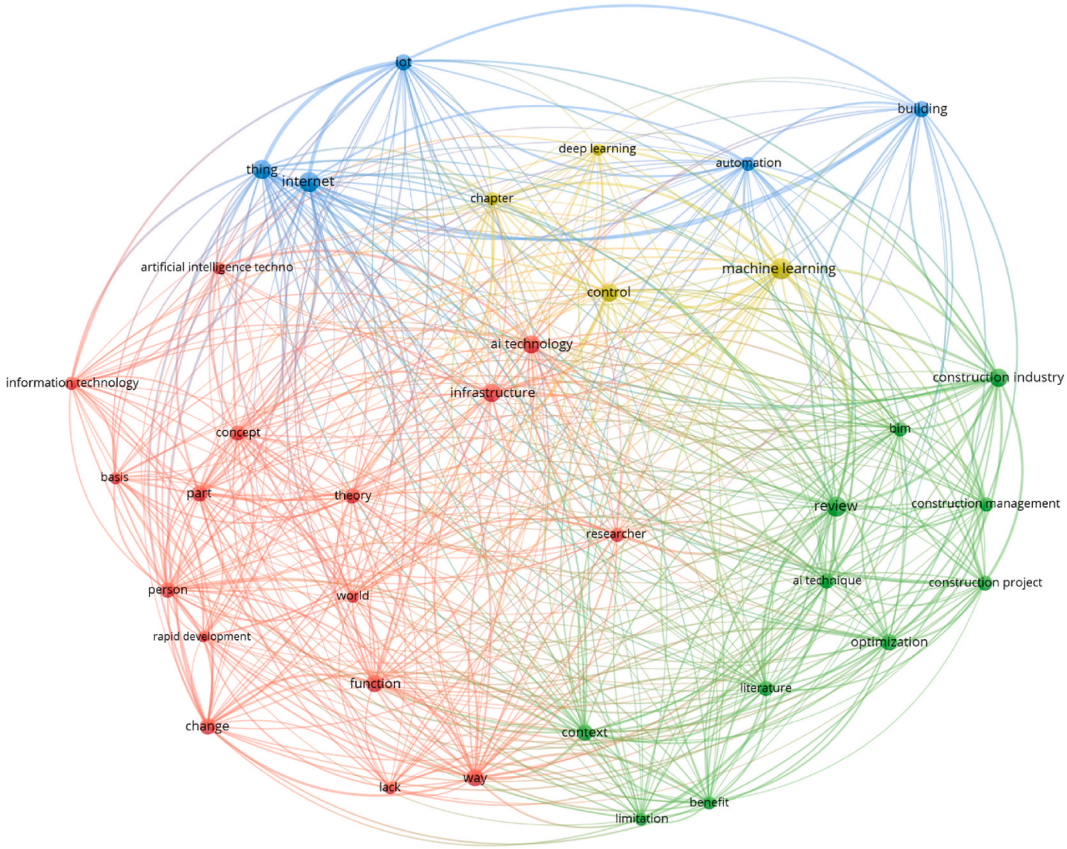

Fig. 2. Network diagram of keywords from the literature review.

progress in cutting-edge technologies like big data analytics and improved computer processing power [17,18]. The concept of AI is defined by Rich, Knight [19] as the discipline focused on developing methods for machines to perform tasks that are currently accomplished with greater human proficiency. They are dividing AI into three primary classifications: “Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Super Intelligence (ASI)”. These classifications represent different levels of AI capabilities [20]. ANI, commonly referred to as weak AI, pertains to a category of AI in which machines exhibit cognitive abilities within particular domains [20]. Examples of ANI include tasks like playing chess, making sales predictions, providing movie suggestions, language translation, and weather forecasting [21]. Rather than possessing ordinary intelligence, ANI focuses on addressing specific areas of expertise. AGI, commonly called strong AI, aims to enable machines to operate at a similar level as humans [21]. It focuses on developing AI systems with a broad range of cognitive abilities and can perform tasks across various domains with human-like proficiency. The fundamental components of artificial intelligence are knowledge representation, learning, perception, action, planning, and communication [22]. The emergence of AI in various industries has led to the identification of several distinct subfields of AI, namely Optimization, Knowledge-based Systems, Computer Vision, Natural Language Processing, Automated Planning and Scheduling, Robotics, and Machine Learning.

ML focuses on creating and utilizing computational algorithms capable of acquiring knowledge and improving performance based on prior data or experiences. Its objective is to develop models that can make predictions, exercise control, or perform tasks without the need for explicit programming. Machine Learning encompasses various methods, including (A) Supervised Machine Learning: this field of study pertains to the process by which machines arrive at decisions by utilizing labeled datasets comprising input and corresponding output pairings. The field of machine learning is subdivided into two main categories: classification and regression techniques. Classification involves categorizing data into predefined classes, while regression deals with predicting numerical values [23]; (B) Unsupervised Machine Learning: This field concentrates on enabling machines to learn the underlying structure within unlabelled datasets. It includes techniques such as clustering, which groups similar data points together, and dimension reduction, which lessens the complexity of the data [24]; (C) Reinforcement Learning (RL): RL pertains to the acquisition of a functional relationship between environmental states and corresponding actions that optimize a reward or reinforcement signal. The considered approach involves a computational framework that acquires knowledge through interactions within its environment [25]; and (D) Deep Learning: Deep Learning represents advanced cutting-edge ML and has demonstrated superior predictive accuracy compared to traditional machine learning techniques. It involves instructing deep neural networks with numerous layers to acquire knowledge and identify intricate patterns from data [26–28]. Deep learning can be described as an advanced form of artificial neural networks, specifically known as deep neural networks. The original proposition of the back-propagation algorithm, which forms the basis of the entire neural network paradigm, instigated the initial surge of machine learning. This technique introduced the concept of propagating errors backward through the network, ultimately enhancing overall performance [29]. Before the introduction of back-propagation, artificial neural networks lacked efficient algorithmic support, which hindered their ability to train multilayer neural networks effectively. The Long-Short Term Memory Networks (LSTM) and LeNet are two notable neural network frameworks that emerged following the introduction of back-propagation [30]. During that period, neural networks faced three primary constraints. Firstly, the algorithm itself posed limitations. As networks became more profound, the issues of vanishing or exploding gradients emerged, rendering it challenging to train networks effectively. Secondly, the availability of labeled data posed a significant challenge. Acquiring adequate labeled data to train powerful neural networks proved difficult. Lastly, hardware constraints were a hindrance. The performance of existing hardware fell short of meeting the computational demands for instructing complex neural networks.

To address the limitations, a significant breakthrough occurred in 2006 when Hinton introduced the deep learning idea and a novel training approach by publishing a paper in Science [31]. This development paved the way for training deeper neural networks effectively. Deep learning encompasses various network structures, among which Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are two notable examples. CNNs offer two primary advantages. Initially, the information contained within a CNN kernel can be efficiently utilized across various segments of a given dataset. For instance, if there are kernels accountable for detecting human beings, they can recognize individuals within an image as a whole, regardless of their specific placement. The attainment of this particular capability poses a challenge when utilizing completely interconnected neural networks, given their rigid connections between input features and neurons. Secondly, CNNs exhibit a significantly lower number of parameters in comparison to completely connected layers. The enhancement in parameter efficiency facilitates rapid learning and allows the integration of more intricate networks without compromising computational effectiveness [32]. Currently, CNNs serve as fundamental structures extensively employed in various fields of Machine Learning, with a predominant focus on computer vision tasks. They are very common in object identification, image recognition, etc. CNNs have proven to be highly effective in analyzing visual data and extracting meaningful features, making them a crucial component in numerous computer vision applications. RNNs are primarily applied in time series processing domains, including tasks like natural language processing and speech recognition. LSTM and Gated Recurrent Units (GRU) stand out as the two prominent variations of Recurrent Neural Networks (RNNs) [33]. Both LSTM and GRU share common functionality, allowing them to store values in specialized cells and retrieve these stored values when needed. Currently, LSTM and GRU have emerged as the prevailing Deep Recurrent Neural Network architectures, gaining significant popularity and utilization in various research and practical applications.

4. Status of AI and ML applications in the construction sector

The level of recognition and progress generated in a particular research field is determined by the yearly publications in that area. Demonstration of the advancements in AI and ML implementation within the construction sector is apparent through the trends depicted in Figs. 3 and 4, respectively. These figures provide clear evidence of the progress made in integrating these technologies into construction practices.

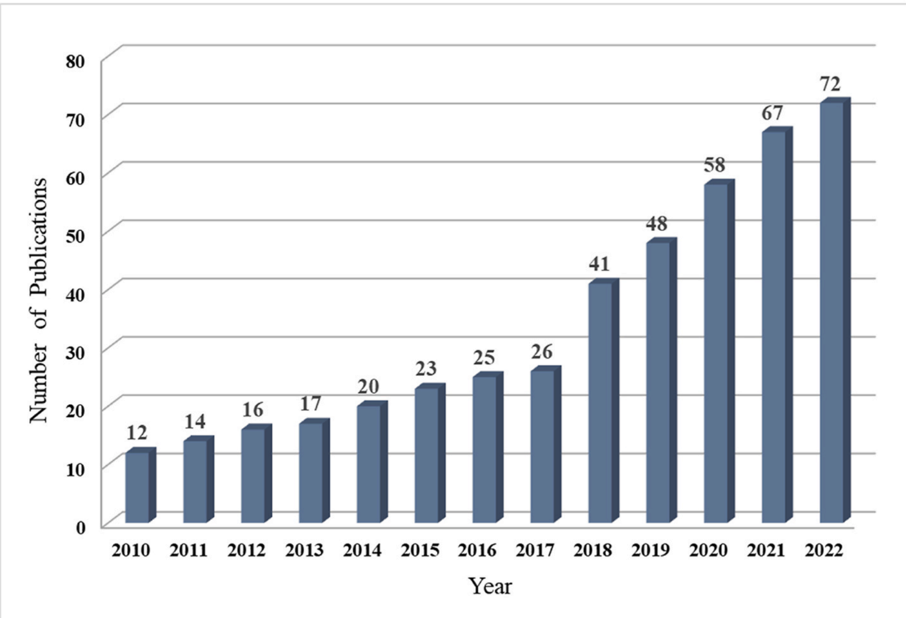

Fig. 3. Yearly trend of AI application in the construction sector.

Figs. 3 and 4 demonstrate that the integration of AI and ML in the construction industry remained relatively modest until 2017. However, a remarkable upsurge in research publications was observed subsequently. Specifically, the number of papers on AI increased from 26 in 2017 to 72 in 2022; for ML, it rose from 15 in 2017 to 153 in 2022. This can be attributed to the initial development phase for AI and ML exclusively in the manufacturing industry, which expanded to other domains, such as the construction industry, leading to increased interest and exploration [34]. Through the examination of research trends in the construction industry, it becomes evident that machine learning has surpassed knowledge-based systems in terms of prominence as a subfield of interest over the last decade. The aforementioned phenomenon might be attributed to the augmented necessity of addressing deficiencies in labor and expertise. Moreover, the integration of robotics has become a significant domain for implementing AI in the construction industry. This has been particularly evident with the advent of technologies like 3D printing, UAV (Unmanned Aerial Vehicle), and exoskeleton systems, all of which have found valuable applications in various construction processes. The construction sector has recently increasingly incorporated more computer vision-based technologies for diverse objectives, including site safety monitoring, enhancing work efficiency, and conducting structural health monitoring [8].

In contrast to traditional sensor-based techniques, vision-based techniques present several significant advantages. These include non-invasive properties, the ability to measure remotely, user-friendliness, and universal accessibility without necessitating supplementary installation of measuring or receiving gadgets [35]. In light of the prevalent accessibility of cost-effective and competent digital cameras, it is anticipated that computer vision-oriented technologies will observe a surge in adoption within the construction industry. This is particularly significant owing to various risk factors in construction sites, including working at heights and handling potentially dangerous construction materials [36]. Vision-based crack detection methods have gained significant popularity in the construction industry as a reliable approach for performing health assessments and monitoring structures and construction processes. This approach has gained popularity due to its effectiveness in detecting cracks in concrete structures [37]. thoroughly examined current methodologies for computer vision-based identification of defects and evaluation of conditions in civil infrastructures constructed with concrete and asphalt. Their findings indicated that image-based systems for detecting and classifying cracks and spalling in these structures have the potential for automated defect detection. While significant progress has been made in image and video data collection, achieving complete automation remains challenging. Jiang et al. [38] presented a methodology for detecting and classifying concrete damages into four categories (rebar exposure, spot, spalling, and crack) using image analysis [38]. Their proposed method exhibited robust performance across different lighting conditions, which is particularly challenging when detecting surface damage under intense sunlight. Moreover, the suggested approach demonstrated enhanced inference time and accuracy compared to widely used CNN algorithms like YOLOv3 and SSD.

Additionally, the utilization of image rectification techniques proves to be a valuable approach for ensuring the safety of workers in construction and accurately counting construction materials [39]. This method serves a dual purpose, enabling effective monitoring of worker safety and efficiently quantifying the quantity of construction materials present. Different researchers conducted an innovative investigation on collision prevention, wherein they implemented a real-time system that relies on camera-captured visual data. This system aims to avert potential accidents between heavy equipment and workers on construction sites [40].

Safety management in the construction industry has traditionally relied heavily on shallow learning algorithms when considering Machine Learning (ML) applications. Seong et al. introduced a method for detecting safety vests, which could potentially serve as a preliminary step toward on-site detection of workers [41]. The proposed approach utilizes the chromatic pixels associated with protective vests to identify workers. Ryu et al. identified another research area of ML that focused on investigating the viability of using a wrist-worn accelerometer for recognizing the movements of individuals on construction sites [42]. In the second decade of the 21st

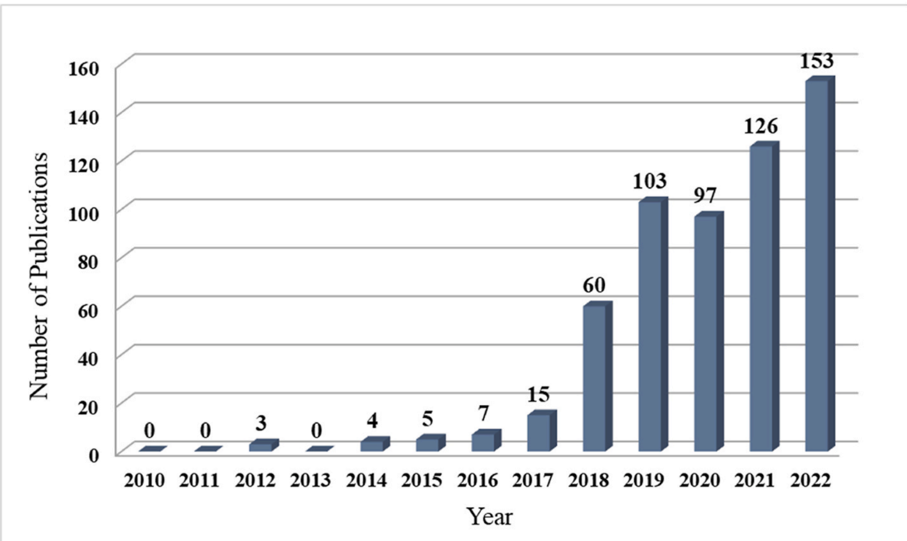

Fig. 4. Yearly trend of ML application in the construction sector.

century, image processing witnessed a paradigm shift as deep learning emerged as the dominant technique. Despite the early development of deep learning algorithms, their integration into the construction industry encountered substantial delays. A notable example is the introduction of RNNs in the 1980s, which, surprisingly, took about twenty-six years before being applied in obstacle avoidance for robotic excavators [43]. It's worth noting that CNNs had their origins in 1989., but it was not until 2012 that they gained popularity, particularly when applied to identify fall hazards on construction sites [44]. Emerging deep-learning technologies are being recognized for the enormous benefits they provide to the building sector, and there has been a notable reduction in the time gap between algorithm development and practical implementation. The YOLOv3 algorithm serves as a notable example. It was introduced in 2018 and effectively applied in 2019 to create an automated system capable of detecting structural defects in sewer pipelines [44].

5. Applications of AI and ML in construction project lifecycle phases

This section comprehensively explores the burgeoning implementations of AI and ML in the construction industry. The investigation is organized based on the various phases that constitute the lifecycle of a construction project. These stages encompass planning, design, construction, operation, maintenance, demolition, and recovery.

5.1. Application in the planning phase

The planning phase holds a crucial position in the construction lifecycle, as it significantly influences a project's overall success with respect to various critical aspects such as cost, time, quality, and quantity [45]. Inadequate planning is a precursor to project failure, leading to unfavorable outcomes and unsuccessful project execution [46]. During the planning stage, various stakeholders play an active role, dedicating significant time to participate in essential tasks. These tasks include scheduling, conducting cost analysis, and performing risk assessments. The involvement of multiple stakeholders ensures comprehensive planning and decision-making processes [47]. However, in recent years the utilization of deep learning artificial Intelligence has emerged to optimize the planning and scheduling of construction processes [48]. Table 2 presents the various applications of AI and ML in the planning phase.

Wauters and Vanhoucke [49] provided a comprehensive overview of five unique AI techniques for predicting project durations. The study revealed that these AI methods outperformed the traditional earned value management and earned schedule methods. Notably, there has been a significant increase in research dedicated to energy use prediction, focusing on utilizing AI methodologies in recent years [50]. AI-based techniques have become more prevalent in recent years due to their simplicity of use and capacity to provide ideal solutions quickly [51]. Pinto, Nunes [52] investigated the progression of ensemble artificial neural network and support vector machine classification models concerning their application in predicting the success of project cost and schedule. Increased

Table 2
Application of AI and ML in the planning phase.

Sector	Title	Year	Application	Ref
AI	A comparative study of artificial intelligence methods for project duration forecasting	2016	Prediction of accurate project duration; Progress evaluation during early stages of the project.	[49]
AI	A review of artificial intelligence-based building energy use prediction: Contrasting the capabilities of single and ensemble prediction models	2017	Building energy use prediction without requiring detailed physical information of the building.	[96]
AI	Predicting construction cost and schedule success using artificial neural networks ensemble and support vector machines classification models	2012	Project cost and schedule success prediction	[97]
ML	Towards a semantic Construction Digital Twin: Directions for future research	2020	Simulating the layout of a construction site with respect to specific zones, strategic positioning of construction equipment.	[54]
ML	Potentials of artificial intelligence in constructionm anagement	2020	Breaking down complex situations in construction projects into smaller separable subtasks.	[98]
ML	Automated vision tracking of project related entities	2011	Tracking of project-related entities using 3D spatial coordinates over time with automated vision-based techniques.	[55]
AI	A review on applications of ANN and SVM for building electrical energy consumption forecasting	2014	Building energy consumption forecasting while coping with complex and varying building system parameters	[50]
AI	Occupational risk assessment in construction industry – overview and reflection	2011	In order to assess and analyze potential occupational hazards, as well as propose effective strategies for risk management, the goal is to prevent any instances of plagiarism.	[52]
ML	Augmented Reality for Construction Site Monitoring and Documentation	2014	Creating a system that employs Augmented Reality to display real-time progress updates of a construction site on-site.	[99]
AI	Application areas of augmented reality and virtual reality in construction project management: A scoping review	2021	Developing an assistive interface for a teleoperated crane by implementing path planning in the context of heavy equipment operator training.	[53]
ML	A critical review of virtual and augmented reality (VR/AR) applications in construction safety	2018	The sequence includes safety training and education, hazards recognition and identification, and safety instruction and inspection.	[56]
ML	Using Deep Learning Artificial Intelligence to Improve Foresight Method in the Optimization of Planning and Scheduling of Construction Processes	2022	More rapidly review and recommend more planning options for scheduling complex construction projects	[48]

predictability of future scenarios is possible by breaking down challenging activities into more manageable, distinct subtasks [53]. A clash detection approach was proposed by Boje et al. [54] for workspaces, explicitly addresses the interaction between temporary site areas and objects with existing or newly constructed ones over time. Marzouk and Abubakr investigated the application of genetic algorithms to identify the most efficient positioning of cranes at a construction site. Albahbah, Kıvrak [53] examined the implementation of genetic algorithms to ascertain the most suitable arrangement of cranes within a construction site. Brilakis, Park [55] presented a model that employs a variety of static cameras to identify and track construction entities, thereby acquiring 2D coordinates in each camera view. Virtual and augmented reality technologies have also progressed from visualization-centered instruction to experience-centered instruction within construction safety. In addition, virtual and augmented reality technologies present novel prospects for efficiently instructing and enlightening inexperienced individuals with advanced safety training, resulting in reduced hazards [56].

5.2. Application in the design phase

Automated tools, including the 4D AutoCAD interface, are employed during the design phase to enhance and simplify conventional processes. However, organizations have recognized the limitations of the existing platform in managing extensive data, leading to a shift towards incorporating AI and machine learning systems [51]. AI has transformed every job site into a valuable data repository from which organizations can derive insights and enhance their existing conventional practices [57]. In the current era, various data sources have emerged as valuable repositories of information, encompassing images, security sensors, drone videos, and building information modeling (BIM), among others. Within this context, the integration of AI and ML assumes a pivotal role in efficiently managing, structuring and analyzing complex design information [58]. Companies are more likely to adopt and use these systems now that they are more cost-effective [59]. Furthermore, the integration of information and knowledge repositories enables more efficient management of various projects [60]. This guarantees that all involved parties can access the most current data and efficiently share information [61]. Table 3 presents a concise overview of existing literature on utilizing AI and ML within the design process.

The process of preparing materials is a crucial aspect of constructing buildings. Implementing AI and ML-derived data as input for generating visualizations of formwork quantity and schedule can minimize the resources allocated towards formwork design [62]. Ensuring a construction project's successful completion across its lifecycle relies on effective stakeholder collaboration. Nevertheless, stakeholders may lack expertise beyond their specific domains. To address this, integrating AI and ML technologies presents an opportunity to create a collaborative platform that enhances the visualization of diverse stakeholder perspectives [63]. Cognitive differences frequently arise between designers and constructors concerning the approaches employed for resolving clashes, as their

Table 3
Application of AI and ML in the design phase.

Sector	Title	Year	Application	Ref
AI	BIM-Based Visualization Research in the Construction Industry: A Network Analysis	2019	Efficient formwork design through the visualization of the formwork quantity and schedule.	[62]
ML	Integration of BIM and GIS in the sustainable built environment: A review and bibliometric analysis	2019	Utilizing visualization and simulation to enhance building safety during various construction phases.	[100]
ML	BIM for Structural Engineering: A Bibliometric Analysis of the Literature	2019	To reduce the quantity of request for information (RFI) items generated by contractors;e nabling every relevant stakeholder to examine multiple existing options and formulate potential design plans.	[63]
AI	Knowledge-based system for resolving design clashes in building information models	2020	Minimizing design clashes;p reventing the possibility of clash between branch MEP components and structural barriers.	[65]
AI	Quantitative Review of Construction 4.0 Technology Presence in Construction Project Research	2020	Enabling estimators to retrieve the relevant information directly from the design and to make their estimates available to other parties.	[101]
ML	Beyond the clash: investigating BIM-based building design coordination issue representation and resolution	2019	Detect clashes automatically among ducts, cable trays, and lighting systems.	[64]
AI	Evaluation of BIM-based LCA results for building design	2020	Assessing life cycle impact: utilizing automated quantity take-off to evaluate Global Warming Potential (GWP) in building design process.	[66]
ML	An Integrated BIM-based framework for minimizing embodied energy during building design	2016	An investigation into the embodied energy linked to the supply chain of building materials, focusing on Environmental Product Declarations (EPDs) provided by suppliers	[67]
AI	Using 4D BIM to assess construction risks during the design phase	2019	The evaluation of construction risks involves analysing unit risk factors associated with design elements, taking into account their frequency, severity, and exposure levels.	[102]
ML	Research trends and opportunities of augmented reality applications in architecture, engineering, and construction.	2013	Enhancing the likelihood of successfully executing a construction project can be achieved by leveraging Augmented Reality's visualization capabilities for the on-site implementation of the planner's concept	[103]
AI	Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications	2022	Utilization of GANs to generate architectural drawings using a trained model with an image dataset and this model was named 'ArchiGAN'. In his work, several steps were followed to finally generate fully furnished architectural plans of a building when the shape of the land is given as the input	[104]

perspectives are influenced by their respective areas of expertise and prior encounters [64]. A parallel neural network (BPNN) system was utilized by Hsu, Chang [65] to acquire their respective knowledge patterns. Simulated annealing (SA) was employed in creating an AI framework that facilitates the automated resolution of design conflicts based on established practices from the constructor's viewpoint. The integration of Building Information Modelling (BIM) opens up possibilities for incorporating sustainability performance metrics into the building design process. Nevertheless, BIM lacks compatibility with conventional life cycle assessment tools, which are essential for analyzing the environmental impacts of construction materials. By leveraging Artificial Intelligence (AI), it becomes feasible to evaluate the overall embodied global warming potential throughout the entire building design procedure [66]. Shadram, Johansson [67] presented is a framework conducive to informed design decision-making and assessment of embodied energy within building material supply chains. Besides, concrete's compressive strength prediction model can be obtained in recent days which reduces extra testing of the concrete specimen [68,69].

5.3. Application in the construction phase

Compared to conventional approaches, the construction phase of the project lifecycle is presently undergoing significant changes.

Table 4
Application of AI and ML in the construction phase.

	Title	Year	Application	Ref
AI	Lean Thinking and Industrial 4.0 Approach to Achieving Construction 4.0 for Industrialization and Technological Development	2020	Construction process automation and elimination of construction waste; sustainable infrastructure production.	[105]
AI	Robotics and automated systems in construction: Understanding industry-specific challenges for adoption	2019	Utilizing off-site prefabrication systems, automated excavation, material transportation, and aerial drone surveys and monitoring tasks are employed.	[106]
ML	Automation and Robotics in Construction and Civil Engineering	2015	Ensuring on-site data gathering and maintaining construction quality control; establishing a digital platform to support interactive game-based education, hazard evaluation, safety awareness, and safety training.	[76]
ML	Unified resources marking system as a way to develop artificial intelligence in construction	2018	To generate a detailed listing of higher-quality materials and dependable vendors.	[77]
AI	Digital skin of the construction site: Smart sensor technologies towards the future smart construction site	2019	To record the identity of each worker using RFID tags; Identification of unsafe conduct in terms of materials handling.	[74]
AI	Trend Analysis of Research and Development on Automation and Robotics Technology in the Construction Industry	2010	Reducing the amount of labour hours necessary to accomplish a project.; Mitigating the adverse environmental impacts of construction-related operations.	[71]
ML	Emerging artificial intelligence methods in structural engineering	2018	Investigating the compressive strength of self-compacting and high-performance concrete.	[70]
AI	Building Information Modelling, Artificial Intelligence and Construction Tech	2020	Robot-based marking systems involve a robotic unit that navigates within the designated workspace and applies paint or other marking substances directly onto the surfaces.	[73]
ML	Data mining methodology employing artificial intelligence and a probabilistic approach for energy-efficient structural health monitoring with noisy and delayed signals	2019	Identifying structural damage using binary signals with noise and delay	[75]
AI	Human–robot collaboration for on-site construction	2023	During the additive manufacturing process, building elements are automatically installed, and printing material is extruded.	[107]
ML	Robotic technologies for on-site building construction: A systematic review	2020	Advanced robotic applications in construction encompass autonomous assembly, in-situ fabrication, bricklaying, spraying, foam concrete printing, and surface unevenness recognition.	[72]
AI	On-site autonomous construction robots: Towards unsupervised building	2020	Creating an automated approach for dry-stacking stones to provide foundation support and the efficient assembly of superstructure components.	[108]
ML	Teaching robots to perform quasi-repetitive construction tasks through human demonstration	2020	Installation of ceiling tiles involves carrying out a semi-repetitive construction activity, which is demonstrated visually by a skilled individual.	[109]
AI	Vision guided autonomous robotic assembly and as-built scanning on unstructured construction sites	2015	Automatic cement block wall construction.	[110]
AI	Construction safety and health hazard awareness in Web of Science and Weibo between 1991 and 2021	2022	Hazard identification by computer vision and virtual reality	[78]
AI	Artificial Intelligent Technologies for the Construction Industry: How Are They Perceived and Utilized in Australia?	2022	To provide real-time insight that will help project managers ensure efficient use of resources, anticipate potential risk, and increase safety.	[80, 111]
ML	Can a chatbot enhance hazard awareness in the construction industry?	2022	Hazard awareness enhancement by chatbot training	[79]
AI	Big Data Technology in Construction Safety Management: Application Status, Trend and Challenge	2022	Construction safety management	[112]
AI	Integration of Building Information Modeling and Artificial Intelligence Systems to Create a Digital Twin of the Construction Site	2022	Hazard identification and risk management	[113]

Automation technologies and construction robots are being used to improve current construction machinery, plants, and task-driven robots. An essential technology for operating robots involves using multiple sensors that offer information to the site manager. The collection and transmission of data by these sensors are of utmost importance, enabling the site manager to monitor and analyze the robots' performance effectively. By leveraging these sensors, site managers can receive real-time information on various parameters, allowing them to make informed decisions and effectively manage the operation of the robots [9]. An extensive examination of the implementation of AI and ML during the construction phase of project lifecycles is presented in Table 4. The table offers a comprehensive overview of their applications, accompanied by pertinent references from the existing literature.

Different ML techniques have been utilized to construct accurate models for predicting the mechanical properties of concrete. These techniques encompass neural networks, fuzzy logic, genetic programming, and support vector machines. Notably, the application of ML algorithms has been particularly remarkable in modeling the characteristics of self-compacting concrete [70]. Son, Kim [71] widely agreed that mechanizing construction tasks has reduced construction costs by minimizing the labor hours necessary to finish a project. Numerous advancements in AI and ML technologies have revolutionized the construction industry, presenting an array of cutting-edge applications. These innovations encompass automated robotic assembly, autonomous installation, in-situ robotic fabrication, robotic bricklaying, automated spraying, unevenness recognition, and printing technology tailored for foam concrete. These developments have led to the creation of specialized robot systems, each dedicated to executing specific tasks efficiently and independently [72]. Construction site setup is a challenging and error-prone process, as it requires interpreting design data amidst incomplete scenes and then accurately applying physical markings on surfaces. The prevailing method employed in this context is implementing an AI-driven robotic total station survey layout system [73]. Moreover, Edirisinghe [74] utilized a blend of real-time location sensors to investigate the ergonomics of construction workers, focusing on analyzing their behaviors during materials handling to identify potential hazards. Salehi, Das [75] presented a groundbreaking structural health monitoring system to detect damage through discrete binary signals. This innovative approach adds a new dimension to identifying structural issues, promising significant advancements in the field. One of the responsibilities inherent to a construction organization involves the punctual and comprehensive facilitation of construction sites with essential materials and technical resources of superior quality. Kim, Chi [76] employed virtual reality technologies to construct a simulated environment that facilitates collaborative distributed safety education, hazard assessment, safety awareness, and interactive game-based learning. Ginzburg, Kuzina [77] suggested an integrated mechanism for labelling construction-related material and technical resources. This process utilizes artificial intelligence and custom-designed barcodes directly applied to the packaging of construction materials. The code in question may encompass both essential and comprehensive details pertaining to the resource, such as the resource's unique identifier, the product line, the company that manufactured it, the date of manufacturing or last use, and any other data that may be used to trace its history and quality. The study conducted by Ref. [78] involved a comparison of 11,829 Weibo microposts on construction safety and health hazard awareness with 769 articles listed in Web of Science (WoS) spanning the period from 1900 to 2021. Safety hazards, including fire, electrical issues, chemical exposure, collapsing trenches, as well as health-related risks like asbestos and heat stress, were scrutinized in the analysis. In

Table 5
Application of AI and ML in the operation and maintenance phase.

	Title	Year	Application	Ref
AI	BIM-enabled facilities operation and maintenance: A review	2019	Augmented visualization; Decision making support; Planning and locating emergency escape routes, simulating and monitoring fire emergencies, and managing facility safety.	[84]
ML	A short-term building cooling load prediction method using deep learning algorithms	2017	Life cycle data management; commissioning and closeout.	[114]
AI	Building Information Modelling (BIM) in Facilities Management: Opportunities to be considered by Facility Managers	2016	Facility managers can fine-tune building equipment for optimal performance by monitoring building performance in real-time.	[85]
AI	BIM in the operations stage: bottlenecks and implications for owners	2015	Ensuring efficient management of information independent of people and time; Using benchmarking and monitoring data to aid in the asset management of a building.	[115]
ML	A review on artificial intelligence-based load demand forecasting techniques for smart grid and buildings	2015	Electrical load forecasting.	[116]
AI	Watch Bot: A building maintenance and surveillance system based on autonomous robots	2013	In order to maintain the building's climate within a designated range and offer lighting according to an occupancy schedule.	[117]
ML	Generalized task allocation and route planning for robots with multiple depots in indoor building environments.	2020	Task-allocation and route-planning for multiple indoor robots with numerous start and destination depots are optimized to enhance operational efficiency.	[87]
AI	The study on the integrated control system for curtain wall building façade cleaning robot	2018	Buildings equipped with built-in guide rail-applied curtain walls require Façade cleaning.	[83]
ML	Self-reconfigurable façade-cleaning robot equipped with deep-learning-based crack detection based on convolutional neural networks.	2019	Automatic glass crack detection for façade-cleaning robot	[118]
AI	Integration of service robots in the smart home by means of UPnP: A surveillance robot case study	2013	Implementing a basic garbage detection routine using built-in camera that allows the smart home system to instruct a service robot to clean whenever garbage is detected.	[88]

another study by Ref. [79], Telegram chatbot safety training and task complexity on hazard awareness were investigated. Results indicated that Telegram chatbot training positively influenced hazard awareness, particularly for participants with limited onsite experience and in less complex scenarios. Regona et al. [80] conducted a systematic review of 66 articles closely aligned with the research topic and objectives. They provided an overview of the current status of big data applications in addressing diverse construction safety issues, examining both the collection and analysis aspects. The study categorized the notable outcomes of big data analysis technology, emphasizing its contributions to enhancing construction safety.

5.4. Application in the operation and maintenance phase

In the phase of operation and maintenance (O&M), the constructor often faces limited control over the project's proceedings. As a consequence, managing and obtaining data from the object becomes challenging. While the computer-generated model could be the actual representation of the structure, there is no correlation between this and the finished building [81]. The users are primarily focused on the reliability and convenience of the project during this phase. Utilizing AI and ML presents a wide array of possibilities across diverse sectors, including facilities management, supply chain management, monitoring, energy simulation, and maintenance management, particularly during the Operations and Maintenance (O&M) phase of projects. By harnessing the potential of AI and ML technology, facility managers gain the capacity to make vital decisions concerning building performance management, energy consumption optimization, and comprehensive monitoring of operational aspects within the building. By collecting real-time data, AI and ML increases the operational efficiency of the project. This data enables predictive maintenance, ensuring that maintenance activities are carried out proactively to prevent issues [82]. Table 5 presents a comprehensive overview of how AI and ML are utilized during the operation and maintenance stage of a project lifecycle. It also includes the relevant literature references associated with each application.

Lee, Kim [83] introduced a novel approach to building maintenance by presenting a façade cleaning system specifically designed for buildings featuring guide rail-applied curtain walls. The author also anticipated a unified command structure to streamline the cleaning procedure. In a study conducted by Gao et al. [84], the module for assessing evacuation integrates with a Fire Dynamics Simulator to evaluate the efficacy of evacuation procedures in the event of a fire. The module for planning escape routes employs AI to determine the adequacy of the distance of such courses. The safety education module furnishes occupants with essential details concerning risky zones and evacuation paths. It incorporates informative videos and directional maps to augment their understanding and vigilance. Augmented Reality (AR) technology is a practical interface for facilitating operations and maintenance tasks, overlaying geometric representations onto the physical environment while integrating AI-driven facility data [85]. Vitale, Arena [86] employed AI-driven methods for indoor climate regulation within predefined parameters. Moreover, the system facilitated lighting control per occupancy schedules while monitoring system performance and detecting equipment malfunctions [87]. proposed a novel approach that leverages ML to improve task allocation and route planning efficiency in a fleet of indoor robots. These robots operate within various depots, each having unique starting and ending points for their tasks. The utilization of integrated cameras in research conducted by Borja, de la Pinta [88] has facilitated the implementation of a rudimentary garbage detection AI algorithm, which enables the smart home to dispatch an intelligent robot to perform cleaning operations upon garbage detection.

Table 6
Application of AI and ML in the demolition and recovery phase.

	Title	Year	Application	Ref
ML	Deep learning model for Demolition Waste Prediction in a circular economy	2020	Estimating the accurate quantity of waste generated during building demolition; Ensuring effective planning for material reuse.	[92]
AI	A financial decision-making framework for construction projects based on 5D Building Information Modeling (BIM)	2016	Demolition waste quantification, disposal charging fee calculation, and pick-up truck planning.	[119]
AI	4D-BIM to enhance construction waste reuse and recycle planning: Case studies on concrete and drywall waste streams	2020	Measuring the production of concrete and plasterboard waste for recycling off-site and reusing on-site.	[93]
AI	Dynamic modelling for life cycle cost analysis of BIM-based construction waste management	2020	Better decision-making in material sorting and deconstruction procedures.	[120]
ML	Vision-based robotic system for on-site construction and demolition waste sorting and recycling	2020	Categorizing and gathering formed construction debris.	[95]
AI	Construction waste recycling robot for nails and screws: Computer vision technology and neural network approach.	2019	Automated recycling of waste from construction.	[121]
ML	A building information modelling-based tool for estimating building demolition waste and evaluating its environmental impacts.	2021	Providing geometric and semantic information for demolition waste estimation.	[122]
AI	Combining life cycle assessment and Building Information Modelling to account for carbon emission of building demolition waste: A case study	2018	Measuring the carbon emissions generated throughout the entire process of disposing of building demolition waste.	[94]
AI	A BIM-Based construction and demolition waste information management system for greenhouse gas quantification and reduction.	2019	To provide a decision support tool for the management of construction and demolition waste that is economically viable and environmentally friendly.	[123]

5.5. Application in the phase of demolition and recovery in construction

Researchers often tend to overlook the entire phase of a construction project as a distinct phase [86]. Comparable to the building industry's other project phases, the integration of AI and ML technologies during demolition and recovery has received less attention. Ensuring sustainability in the construction industry hinges on identifying the most advantageous financial and environmental value that can be extracted from a building before its end-of-life phase, encompassing deconstruction and demolition processes [89]. Approximately 35% of the total generated waste is attributed to the construction industry [90]. Despite numerous studies devoted to the matter, the extent of construction waste in the US, Canada, Hong Kong, Australia, and the UK remains notably high. Specifically, the respective percentages of construction waste in these countries are approximately 33%, 65%, 35%, 50%, and 30% [91]. In the context of the demolition and recovery stage in construction projects, Table 6 offers a comprehensive summary of the various applications of AL and ML.

The advancement of deep learning models has dramatically simplified the prediction of the quantity of waste materials (measured in tons) that can be salvaged from buildings during their end-of-life stage before demolition occurs [92]. Despite considerable attention given to waste management, the recycling and reutilization of construction waste remain underutilized. Researchers propose a novel approach to address this challenge, which involves integrating temporal-based algorithms alongside 4D-BIM (4D Building Information Modelling). By doing so, a systematic plan can be devised to efficiently manage the removal and replacement of concrete and drywall waste throughout the different phases of construction projects [93]. Nails and screws, crucial elements within the construction waste environment, pose a significant detection challenge. Their presence may endanger the construction site's safety and result in material wastage. The research performed by Li [88] employed a neural grid to facilitate the robot round in an unfamiliar work setting and to utilize quicker R–CNN techniques to detect dispersed pins and screws in actual time, thereby enabling the robot to retrieve said nails and screws autonomously. The impact of carbon emissions resulting from managing demolition waste in buildings has been widely disregarded. A conceptual framework was established by Wang, Wu [94] to facilitate the assessment of carbon emissions generated during the entire process of demolishing a building's waste. Moreover, Wang, Li [95] describes an innovative AI-driven prototype for efficiently sorting and gathering shaped construction debris, a crucial phase in the recycling of construction and demolition waste (CDW).

6. Practical implications and future research

This research investigates the present state of AI and ML integration in the construction sector. We offer a succinct survey of the diverse applications of these technologies across various stages, including planning, design, construction, operation, maintenance, demolition, and recovery. The insights from this study aim to support industry professionals and stakeholders interested in adopting AI and ML solutions to tackle the numerous challenges encountered within the construction domain. This would improve the course of policymaking with regard to the adoption of these intelligent systems in specific phases from initiation to completion of a construction project. In addition to its usefulness for research, our findings have some significant impact on everyday life. Our analysis explicitly identifies the categories of AI and ML applications that corporations are most interested in developing in the construction sector and, consequently, are most interested in academics. The various AI uses and technologies that are now the focus of study give practitioners some insight into potential future deployments and prevalent technology in businesses. The fact that ML applications are the AI technology that has received the most study might help determine where future investments should be made and what kind of predicted economic value can be obtained. Having this knowledge, construction managers can start testing these methods within their companies and investing in the necessary expenses to gradually incorporate these solutions into industries where they can be extremely valuable.

The review of studies also highlights those that can help practitioners learn crucial lessons from using AI technologies, identify approaches that have been used and what common problems arise, and identify studies that offer general guidance and best practices. Many practitioners find it challenging to locate empirical research that is useful to them because of the wide-ranging and vast literature on AI in organizational contexts. Through the synthesis of findings and the presentation of studies categorized thematically, practitioners can more quickly uncover the research that addresses the challenges they and their organizations encounter in AI deployments.

Despite the significant contributions made by this research, certain limitations are worth noting. The study was confined to utilizing databases like Google Scholar, Scopus, and Web of Science, potentially overlooking other relevant publications on AI and ML adoption in the construction industry. Consequently, the research findings might not fully encompass the entire body of literature on AI and ML applications in diverse lifecycle phases of construction projects. The dynamic nature of the AI field continuously introduces new opportunities and challenges, with outcomes often varying due to differences among companies. The primary objective of this study was to provide an overview of AI and ML applications in the construction industry by analysing existing research. However, no experiments were conducted with additional datasets, including sensitive data collected from professionals working on construction sites, which could have offered valuable perspectives through interviews and surveys on the opportunities and challenges of implementing these technologies in real-world scenarios. This study highlights the necessity for further research, employing case studies to augment the subjective perspectives of researchers whose works were included in this investigation. Incorporating case studies can provide a more comprehensive understanding of AI and ML implementation in construction.

7. Conclusions

As an innovative approach to enhancing productivity and tackling issues, AI and ML are set to significantly influence how things are done across various sectors. As more data is generated throughout a building's existence, coupled with advancements in digital technology, AI and ML can utilize this information and work with other technologies to enhance the construction process. In this study, it was investigated the utilization of AI and ML throughout the construction life cycle to address the research questions posed in our research endeavour. Besides recent research, we examined pertinent studies published within the last 12 years across various building-related applications. The works utilizing these AI and ML are defined, together with the ideas, components, types, and subfields of AI. The summary of AI and ML applications, benefits, and implementation in each stage of the building construction lifecycle was analysed comprehensively.

The present study employed a qualitative methodology by comprehensively analysing publication patterns about AI and ML. The relevant databases were explored to conduct searches across various platforms, including Google Scholar, Web of Science, and Scopus. The scope of the search extended over several decades. The selection of these databases was predicated upon their strong reliability and credibility, with the primary objective of mitigating bias. Based on the data gathered, the AI and ML applications on the life cycle basis in construction research can be obtained and discussed. Many researchers have noted that a significant concentration of AI and ML applications lies within the construction and project planning stages. This study demonstrates that although various AI and ML technologies have been utilized in construction-related research, notable advancements have resulted in significant improvements. Despite the promising potential of advanced AI technologies, their adoption in the construction industry has been relatively slow. Deep learning, which can generate more accurate predictions than conventional machine learning methods, has not been fully exploited.

The construction sector is still in the initial stages of embracing AI and ML, a novel concept for the industry. Consequently, this paper aims to highlight the significant contributions and advancements in this domain.

- A novel and previously unexplored domain of knowledge focused on applying both AI and ML technologies in the construction sector.
- A brief overview of the inception, underlying principles, and technological advancements of AI and ML.
- Exploring the present state of AI and ML implementation in the construction sector.
- A comprehensive examination of AI and ML implementations across different stages of construction projects
- A foundation for forthcoming research derived from the data analysis outcomes.

Data availability

Data will be made available on request.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Shuvo Dip Datta: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Mobasshira Islam:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation. **Md Habibur Rahman Sobuz:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Shakil Ahmed:** Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Formal analysis, Conceptualization. **Moumita Kar:** Writing – review & editing, Visualization, Software, Resources, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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