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# Intelligent robots and human–robot collaboration in the construction industry: A review

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ABSTRACT

The construction industry is a typical labor-intensive industry, which suffers from low productivity and labor shortage in the past decades. Recently, the developments in robotics and artificial intelligence technologies highlight the evolutionary reforming potential in the construction industry. An increasing number of robots are joining construction tasks and collaborating with human workers. This study reviews the major developments in intelligent robots and human–robot collaboration (HRC) in the construction industry. The technological foundations and fundamental concepts of construction robots and collaborative robots are reviewed, organized, and discussed to reveal that progress has been made. Based on a comprehensive review, the major challenges and future research directions of HRC have been proposed and examined. This study finally developed a comprehensive and in-depth discussion of the state-of-the-art implementation of robotics technologies in the construction industry and shed light on its path to future development.

## 1 Introduction

The construction industry is a labor-intensive industry that relies on the manual operation of human workers. Its labor productivity has been gradually improved over the past decades [1] and facing a rapid increase in the demand for modern urbanization. Robotics technologies have attracted increasing attention and shown significant application potential in addressing challenges in the construction industry. Many incentives utilize robots for construction projects. First, labor productivity has stagnated for years [2, 3], and employing can improve the efficiency of task operation during construction. Productivity has remarkably increased in the manufacturing industry with the introduction of industrial robots. Implementing robots can help construction teams gain substantial productivity over the years [4, 5]. Second, robots can free workers from hazardous working environments and reduce the chances of injuries and fatalities [6]. In addition, replacing human workers with robots for some tasks can reduce occupational musculoskeletal disorders [7] and the cost that is invested in fall protection structures, personal protective equipment, and management teams [8]. Third, using robots can address the shortage of labor forces [9]. Fourth, robots can continue the working process during extreme events, such as pandemics [10]. For example, during the novel coronavirus (COVID-19) pandemic, many priority buildings, such as healthcare facilities, should be constructed; however, human labor can increase the risk of disease spread [10].

Although implementing robots on sites has various benefits, construction projects seldom receive significant productivity compared with the manufacturing industry. This finding is due to the uniqueness and complexity of construction tasks [11]. In addition, it is impossible to deploy several dedicated robots in a static construction environment because of the unicity of robot's functionality and the complicated and dynamic working environment

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[12, 13]. Therefore, the operation on construction sites with robots always involves human workers' participation. In recent years, You et al. [14] have proposed a new concept of collaborative robot teams (cobots) to assist human workers. Similarly, the concept of human–robot collaboration (HRC) was also proposed by Ajoudani et al. [15] to define the fundamental schemes for practical implementation. The HRC aims to transform the current fully manual operation into the shared task allocation by humans and robots. Under such a paradigm, the human workers will be in charge of decision-making, planning, and organizing of tasks, whereas the robots will take care of the repetitive physical operation, such as lifting, installation, transporting, and welding. Given the rapid evolution of robotics technologies in the construction industry, this study aims to conduct a systematic review of the existing state-of-the-art scientific research. In particular, the reviewer will conceptualize the origin, research logic, and directions of HRC. Hence, the researchers can provide the insight into the trends and challenges of adopting intelligent robots and enabling HRC.

## 2 Robotics in construction

### 2.1 Technological foundations

In the manufacturing industry, the automated production relies on the understanding of the process and workflow as well as the acquisition of the current working conditions of machinery. Similarly, the construction process depends on the real-time data acquisition and information model of the environment. Implementing robots in the construction process involves the use of advanced sensing technologies, building information models (BIMs), and artificial intelligence algorithms [16]. The acquisition and/or transmission of automated data by robots should occur during construction. Therefore, the foundation of construction-robot deployment includes technologies for (1) positioning and tracking, (2) progress monitoring, (3) control and operation, (4) BIM and information modeling, and (5) cyber-physical support.

#### 2.1.1 Positioning and tracking

Robots that perform construction tasks need correct information about their positions within their surroundings, and such localization is critical to the success of their tasks [17, 18]. Localization problems can be categorized into three types: position tracking, global positioning, and the kidnapped-robot problem [19, 20]. At present, techniques used to solve such problems include odometry, probabilistic modeling, simultaneous localization and mapping (SLAM), and radio-frequency identification (RFID) [17, 18, 21]. In particular, odometry refers to the use of motion sensors to measure robots' location changes relative to a known initial position, but its unbounded accumulation of errors limits its localization capability [22]. On the contrary, probabilistic approaches can be used to calculate the probability of a robot being in a certain position within an unknown environment [17], including Markov localization [18], Monte Carlo localization [20], and Kalman-filter localization [23]. Meanwhile, SLAM determines the position and pose of a robot as it moves, and it can simultaneously map the environment. Considering that SLAM is a pivotal component of truly autonomous robots [24], it has been widely used in Refs. [21, 25]. The RFID technique has also been used to locate robot positions [26, 27]. After RFID tags are placed in grid patterns in an unfamiliar environment, robots with RFID readers can detect the tags when passing by and extract location information from them [28].

#### 2.1.2 Progress monitoring

Traditional construction inspection is labor-intensive, inefficient, and frequently delayed by scheduling conflict, and it often costs more than anticipated. For these reasons, it is gradually shifting to a remote format, facilitated by robots [29, 30]. Robot monitoring of construction progress consists of three stages: data collection, information processing, and visualization. Various sensing technologies have been adopted for data collection [29, 31, 32], including vision-based sensing [33] and laser scanning [34]. For example, Asadi et al. [33] installed a monocular camera as a vision sensor on their mobile robot to enable it not only to detect obstacles in construction environments but also to extract construction scenarios for autonomous navigation and construction progress monitoring. In the information processing stage, computer vision technologies have been widely used because of their capability to extract useful information from commonly collected visual data (e.g., images and videos) [29, 30]. For example, Zhang et al. [34] utilized a computer vision technique to quantitatively measure the area paved with tiles at an indoor construction site in real-time by analyzing continuously updated video data collected using sensors. Considering that the size of the tile-paved area could be calculated continuously, Zhang and Arditi's system [34] achieved automatic monitoring of tile-paving progress. In the visualization stage, virtual reality [35], augmented reality (AR) [36], and mixed-reality [37] technologies have been incorporated into monitoring robots to help that stakeholders intuitively make observations of the construction progress that will guide their decision-making [29]. For example, Halder et al. [29] used a quadruped robot mounted with an AR device to remotely monitor the construction progress. Using a web–client interface, stakeholders could observe such progress by comparing an AR model of the as-planned building with the as-built structure observed by robots.

#### 2.1.3 Control and operation

Control systems in robotics deliver commands to robots and control them as they complete their operation [38]. In general, robots' control systems have two main functions: command generation and command execution [39]. In the former, hardware and software must work simultaneously to deal with the collected data, with the hardware serving as the powerful computational support and the software arriving at the optimal command via various algorithms [40]. Such algorithms vary with robots' task types. For example, an iterative inverse kinematics algorithm has been utilized to compute the desired joint position of an end-effector [40], whereas a path-planning algorithm has been applied to robot's movement tasks. For the command–execution function, a controller is an essential component [41]. The types of controllers incorporated into robots also vary with the types of construction tasks that robots are involved in. For example, a force controller, a visual servo controller, and an inverse-dynamics tracking controller have been used for a grasping task, a harvesting task [42], and a base motion planning [40], respectively. In reducing mission difficulties and robot control systems' computational burdens, modular designs that can decompose a complex construction mission into several easy-to-execute robot actions are necessary. For example, in enabling robots to conduct facade-cleaning tasks, Gambao and Hernando [43] decomposed a robotic cleaning system into four modules, that are a cleaning module, a kinematics module, a carrier module, and a control module. Similar modular designs for robot cleaning systems have also been widely adopted by Refs. [40, 44].

#### 2.1.4 BIM

When robots monitor progress and perform other tasks on a construction site, they should be provided with regular updates on the state of their surroundings, as such sites repeatedly change over time as construction proceeds [45]. The BIM can promote robots' performances of monitoring and other construction-related tasks because it can incorporate a wide range of information from across buildings' life cycles, including geometric, building process, and construction-schedule data [46]. However, conventional BIM technology is incompatible with robotics [47]. To break down this information barrier between BIM and robots and allow them to interact directly, the industry foundation class file format, a text-based data schema intended for the description of model data, is increasingly being used [45, 48]. Consequently, the integrating BIM with robotics in this manner has allowed several construction tasks to be conducted by robots autonomously. For example, Ding et al. [48] imported geometry, schedule, and site information from a BIM model into a robot's control system to generate brick-placement point coordinates, thereby allowing the robot to autonomously complete the assembly of brick structures such as walls, stair, and pyramid. Based on the BIM building-design data (e.g., the locations, dimensions, and weights of building elements), Chong et al. [47] proposed an approach to simulating the automatic wood-frame assembly of the robot. In achieving automated three-dimensional (3D) printing of concrete, Davtalab et al. [49] proposed an integrated BIM–robotics platform that could serve as an information processor, analyzing and reporting construction information to allow for the adjustment of robot's parameters, thereby controlling the printing process.

#### 2.1.5 Cyber–physical systems (CPSs)

CPSs are engineering systems that combine computational entities and physical ones through networking [39, 50–52]. They encompass three components: physical, software, and communication technologies [53]. In particular, their physical components include the hardware embedded in engineering systems, such as sensors, RFID tags, and robots. Their software components, such as computational algorithms and various data-processing and decision-making techniques, allow such systems to work logically. Finally, their communication components handle data transmission and interaction issues between the hardware and software components, thereby allowing network-wide inter-connections and feedback loops. Therefore, the communication plays a crucial role in the CPS by serving as a bridge between its virtual and physical worlds. Using CPS technologies, the robots' communication with the physical and virtual worlds can be achieved. The broad types of robot communication that can be supported by CPSs include robot-to-device communication and robot-to-human communication. For example, Tan et al. [54] based shop–floor assembly on CPS-assisted interactions among robots, sensors, RFID, logistics equipment, and AR devices in the physical world. Nikolakis et al. [55] proposed a CPS-based safety approach to enabling HRC within a shared working space. In the latter case, the CPS consisted of all the operating resources of the physical space, including robots, other hardware systems, and human workers.

### 2.2 Theoretical frameworks for robotics application

Applying suitable robots on site must identify the suitability based on the task needs, technology features, and characteristics of human operators. Therefore, Goodhue and Thompson [56] have proposed a theoretical framework to discuss such suitability as a task–technology fit (TTF) framework. Under the scheme of TTF, the application of a certain type of new technology depends on three major factors, including task, technology, and individual characteristics. Task characteristics define the difficulty and proficiency requirement of a task, technological characteristics define the attributes, intrinsic nature, and functionality of the technology, and individual characteristics define the level of knowledge, skill, and experience of the human operator. In general, a construction project has long and distinctive stages (e.g., planning, design, construction, operation, and demolition) in its life cycle [57]. Task characteristics vary over the execution process. In addition, construction tasks are conducted by different trades and workers who have different specific sets of skills and competencies because of their unique requirements [58]. For the same type of trade, the individual characteristics of the crew could be diverse because of the skill level, training level, and educational level of workers. Therefore, the application of robots in the construction industry must be categorized on the basis of scenarios and tasks. Given various control logic, hardware capability, algorithm design, environmental awareness, decision-making, and task execution ability, construction robots can be divided into different types based on different principles. For example, based on control logic, the robots can be grouped as remotely controlled robots, local-controlled robots, real-time controlled robots, and preprogrammed robots.

Current application in the construction industry lacks an effective management platform and human–computer interactive mechanism. First, most of the current construction robots are designed and built for the single operation. Even a single task involves the participation of many robots, which increases the deployment and management costs. Second, integrated management systems are necessary to provide effective support and coordination between robots and human workers. Third, high-level HRC requires dynamic monitoring and simultaneous calibration of robot mechanical systems. Fourth, an agile mechanism for robots is necessary for distinctive features and requirements of tasks to quickly learn human experiments and skills. Fifth, as a prior concern, safety must be ensured in the HRC process.

### 2.3 Applications based on locations and tasks

Construction activities have high-intensity repetitive operation combined with complicated transitional operation. These tasks are highly associated with the locations and stages of the construction progress. Organizing and adjusting the workflow and proper arrangement of professional workers entering designated sites in accordance with the preplanned production sequence can improve construction efficiency [59]. Based on locations, robots can conduct different types of operation, such as bricklaying, concrete pouring, spraying, laying, and installation. Xiao et al. [60] also categorized location-specific robots as on-site operation robots, off-site manufacturing robots, and additive manufacturing robots. Recently, the developments of modularized construction and design promote the prefabrication and assembly of building components with robotic manipulators in advance at the factory away from the construction site. On the contrary, addictive manufacturing can rapidly and accurately produce building components by adding a material layer by layer on site. For example, Le et al. [61] developed a concrete component printing method without the framework by 3D printing robots, which effectively reduces waste production.

A complete construction process is composed of tasks, which requires the cooperation of workers with different professional skills and trades. Therefore, substituting human labor with robots depends on the task competence of robots [11]. Recent industrial and academic efforts primarily focus on developing task-oriented robots in completing on-site measurement, cleaning, installation, and other construction work. For example, Woo et al. [62] developed a cooperative painting robot to perform painting operations, allowing the painting plans autonomously based on the worker's judgment and perception during painting. Gautam et al. [63] presented a cobot that can screw gypsum board panels to the room ceiling or other connecting parts. Task-based robots are feasible solutions for repetitive task substations. However, these studies also concluded that versatile robots that can support the continuous execution of multiple construction tasks are lacking.

For the HRC, identifying locations and tasks using dialog and interaction tools can improve the robots' ability to understand workers' judgments and perceptions. For example, Wang et al. [64] proposed an integrated digital twin system in virtual reality to enable bidirectional communication between human and robot partners. Using such an interface, workers can conduct visual supervision and complex task planning in accordance with the workspace sensing and monitoring data transmitted by robots. Then, robots can make more detailed motion planning and physical execution of the work. Similarly, Jung et al. [65] developed an automation interface for steel structure construction. This interface allows workers to operate a robotic crane and move machinery through a haptic device and vision system. Wang et al. [66] developed a mobile unit design and corresponding assembly method with a parametric design. The construction process can be assumed by robots in multiple construction steps at different locations. Using laser scanning and software interaction, robots can complete the task with high accuracy.

### 2.4 Adoption of robots on site

As an essential innovation, robots developed for the construction industry are similar to other innovations, which should be considered from an organizational perspective. Therefore, the decision to utilize innovation should benefit the performance or effectiveness of the adopting organization [67]. Similar adoption studies have been conducted for several existing technologies, such as BIM [68] and virtual reality [69]. The technology–organization–environment (TOE) framework has been proposed by Drazin [70] in the 1990s. The TOE framework defines a study on innovation diffusion based on three fundamental contexts, including (1) technological context (such as perceived advantages, compactivity, complexity, and cost), (2) organizational context (such as top management support, firm size, and organizational readiness), and (3) environmental context (such as market competition, market demand, regulatory support, and partner support) [71]. From the technological context, applying robots provides relative advantages of replacing or assisting humans to conduct difficult and dangerous work [72]. Complexity is another major concern as a lack of expertise can cause new uncertainties during construction tasks [73]. Given the relatively small-scale application of robots, the price of using construction robots remains high [74]. From the organizational context, large companies with the top management team support tend to be more open-minded to new technologies [75]. From the environmental context, labor shortage and low productivity post the large competitive pressure on all companies in the industry, leading to an evident demand [74]. Pan and Pan [71] based on the TOE framework developed quantitative analyses of 12 major factors that affect the adoption of robotics technologies, and then they draw and validated four major conclusions. First, relative technical advantages are the main driver of robot adoption, and high cost is the main barrier. A cost-sharing contract between partners can effectively reduce costs and improve innovation diffusion [76]. Second, the uniqueness of the project is primarily responsible for the compatibility issue. Third, the awareness of the top management in the technology can earn the support from the top management team. Fourth, market competitive pressure contributes to the on-size and off-size adoption of construction robots.

## 3 HRC

### 3.1 Taxonomy of robot autonomy

In the practical application of robots, the capacity, technical difficulties, and feasibility of optional robotic systems as well as the suitability of scenarios must be understood. Therefore, a proper taxonomy of robot systems is necessary. The common taxonomy of automated systems is the level of auto-driving systems defined by the Society of Automotive Engineers [77]. Later, Beer et al. [78] proposed a ten-level level of robot autonomy (LoRA), including manual control, action support, batch processing, shared control, decision support, blended decision-making, rigid system, automated decision-making, supervisory control, and full automation. For the construction industry, Saidi et al. [79] categorized robot systems as teleoperated systems, programmable construction machines, and intelligent systems. Later, Liang et al. [80] proposed a six-level taxonomy based on the collaborative level of humans and robots. The six-level taxonomy includes manual, preprogramming, adaptive manipulation, imitation learning, improvisatory control, and full autonomy [6]. The taxonomy of robot systems is summarized in Table 1.

The taxonomy specifies not only the level of intelligence of robots, but also the workload distribution between human workers and robots. According to Liang et al. [80], the latest research primarily focuses on the imitation learning level. In the imitation learning stage, robots are trying to learn the skills and working plans generated by human workers and to mimic their operations. These duties are often equally shared by humans and robots. An ideal HRC implementation should promote the improvisatory control level, under which human workers supervise the work plan and interference only when necessary.

**Table 1** Taxonomy of LoRA

| Auto driving autonomy [77] | | LoRA [78] | | LoRA in construction [6] |
|---|---|---|---|---|
| Level | Description | Level | Description | |
| 0—No automation | Manual control. The human performs all driving tasks. | Manual control | Humans conduct all operations, such as monitoring, commanding, and carrying out actions. | Manual |
| 1—Driver assistance | The vehicle features a single automated system. | Action support | Automation assists human-specific actions. | Preprogramming |
| 2—Partial automation | Automatic data acquisition system (ADAS). The vehicle can perform steering acceleration. The human still monitors all tasks and can take control at any time. | Batch processing | The human generates commands and lets the robot carry out actions. | Adaptive manipulation |
| | | Shared control | The human and programs generate options, and humans select options to implement. | |
| 3—Conditional automation | Environmental detection capabilities. The vehicle can perform most driving tasks, but human override is still required. | Decision support | The program generates decision options for the human to select. | Imitation learning |
| | | Blended decision-making | The program automatically generates and executes options with human consent. | |
| | | Rigid system | The program provides a set of options, and the human has to select one of them. | |
| 4—High automation | The vehicle performs all driving tasks under specific circumstances. Geofencing is required. Human override remains an option. | Automated decision-making | The program selects and carries out an option. Humans can create and decide alternatives by giving inputs. | Improvisatory control |
| | | Supervisory control | The program generates options and carries out these options. The human only monitors the system and intervenes if necessary. | |
| 5—Full automation | The vehicle performs all driving tasks under all conditions. Zero human attention or interaction is required. | Full automation | The system carries out all actions with human intervention. | Full autonomy |

### 3.2 Competence and skills of human workers

The LoRA depends on the extent of human competence that can be substituted by the robot operation. Parasuraman et al. [81] categorized human competence into four major skills: information acquisition, information analysis, decision and action selection, and action implementation. Based on Ref. [81], Ma et al. [11] also summarized all skills into four types, including perceptual skills, analytical skills, decision-making skills, and executive skills. Perception skills are the ability to acquire information from the surrounding environment and store such information for further processing. These skills can be easily substituted by various sensors, such as vision sensors, motion sensors, and geolocation sensors [82]. Analytical skills are the ability to process, operate, transform, and integrate data sources and extract important and useful information for future operation. Using properly designed mechanisms, robots have a powerful computational strength to assist humans in conducting analysis and retrieving knowledge [83]. Decision-making skills are the ability to compare different options and optimize potential outputs. Such a process can be supported by machines to a certain extent by learning from human reasoning and historical data [84]. Executive skills refer to the ability to take action to respond to decisions. In general, robots have actuators to perform such actions, such as movement, load carrying, and installation. Based on Section 3.1, the level of autonomy and the number of skills can be replicated by robots. Therefore, various technologies must be utilized to substitute human manual skills with sensors, processors, and actuators of robots and improve the level of autonomy.

### 3.3 Human-sensing technologies in construction

Sensors are a major hardware type that is utilized in most robots and engineering HRC. Sensing technologies enable the perceptual skills of robots and provide a large amount of human factor data. These data served as the basis for robotic humanoid training and autonomy improvement. In the construction industry, various sensing technologies have been studied and implemented in the hazard detection area, safety protection, human–computer interaction, etc. Sensor-equipped wearable devices (smart glasses, smart watches, smart wristbands, etc.) are the most popular equipment for workers' physical condition detection [85]. These physical statuses, such as heart rate, respiration rate, and calorie expenditure, can be monitored in real-time to reflect their task exertion and assess their health conditions. Liu et al. [39] also adopted the concept of the brain–computer interface, utilizing neural sensors to continuously capture workers' brain waves and convert them into robot commands.

Instead of sensing the human physiological status, another branch of sensors can capture and predict human motions for robot-related applications. Such applications allow remote control of the robot and dispatch of robots to hazardous environments. For example, during the COVID-19 pandemic, remotely controlled robots can be used for the construction of hospitalization facilities [86]. Extending motion capturing, human motion prediction that estimates human's movement in a short period with historical movements or certain leading indicators [87] has the significant application potential in HRC. To this end, Guerra-Filho and Biswas [88] developed a dataset for human motion prediction with additional cognitive features. However, datasets that are specifically designed and customized for the construction works are still needed to improve feature matching [89]. Human-sensing technologies are limited to not only human physiological status and motion, but also broader interactive inputs, such as voice, touch, and pressure. In addition, using computational methods, such as computer vision, synchronous location mapping, mixed reality, or other technologies, remote control or human task substitution can be achieved [90].

However, human-sensing technologies cannot overcome all the barriers of practical HRC. First, human-sensing technologies have to confront complex and dynamic construction environments. The accuracy and reliability of sensing systems can be affected by the environmental "noise", such as the human and machinery's sound and movement [91]. Second, many sensing systems must be used for real sites and workers, as the majority of studies have been conducted in the lab environment with students, who lack sufficient experience and perceived risks [14]. Third, the mechanical responses of robots make humans infer and react properly based on robots' movements [92]. For robots with built-in sensors, continuous reports of robots' working conditions and intentions are important to human participants in HRC.

### 3.4 Applications of HRC in construction

As shown in Table 1, most construction robots remain at the low level of LoRA. In practice, workers must touch or make specific action commands to instruct robots for specific tasks [93]. Considering that these robots need instant monitoring and operation commands from workers, they have to be applied in situations where workers' movement is less restricted. They also have to be used in tasks with high repetition, low flexibility, and few control parameters (such as building walls). In recent years, Wang et al. [64] have explored the potential of changing workers from manual task performers to robot managers. Hence, humans must overcome the limits of touch control and frequent movements. For example, Kim et al. [94] equipped the construction machinery with vision sensors, which allow them to identify workers' locations, calculate collision risks, and implement safety measures accordingly. Linares-Garcia et al. [95] implemented human voice as a media for a virtual collaboration agent. Consequently, the robots can collaborate with human workers on spraying and masonry tasks. Virtual reality can also serve as the interface for remote human–computer interaction. For example, Adami et al. [96] utilized virtual reality to train workers on remote robot control and operation. An ideal scenario for HRC is redesigning the construction process to reduce duplicated and repetitive work by employing robots. Humans and robots can share a workspace, where humans are responsible for understanding and demonstrating operations, and robots learn and repeat [97]. In a recent development, robots become more lightweight and closer to the human body, and then HRC can be applied to more precise labor-intensive tasks such as component classification and screw installation [98]. In the future, HRC not only can improve on-site productivity but also can contribute to career equality, and wherein people with disabilities can perform effectively with extended capabilities by robots.

### 3.5 Human-augmented robotics

In recent years, a new type of high-level collaborative robot, namely exoskeleton, has been studied and introduced in the construction industry. Exoskeletons are typical wearable human strength augmentation robots [99]. They are suitable for implementation in the construction industry because of a large amount of demanding and load-bearing tasks. These robots allow workers to move faster and carry heavier loads with higher endurance and meet the needs of industrial applications [100]. Existing exoskeletons can be categorized by body parts of augmentation, including back assists, shoulder/arm assists, leg assists, and full-body assists [100]. Depending on the type of actuators, the exoskeletons can also be categorized as active and passive systems. The active systems receive power support from electric motors, pneumatics, and hydraulics, whereas the passive system usually has the mechanical parts of dampers and springs [101]. In recent years, many exoskeleton prototypes have been developed to experiment or verify their application in various industries, such as SPEXOR [102], hybrid assisted limb [103], and Berkeley Lower Extremity Exoskeleton [104]. For the application in the construction industry, Yu et al. [105] developed an upper-limb exoskeleton robot for steel manufacturing. Robots have been adopted in helping refractory construction operations in furnaces. Ren et al. [106] developed a lower-limb exoskeleton and an iterative adaptive controller to assist the load-bearing and carrying movement of construction workers.

Although studies suggest that using exoskeletons can improve the working efficiency and extend human capacities, they also introduce additional hazards. Human safety, comfortability, operational errors, and physical stress are the major concerns from the wearers' perspective [107]. In addition, the reliability of the electrical, mechanical, and power systems of the robots can cause unpredictable errors or injuries [108]. Moreover, as heavy and expensive equipment, security is another unavoidable risk, such as unauthorized access or operational situation awareness [109]. Therefore, future studies that can solve these technical problems and safety hazards can promote the wide adoption of these augmenting robots.

## 4 Discussion

### 4.1 Challenges of HRC

Researchers have made great progress in developing robotics technologies and promoting HRC; however, previous studies have revealed several major challenges to be resolved in future studies. First, safety concerns are the major consideration of using robots and major problems that needs to be solved for the usage of robots. Many researchers [110–112] have proposed the application of vision and motion sensors to ensure the safety of humans when they work alongside the robots. However, a standard to define the interactive content and mechanism is necessary [6]. Many studies associated with worker activity identification [113] and real-time robot tracking systems [114] can provide some solutions for this concern. Second, the lack of automation design results in incomparability between robots and task operations. Complementary changes in design, construction process, team organization, and business model should be changed to fully develop the application potential of robotics [115]. Third, trust for human operators, collaborators, and robots should be established [116]. You et al. [14] suggested the separation of workplaces to mitigate the worry and fear of the unreliability of robots.

### 4.2 Future research trends and recommendations

Adopting robots promotes the automation level and improves the working conditions of construction workers. More specialized and intelligent robots would participate in a more complicated construction process. Thus, future studies on the following topics are highly recommended.

#### 4.2.1 Learning robots and autonomy algorithm

Intelligent robots should not only be passively programmed but also actively learned from humans. A major advantage of HRC is knowledge transfer, which allows robots to directly imitate workers' behaviors and absorb their skills [6]. Programming robot control algorithms are often complex and difficult to be implemented in all tasks, whereas capturing humans' activity and automatically translating it to control signals are the universal and practical solution. In addition, robots do not necessarily have the precise operation as humans. Rough completion of work can be finalized by human workers, or robots can perform the improvised operation with a consent from a human worker [117]. On the contrary, the LoRA can be further improved with more advanced control algorithms and planning systems. Studies on artificial intelligence have been elevated by the rapid development of deep learning algorithms. The existing robotic operation systems can adapt such methods for complicated requirements and unseen scenarios [118]. For example, as a popular metric for robot control, deep reinforcement learning can enable robots to make independent decisions even in unforeseen tasks [119]. These algorithms are suitable for conditions with limited training samples and for construction projects, which are usually composed of heterogeneous and various tasks. In the future, more open design systems and sophisticated algorithms are needed for the new generation of HRC.

#### 4.2.2 Robot-to-robot collaboration

The communication systems between robots and robot swarm theories have been well-studied in the past years [120]. Allowing communication and cooperation among robots is a big leap to increase LoRA. For example, Im et al. [121] developed an inter-robot communication network with data filters that allow robots to avoid collision and ensure signal connection with other cooperating robots. Miura et al. [122] developed a multi-robot system to operate four robots (an investigation robot, a transfer robot, and two relay robots) for tunnel inspection. Each robot is equipped with unique sensors, and it is in charge of single tasks. The multi-robot system can be adopted to more complicated and unexpected construction scenarios. At present, multi-robot collaboration is an emerging research direction that needs further studies. Furthermore, data alignment, control signal communication, environment awareness, and task planning can be directly applied to HRC schemes.

#### 4.2.3 BIM-based robots

Compared with other industries, the building industry has a unique advantage in constructing robot navigation systems [123]. A modern project management requires the project team to develop a digital model for their product, which is known as BIM. Apart from robotic navigation, BIM provides a digital virtual environment for simulation and teleoperation [124]. Yang et al. [125] proposed an integrated robot and the BIM package to facilitate data exchange between them. However, the benefits of BIM models have not been fully exploited by the HRC. Thus, more in-depth developments are highly encouraged for the future research. First, automated component extraction can be applied to robot simulation and operation platform. BIM models are more precise than the vision based on SLAM methods. Extracting building components and layers can significantly improve the reliability and precision of robot routing. Second, digital building models can help robots understand the physical logic and connections among building components. Such the high-level understanding improves all robot-based assembly works. Third, the BIM model provides a series of powerful visualization tools for robot control and operation. With in-depth integration, the BIM will be a powerful supplement for HRC in practice.

#### 4.2.4 Module fabrication robots

In recent years, modular construction becomes a trend in reforming the entire construction industry. Modular construction uses the same materials and processes to construct building components at off-site factory-like workshops and assemble the components into the final building product on site. Such efforts aim to enhance productivity by transforming the process into a manufacturing-like process [126]. This process reformation simplifies the comprehensive component-building process into a repetitive step; thus, the working efficiency can be significantly improved. Therefore, robotic systems are ideal options to assume such tasks. For example, Wagner et al. [127] proposed the semi-industrial production for the timber assembly work, and the validation results show a remarkable improvement. In implementing such concepts, studies associated with the construction process transformation, material improvement, structural component design, and robot controller optimization should be further investigated to ensure their suitability for modular construction.

## 5 Conclusions

This paper systematically investigated the state-of-the-art application of robots in the construction industry. The review of the latest literature explained the rationale for the adaption of robots in the field and its technological foundations. Given the low level of autonomy and complexity of construction tasks, HRC is a feasible and unavoidable solution to improve the productivity and efficiency of the industry. However, the further investigation on the topic must be conducted because of safety concerns and a lack of specifically designed and customizable management platforms. In the future, studies that focus on automated learning robots, robot–robot collation, BIM-based robots, and module fabrication robots are highly recommended.

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## Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

## Author contribution statement

All authors have given approval to the final version of the manuscript.

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