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RESEARCH ARTICLE

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Industry perception of competencies for human–robot collaboration in the construction industry: A Delphi study

Abstract Robots present an innovative solution to the construction industry's challenges, including safety concerns, skilled worker shortages, and productivity issues. Successfully collaborating with robots requires new competencies to ensure safety, smooth interaction, and accelerated adoption of robotic technologies. However, limited research exists on the specific competencies needed for human–robot collaboration in construction. Moreover, the perspectives of construction industry professionals on these competencies remain underexplored. This study examines the perceptions of construction industry professionals regarding the knowledge, skills, and abilities necessary for the effective implementation of human–robot collaboration in construction. A two-round Delphi survey was conducted with expert panel members from the construction industry to assess their views on the competencies for human–robot collaboration. The results reveal that the most critical competencies include knowledge areas such as human–robot interface, construction robot applications, human–robot collaboration safety and standards, task planning and robot control system; skills such as task planning, safety management, technical expertise, human–robot interface, and communication; and abilities such as safety awareness, continuous learning, problem-solving, critical thinking, and spatial awareness. This study contributes to knowledge by identifying the most significant competencies for human–robot collaboration in construction and highlighting their relative importance. These competencies could inform the design of educational and training programs and facilitate the integration of robotic technologies in construction. The findings also provide a foundation for future research to further explore and enhance these competencies, ultimately supporting safer, more efficient, and more productive construction practices.

Keywords industry perception, competencies, human–robot collaboration, construction industry, Delphi study, workforce development

1 Introduction

The construction industry is currently grappling with a host of critical challenges that threaten its operational efficiency and future viability. A significant issue is the acute shortage of skilled labor, intensified by an aging workforce and high retirement rates (Karakhan et al., 2020). Labor shortages are critical issues across industries, with the construction sector facing the most severe challenges (Elbashbishy and El-Adaway, 2023). The construction industry in the United States (US) is projected to require 663,500 new workers annually, driven by both employment growth and the replacement of those leaving the workforce (Bureau of Labor Statistics, 2024a). This figure surpasses the 622,000 unfilled positions in manufacturing (US Chamber of Commerce, 2024) and the healthcare sector's shortage of 195,400 registered nurses (Bureau of Labor Statistics, 2024d). This shortage jeopardizes project timelines, inflates costs, and puts immense pressure on an already strained industry (Elbashbishy and El-Adaway, 2024). Concurrently, safety remains a paramount concern, with the construction sector consistently experiencing high rates of worker fatalities and injuries despite ongoing safety initiatives and improvements (Ghosh et al., 2024). In 2022, it was reported that there were 1,092 construction worker deaths, accounting for nearly 20% of all workplace fatalities in the US (Bureau of Labor Statistics, 2024b). These safety issues endanger workers and contribute to project

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delays and increased costs, further compounding the industry's challenges. Additionally, the industry has been facing a notable decline in productivity and efficiency (Kumar and Rana, 2022; Pradhananga et al., 2021). The Bureau of Labor Statistics (2024c) reported that productivity trended downwards in the residential construction industries from 2007 to 2019, and since then, productivity has declined in single-family residential construction. This has resulted in the industry struggling to meet its demand for new housing and other infrastructure (Bahr and Laszig, 2021). Traditional construction methods, which heavily rely on manual labor and outdated techniques, are proving increasingly unsustainable in the face of growing infrastructure demands, persistent labor shortages, and heightened safety concerns. Without strategic interventions, the industry risks stagnation, leading to even longer project timelines, inflated costs, and an inability to meet the demands of rapidly expanding urban populations. Consequently, there is a pressing need for innovative solutions to improve construction processes and address the challenges.

Robotic automation has emerged as a promising technological advancement with the potential to address these challenges. The deployment of robots on construction sites offers the advantage of performing repetitive and hazardous tasks, which can reduce human risk and enhance productivity (Brophy et al., 2022; Pereira da Silva and Eloy, 2021). Robots can undertake tasks such as material handling, site inspection, and even complex assembly processes, potentially revolutionizing traditional construction practices (Delgado et al., 2019). Robotic technologies in construction have been categorized according to their functionality and application (Gharbia et al., 2020). For example, Zeng et al. (2024) classified these technologies into four general categories: off-site prefabrication, onsite automated and robotic systems, drones and autonomous vehicles, and exoskeletons. Off-site prefabrication involves the use of robotics in controlled factory settings to manufacture building components, improving precision and reducing waste. On-site automated and robotic systems include robots for bricklaying, concrete printing, and other automated construction tasks. Drones and autonomous vehicles are used for site surveying, inspections, and material transportation, enhancing efficiency and safety. Exoskeletons are wearable robotic systems designed to augment human capabilities, reducing physical strain and improving worker endurance.

Compared with industries such as manufacturing, where robotic automation is extensively integrated, construction has been slower in adoption due to the unique and dynamic nature of construction sites, which often require high levels of adaptability (Delgado et al., 2019). Moreover, the construction industry is inherently labor-intensive and human-centric, relying heavily on skilled workers whose expertise and intuition are crucial for navigating the unpredictable challenges of the worksite. Consequently, the integration of robots must be carefully designed to complement human skills, as the overall effectiveness of robotic deployment hinges on the quality of interaction and collaboration between human workers and automated systems (Burden et al., 2022; Liu et al., 2025).

This realization underscores the importance of human–robot collaboration (HRC), wherein humans and robots work together through coordinated actions, shared workspaces, and mutual adaptability (Liu et al., 2025). In such environments, robots handle specific tasks, while humans oversee operations, make judgment calls, and perform tasks that require complex problem-solving and adaptability (Othman and Yang, 2023). The success of HRC is contingent on the presence of a skilled workforce capable of managing and interacting with robotic systems (Othman and Yang, 2023; Yang et al., 2024). The current shortage of workers with the necessary competencies for HRC presents a significant barrier to the widespread adoption of robotic automation in construction (Aghimien et al., 2024). Addressing this gap requires identifying the competencies needed for effective HRC in construction. These competencies could inform the development of educational and training programs, ensuring that the workforce is adequately prepared for collaboration with robotic systems. Moreover, defining these competencies could help tackle broader industry challenges, such as labor shortages and safety concerns, by fostering a workforce that is both adaptable and proficient in HRC (Li, 2024). Ensuring that these competencies align with industry needs and expectations is crucial for facilitating smooth technology integration.

As the construction industry remains in the early stages of robotic adoption, most professionals have limited exposure to multiple robotic systems. Given this reality, an essential first step in addressing gaps in HRC competency is the establishment of unified, foundational competencies. Such competencies could create a more flexible workforce capable of interacting with various robotic systems. This approach would accelerate workforce readiness, facilitate smoother integration of new technologies, and prevent training programs from becoming obsolete as robotic technologies continue to evolve. Additionally, a broad competency framework would promote cross-disciplinary knowledge transfer, enabling workers to apply fundamental HRC skills across different robotic platforms instead of being confined to a single technology. This adaptability is particularly valuable amid ongoing labor shortages in construction, as it fosters a more versatile workforce that can adjust to automation trends without requiring constant retraining.

Therefore, this study aims to capture the perceptions of industry professionals regarding the foundational competencies required for HRC in the construction industry. Identifying foundational competencies broadly applicable across diverse robotic technologies for HRC in construction would provide insights into the knowledge, skills, and abilities needed to facilitate HRC, improve industry performance, and address the shortage of workers with HRC competencies. It would also ensure that the competencies identified are generalizable and relevant across the diverse and rapidly evolving landscape of construction robotics, making them applicable to current and emerging technologies. The remaining sections of this paper are structured as follows: the background section reviews relevant literature on the current state of HRC in construction and identifies the necessary competencies. The methodology section presents the Delphi survey technique and the data analysis method. The results section presents the findings of the study. The discussion section interprets the findings, and the last section includes the conclusion, limitations, and recommendations for future research. This research contributes to the body of knowledge by establishing construction industry professionals' perceptions regarding the competencies for HRC in construction. It also identifies the top-rated competencies industry professionals prioritize for implementing HRC in construction. These competencies contribute to knowledge on HRC, offering valuable information for both industry practitioners and academic researchers focused on enhancing construction practices through technology.

2 Literature review

2.1 Current state of human–robot collaboration in construction

Recent advancements in robotics and enablers of artificial intelligence (AI), including data sensing technologies and machine learning techniques, have influenced the implementation of HRC in various industries, including manufacturing, healthcare, agriculture, and construction (Okonkwo et al., 2024). HRC has been integrated into automotive manufacturing primarily to enhance production efficiency and address ergonomic concerns for human workers (Wang et al., 2023a) and standardization issues in heavy vehicle manufacturing. In healthcare, HRC has been implemented for diagnosis, medication development, and treatment targeted at improving patient outcomes and the efficiency of healthcare practitioners' work (Gürce et al., 2023). It has also been adopted to address the issue of shortage of medical staff for tasks such as hospital disinfection, delivery of food and medical supplies, and collection of physiological materials (Buxbaum et al., 2019). It has also helped reduce the risk of infection for healthcare workers (Buxbaum et al., 2019). Similarly, in agriculture, HRC has been applied to labor-intensive tasks such as planting, spraying, and harvesting, where the complex and unstructured agricultural environment challenges fully autonomous systems, but the combination of human decision-making with robotic precision and endurance helps to overcome these obstacles (Adamides and Edan, 2023; Vasconez et al., 2019; Yerebakan and Hu, 2024). HRC systems aim to enhance efficiency, safety, and productivity on construction sites by leveraging humans' and robots' capabilities and complementary roles (Fu et al., 2024). Robots handle repetitive, dangerous, and precise tasks, while humans oversee complex decision-making and adaptive problem-solving (Musić and Hirche, 2017). Current HRC systems in the construction industry include robots that can operate with some level of independence but still require human supervision or intervention (Zhang et al., 2023). These semi-autonomous robots include bricklaying robots, 3D concrete printers, material unit lift enhancers (MULE), exoskeletons, rebar tying robots (e.g., TyBot), and welding robots (Kamran, 2023), which have enabled various HRC applications in the construction industry.

HRC applications in construction are diverse and expanding (Wei et al., 2023; Zhang et al., 2023). Robots are used for construction tasks ranging from autonomous surveying and site inspection to automated machinery operation and precision construction activities (Sawhney et al., 2020). For instance, robots have been applied to wall painting (Asadi et al., 2018), gypsum ceiling installation (Gautam et al., 2020), robotic glass installation (Lee et al., 2007), sheathing, drywall installation, and timber frame construction (Wang et al., 2023b), construction waste sorting (Chen et al., 2023a), unmanned aerial and ground vehicle (UAV-UGV) systems for autonomous collection of construction site data (Asadi et al., 2020), and surveying and aerial mapping (Nguyen et al., 2020). Additionally, robotic solutions have been implemented in modular construction manufacturing (Fu et al., 2024) and off-site prefabrications (e.g., modular construction of buildings) (Richter et al., 2024). Furthermore, exoskeletons have been applied to provide mechanical support to reduce the physical strain associated with repetitive and heavy lifting tasks (Okpala et al., 2022). These applications improve efficiency and precision, address labor shortages, and mitigate safety risks associated with hazardous construction environments (Liang et al., 2021; Okpala et al., 2023). However, the implementation of HRC in construction depends on other supporting technologies to enhance automation and collaboration.

Supporting technologies such as machine learning, computer vision, the Internet of Things (IoTs), building information modeling (BIM), and robot operating systems (ROSs) play crucial roles in enhancing the capabilities of robots in the implementation of HRC applications in construction (Park et al., 2025; Wang et al., 2020). For instance, the collaborative robotic painting HRC system (Pictobot) by Asadi et al. (2018) integrates supporting technologies to enhance task execution, while human workers set painting parameters, navigate workstations, and ensure quality control. Supporting technologies used in the implementation of Pictobot include distributed control subsystems, two onboard personal computers (PCs), and sensor-driven control and feedback systems such as laser scanners, rangefinders, sonar sensors, and first-person view (FPV) cameras, which enable precise surface coverage and ensure adaptive robotic painting operation based on real-time feedback. The UGV-UAV-based HRC system implemented by Asadi et al. (2020) for autonomous construction site data collection enables human operators to select data collection points, monitor the system remotely, and intervene when needed. The UAV-UGV system is integrated with localization systems such as real-time appearance-based mapping (RTAB-Map) and visual-inertial navigation system (VINS-Mono), along with sensors including stereo cameras, light detection and ranging (LiDAR), and inertial measurement units (IMUs) to ensure accurate mapping and navigation. A ROS, embedded systems like Raspberry Pi, and wireless communication facilitate real-time data transfer and processing, allowing human operators to analyze site conditions. Similarly, the gypsum ceiling installation HRC system by Gautam et al. (2020) involves a Universal Robot (UR5) collaborative robotic arm enhanced with 3D scanning technology (ATOS Compact Scan System) and a machine vision system (i.e., wrist-mounted camera) to facilitate accurate placement. A built-in force limitation system ensures safe human–robot interaction (HRI) during the gypsum ceiling installation. Furthermore, the glass installation HRC system by Lee et al. (2007), involving a multiple degree-of-freedom (DoF) KUKA robotic arm, operates in coordination with an aerial lift system and control mechanisms such as dual six-axis force/torque sensors and kinematic control algorithms for precise positioning and safe handling of fragile materials. Additionally, in the timber framing, drywall, and sheathing installation HRC system proposed by Wang et al. (2023b), the robotic arms leverage digital twin technology, 3D and virtual reality (VR) interfaces, and BIM to simulate and optimize the construction process, while fiducial marker-based object localization and Gazebo-based robot operating environment (ROE) simulations enhance real-world accuracy. The integration of these supporting technologies with robotic systems ensures that HRC applications in construction are more efficient, precise, and collaborative, allowing human workers to focus on supervisory and adaptive tasks while robots handle repetitive and physically demanding operations. Table 1 presents a summary of the applications, robots, and supporting technologies employed in implementing HRC in construction.

However, despite the benefits offered by HRC, which is driven by robotic and ancillary technologies in executing construction tasks, its implementation has been hindered by the industry's reluctance to adopt new technologies (Ahmed and Sobuz, 2019). High initial investments for small and medium-scale enterprises (Abankwa and Rowlinson, 2021; Lasni and Boton, 2022), financial risks associated with digital technology utilization deterring many companies (Bello et al., 2024; Sepasgozar and Davis, 2019), and employee resistance to change (Lasni and Boton, 2022) have contributed to this challenge. Additionally, several studies have highlighted that a lack of skilled workers is a major barrier to adopting robotics and HRC in construction (Tomori et al., 2024). For instance, Emaminejad et al. (2024) highlighted that the lack of proper knowledge and training is one of the key barriers to the widespread adoption of HRC in construction. Chen et al. (2023b) identified a lack of training and skills as a critical risk factor for HRC implementation during the construction of engineering projects. Moreover, Davis (2022), in a report prepared for the Construction Management Association of America (CMAA), highlighted that despite the increasing adoption of robotic automation in construction, skilled labor remains essential to ensure efficient operations. Hence, it becomes imperative to identify the essential competencies for implementing HRC in construction. Furthermore, identifying and defining relevant and accurate competencies requires input from industry professionals (Kobets et al., 2021) to ensure that educational programs and training align with the actual needs of the industry and the requirements of the technology (Banasova et al., 2010; Kobets et al., 2021). Therefore, it is crucial to investigate these perceptions to ensure that the competencies identified are relevant and applicable within the industry.

2.2 Competencies for human–robot collaboration in construction

Several studies have defined competencies as a set of interrelated knowledge, skills, and abilities that form a crucial aspect of an individual's job role and responsibilities, directly influencing their performance in the workplace (Amaris et al., 2022; Bradbury and Sturm, 2024; Helmold, 2021; Oubibi and Zhao, 2019; Srour et al., 2006; Wong, 2020). To provide a structured framework for understanding and developing HRC competencies, they can be categorized into three interdependent dimensions: knowledge, skills, and abilities. This classification ensures that individuals are equipped not only with theoretical understanding (knowledge) but also with practical expertise (skills) and the cognitive and behavioral capacities (abilities) necessary for collaboration with robotic systems (Amaris et al., 2022; Helmold, 2021). The clear distinction between these three categories is crucial for aligning training, evaluation, and competency development strategies with industry needs (Nováková et al., 2024). Given the limited studies that have explicitly defined the knowledge, skills, and abilities required for

Table 1 Summary of HRC applications and robotic technologies in construction

HRC Applications	Robotic Technologies	Supporting technologies
Construction site data collection (Asadi et al., 2020)	UGV (Custom-built robot built on a Clearpath Husky A200 mobile robotic platform) – UAV (custom-built blimp made of 3D-printed parts)	Localization systems (RTAB-Map and VINS-Mono), sensors (stereo camera, LiDAR, IMU, and wheel encoders), robotic middleware and communication (ROS, Wi-Fi, and network communication), embedded systems, and hardware (Raspberry Pi and motor control system)
Autonomous excavation and material handling (Yang et al., 2021)	Capper, a gate-type autonomous material transportation robot	Augmented reality (AR) markers, machine vision and sensors (industrial cameras and laser rangefinders), wireless communication system (routers and PCs), and task planner system
Structural inspection (Xia et al., 2022)	Ground robot	Realistic building damage simulation (finite-element analysis and dynamic force analysis module), damaged building modeling (Unity and VR), robotic navigation and object recognition simulation (using ROS), and object recognition and damage detection autonomous algorithm (with rapidly exploring random tree (RRT))
Wall painting (Asadi et al., 2018)	Industrial robotic arm	Sensor integration system, computer-controlled system (PCs), sensor-driven control and feedback system (laser scanners, rangefinders, sonar sensor, and FPV camera)
Gypsum ceiling installation (Gautam et al., 2020)	UR5 collaborative robot (cobot): a lightweight, force-limited robotic arm	3D Scanning (ATOS Compact scan system), 3D printing (3D-printed adapter), machine vision system (wrist-mounted camera), and built-in force limitation system
Glass installation (Lee et al., 2007)	Multi-DoF KUKA industrial robotic arm adapted for ceiling installation	Aerial lift system (truck-mounted telescopic boom lift), control systems and automation technologies (dual 6-axis force/torque sensors), kinematic control system (inverse kinematics and dynamic control algorithms), collision detection and force limitation system (force/torque sensors and safety stop mechanism)
Timber framing, drywall, and sheathing installation (Wang et al., 2023b)	Robotic arms	Digital twin for scene observation (3D/VR interface) and interaction with physical objects (fiducial marker-based object localization and TwinCAT automated device specification), ROE simulation in Gazebo, and middleware (ROS), BIM, and Grasshopper
Construction waste sorting (Chen et al., 2023a)	Robotic arm with an end-effector dedicated to sorting tasks	AR for HRI (visualization, communication, and ergonomic benefits), ROS (communication, data processing, and coordination), and perception module (computer vision sensors)
3D printing (Xu et al., 2022)	Mobile robotic 3D printing system	Material transportation system, path-operate system, and controllers (robot, lift table, print head, spraying ring, and mobile platform controllers)
Offsite prefabrication (Yang et al., 2024)	Articulated robotic arms	Computational workflow (Grasshopper to facilitate bi-directional communication between computational models and robotic control), real-time communication interface, task planning (offline pre-programming with online adjustments and cyber–physical feedback systems)
Demolition (Corucci and Ruffaldi, 2016)	Demolition robots	3D perception system, laser designation-based HRI, real-time 3D modeling update and feedback system, ROS, and Point Cloud Library for perception and planning
Bricklaying (Lin and Wu, 2022)	Bricklaying robots	HRI simulation and modeling (AnyLogic software) and a sensor-based real-time feedback system

HRC, content analysis was employed to extract these competencies from applications of HRC in construction. According to Drisko (2014) and Kleinheksel et al. (2020), concept definitions can guide content extraction during content analysis. This approach ensures analytical consistency and rigor, leading to reliable research outcomes (Elo and Kyngäs, 2008). The identified competencies are categorized into HRC knowledge (K-1 to K-20), skills (S-1 to S-10), and abilities (A-1 to A-12) and summarized in Table 2. Each category is further elaborated in the following sections.

2.2.1 Knowledge

Knowledge refers to theoretical and conceptual understanding of a subject (Oubibi and Zhao, 2019; Vivas and Scifo, 2023). It includes facts, information, and principles acquired through education or experience (Oubibi and Zhao, 2019). In the context of competencies, knowledge is the foundational element that informs skills and abilities (Oubibi and Zhao, 2019). It encompasses key principles, methodologies, and technical aspects that support the development of practical skills and cognitive abilities. In HRC, knowledge includes, but is not limited to, an understanding of robotic systems, human–robot interfaces, artificial intelligence, safety protocols, and relevant industry standards (Parra et al., 2020; Simões et al., 2022). For example, knowledge of robotic kinematics and sensor technologies allows workers to anticipate robot behaviors and optimize collaboration. Additionally, theoretical knowledge facilitates effective problem-solving by enabling workers to diagnose system failures or inefficiencies. The implementation of HRC applications in construction requires knowledge in several fundamental areas. For instance, implementing the robotic construction waste sorting (CWS) described in Chen et al. (2023a) would require knowledge of the type of robot (e.g., manipulators), robot anatomy and technical specifications such as end effector and vacuum gripper, and sensors such as RGB-D camera used in the perception module, augmented reality (AR) human–robot interface, HRC-related fields such as physical and cognitive ergonomics, robot control mechanism for controlling robots for waste sorting, and modeling and simulation of a model for human–robot collaborative sorting in AR. Additionally, knowledge of data analytics and machine learning, such as computer vision algorithms for locating and sorting construction wastes, system integration (including perception, robotic sorting, AR, and communication modules), robot learning techniques, immersive virtual environments such as AR module for monitoring and instruction, safety and relevant standards, and robot operating system (ROS) are also crucial. Similarly, Asadi et al. (2018) designed a cooperative painting robot (Pictobot) for interior finishing of industrial developments. The implementation of this robotic painting system requires knowledge of painting task analysis, painting robot anatomy, and technical specifications (such as payload, maneuverability, degree of freedom, jack-up mechanism, spray gun, manipulator, painting head, and electric actuators), and robot architecture, including painting control and the feedback systems. The UAV-UGV system proposed by Asadi et al. (2020) requires knowledge of system integration for integrating context-aware, UAV-UGV, localization and mapping, and control mapping modules. It also requires knowledge of sensors (e.g., stereo cameras and LiDAR, robot actuators (e.g., UGV locomotion, motors, and servos), and ROS for exchanging data between different modules.

2.2.2 Skills

Skills are the practical application of knowledge (Helmold, 2021). They are learned to perform tasks with proficiency and efficiency (Bradbury and Sturm, 2024). Skills can be technical, such as using specific tools or software, or soft, such as communication and teamwork (Oubibi and Zhao, 2019). As illustrated in Table 2, the CWS application proposed by Chen et al. (2023a) needs practical capacities such as proficiency in AR human–robot interface, effective communication between humans and robotic manipulators during the sorting process, technical skills specific to CWS, and the application of machine learning algorithms such as computer vision algorithms for sorting tasks. Other essential skills include safety management focusing on parameters needing immediate attention (e.g., safety alarms and robot intentions), CWS task planning, simulation and modeling, and data analytics and management, including image data processing. Asadi et al. (2018) also proposed cooperative task automation to improve the productivity of many construction tasks due to the difficulties in developing robotic systems capable of assessing and adjusting their work in real-time. This cooperative task automation requires a human operator with technical skills to select an appropriate spray nozzle or paint type or adjust parameters like spraying pressure and paint thickness based on the user's specified finishing requirements. Selecting the painting specifications requires proficiency in human–robot interface to set the one-time configuration of parameters, with values selected from a predefined library corresponding to various paints and specifications. Human workers also teleoperate Pictobot navigation between adjacent workstations.

2.2.3 Abilities

Abilities are the inherent qualities or capacities that enable individuals to perform tasks (Helmold, 2021). They encompass cognitive, psychomotor, and affective domains, allowing individuals to mobilize and apply their knowledge and skills in various situations (Paquette et al., 2021; Vivas and Scifo, 2023). As indicated in Table 2, essential abilities required for robotic CWS by Chen et al. (2023a) include teamwork, where the robot identifies and sorts the waste while the human monitors and enhances sorting quality and modifies the information from the perception system. Other critical abilities include communication for seamless interaction, problem-solving for troubleshooting issues with the robot manipulator, attention to detail to ensure accurate sorting, safety awareness, and spatial awareness in the AR environment. Asadi et al. (2018) also emphasized attention to detail and safety awareness of the human operator of the robotic painting system. Similarly, implementing the UAV-UGV system proposed by Asadi et al. (2020) requires spatial awareness at indoor locations where GPS cannot receive signals.

2.3 Research gap

Despite the potential of robotic systems in addressing critical issues in the construction industry, such as safety, skilled labor shortages, and productivity challenges, there remains a gap in understanding the specific competencies necessary for effective HRC (Onososen et al., 2022; Shayesteh et al., 2023). While existing research acknowledges the benefits of integrating robotics into construction (Delgado et al., 2019; Musarat et al., 2024; Tomori et al., 2024; Wang et al., 2024b), limited efforts have been made to identify the knowledge, skills, and abilities required for workers to engage safely and effectively with robotic systems (Kim et al., 2024). Most studies focus on the technological advancements of robotics in construction (Xiao et al., 2022), often overlooking workforce preparedness and competency frameworks, leaving a critical knowledge gap. Additionally, there is no established consensus among industry practitioners on a clear competency framework for facilitating HRC in construction (Tomori et al., 2024). Without this shared understanding of these competencies, construction companies and educational institutions face challenges in developing effective training programs, potentially leading to inconsistent implementation, reduced efficiency, and increased safety risks (Kim et al., 2024). Given these gaps, it is imperative to evaluate industry professionals' perceptions and establish an objective, expert-driven consensus on the competencies necessary for successful HRC in construction. A Delphi method is particularly suitable for this purpose, as HRC in construction remains an emerging field with limited empirical studies and no universally

Table 2 Identified competencies for HRC in construction

HRC Competency Compodnents	Code	HRC Competencies
HRC Knowledge	K-1	Types of robots (Asadi et al., 2018; Attalla et al., 2023; Chen et al., 2023a)
	K-2	Construction robot applications (Liu et al., 2024a)
	K-3	Robot anatomy and technical specifications (Chen et al., 2023a; Suzumori and Faudzi, 2018)
	K-4	Sensors (Asadi et al., 2018; Chen et al., 2023a; Li et al., 2020)
	K-5	Task planning (Asadi et al., 2018; Kim et al., 2021)
	K-6	HRC ethics and regulation (Leenes et al., 2017; van Wynsberghe et al., 2022)
	K-7	HRC safety and standards (Rosenstrauch and Krüger, 2017)
	K-8	HRC evaluation (Spatola et al., 2021)
	K-9	HRC-related fields (Chen et al., 2023a; Giallanza et al., 2024)
	K-10	Immersive virtual environments (Chen et al., 2023a)
	K-11	Communication modes and technologies (Bonarini, 2020; Zhang et al., 2023)
	K-12	human–robot interface (Chen et al., 2023a; Zhang and Wang, 2021)
	K-13	Robot control system (Asadi et al., 2018; Chen et al., 2023a; Gustavsson et al., 2018)
	K-14	System integration (Asadi et al., 2018; Asadi et al., 2020; Chen et al., 2023a)
	K-15	Programming (Chen et al., 2023a)
	K-16	Modeling and simulation (Bächer et al., 2021; Chen et al., 2023a)
	K-17	Data analytics and machine learning (Chen et al., 2023a; Rathore et al., 2021; Zhang and Wang, 2021)
	K-18	Robot learning methods (Chetouani, 2023)
	K-19	Computation design (Bächer et al., 2021)
	K-20	Robot operating system (Chen et al., 2023a)
HRC Skills	S-1	Effective communication (Bonarini, 2020; Chen et al., 2023a)
	S-2	Task planning (Asadi et al., 2018; Chen, Fu et al., 2023; Kim et al., 2021)
	S-3	Regulation standard compliance (Leenes et al., 2017)
	S-4	Safety management (Chen et al., 2023a; Tehrani and Alwisy, 2023)
	S-5	Technical skill (Asadi et al., 2018; Chen et al., 2023a; Suzumori and Faudzi, 2018)
	S-6	Programming (Chen et al., 2023a; Rathore et al., 2021)
	S-7	Data analytics and management (Liu and Jebelli, 2024; Wang et al., 2019)
	S-8	human–robot interface proficiency (Asadi et al., 2018; Chen et al., 2023a; Zhang and Wang, 2021)
	S-9	Application of machine learning algorithms (Chen et al., 2023a; Zhang and Wang, 2021)
	S-10	Simulation and modeling (Bächer et al., 2021; Chen et al., 2023a)
HRC Abilities	A-1	Teamwork (Ma et al., 2022)
	A-2	Communication (Bonarini, 2020; Chen et al., 2023a)
	A-3	Continuous learning (Shen and Hsu, 2023)
	A-4	Problem-solving (Chen et al., 2023a; Kimaporn and Nunkaew, 2024)
	A-5	Adaptability (Vianello et al., 2024)
	A-6	Attention to detail (Asadi et al., 2018; Stumm et al., 2017)
	A-7	Analytical aptitude (Semeraro et al., 2023)
	A-8	Decision-making (Leonard, 2009; Liu et al., 2024b)
	A-9	Critical thinking (Ren et al., 2023)
	A-10	Spatial awareness (Chen et al., 2023a; Grushko et al., 2021)
	A-11	Cultural and social awareness (Lim et al., 2021)
	A-12	Safety awareness (Asadi et al., 2018; Chen et al., 2023a; Ojha et al., 2023)

accepted competency frameworks. Delphi surveys enable a structured process for expert consensus-building, making them an effective methodology for domains with evolving knowledge bases and diverse stakeholder perspectives (Barrett and Heale, 2020; Sourani and Sohail, 2015). This method would ensure that the identified competencies are relevant and applicable, drawing on the nuanced knowledge of those most familiar with HRC's technological and practical demands in construction.

3 Methodology

This study is conducted to understand the perceptions of construction industry professionals regarding the competencies required of the current and future workforce for HRC in the construction industry. Figure 1 presents an overview of the approach employed to execute this study, which includes a literature review and content analysis to identify HRC competencies (see Section 2.2), a Delphi survey to capture construction industry professionals' perceptions of the competencies for HRC, and the analysis of the data obtained from the Delphi survey.

3.1 Overview of Delphi study

The Delphi study, developed by the Rand Corporation for the US Air Force in the 1950s (Tymvios and Gambatese, 2016), was initially designed to forecast military priorities, particularly those related to evolving technologies. It involves gathering opinions from subject-matter experts and achieving consensus on a topic with limited established consensus (Landeta and Lertxundi, 2024). The characteristics of the Delphi study that make it unique and valuable in the field of research include the following: first, it involves a panel of experts selected based on their expertise and knowledge of the subject being studied (Barrett and Heale, 2020) to ensure that the opinions and insights gathered are well-informed and reliable. The recommended size for Delphi studies ranged between 10 and 30 experts to balance diverse perspectives and manageability (Akins et al., 2005; Pamidimukkala and Kermanshachi, 2022). Secondly, the Delphi study employs a systematic and iterative approach, where participants provide their input anonymously and then review and revise their responses based on feedback from other panel members (Chalmers and Armour, 2019). This process helps to eliminate biases and allows for a more comprehensive exploration of ideas and perspectives.

Researchers in different disciplines, including construction, use the Delphi method (Alomari et al., 2020). In the construction sector, the Delphi technique has been applied to new technology implementation (Wu et al., 2017), facility management (Naji et al., 2023), safety (Alomari et al., 2020), and competencies studies (Simmons et al., 2020). This research protocol, approved by Virginia Tech's Institutional Review Board (IRB), utilized a two-round Delphi survey to measure the perceptions of construction industry professionals concerning the competencies required for HRC due to the lack of an established framework and consensus on the subject within the construction sector. The Delphi method offers a structured approach to achieving expert

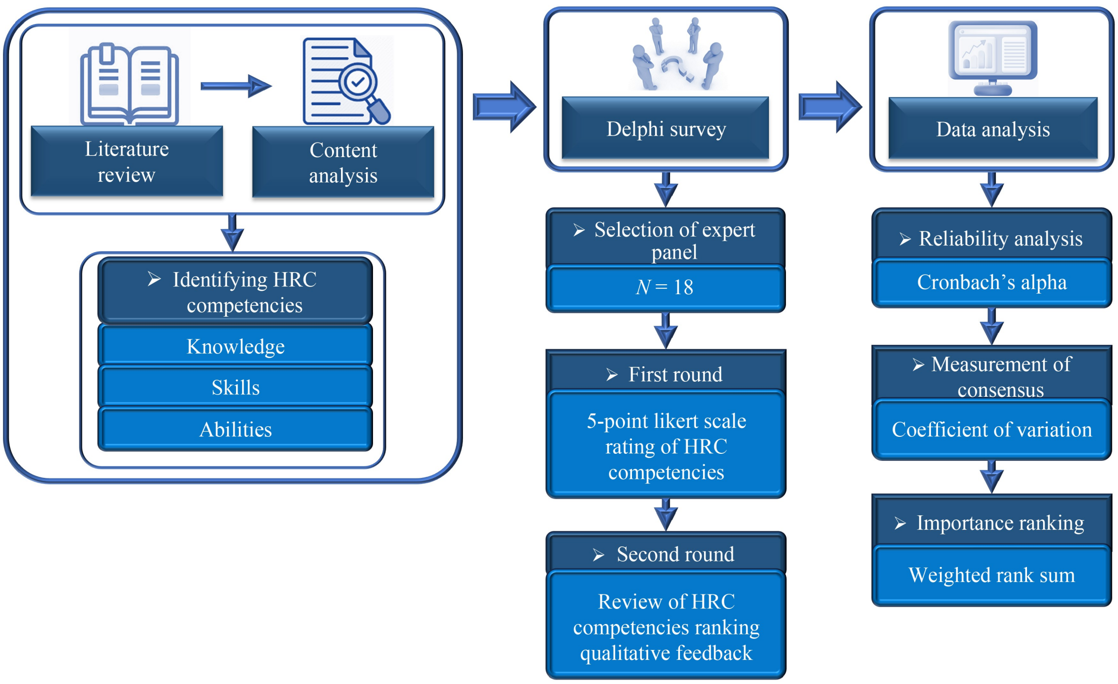

Fig. 1 Overview of the research methodology.

consensus on complex issues, such as competencies for HRC in construction (Landeta and Lertxundi, 2024). Unlike focus groups, which rely on real-time interaction and can be influenced by dominant voices or groupthink, Delphi maintains participant anonymity to ensure balanced input from all experts (Chalmers and Armour, 2019). Similarly, while interviews provide in-depth insights from individuals (Akins et al., 2005), they lack the iterative feedback and consensus-building process that Delphi facilitates (Landeta and Lertxundi, 2024). Additionally, the Delphi method allows for the inclusion of geographically dispersed experts and iterative rounds of feedback, enabling a refined synthesis of diverse perspectives (Shang, 2023), which is critical for addressing specialized and emerging topics like competencies for HRC in the construction industry. The panel of experts selected for this study comprises professionals carefully selected from the construction industry. The participant selection process, the structure of the Delphi survey rounds, and the data analysis methods are detailed in the sections below.

3.1.1 Selection of expert panel

The recruitment and selection of qualified industry professionals with sufficient experience and deep knowledge of construction robotics for this Delphi survey involved a call for participation and gathering of background information. The link to the question designed on QuestionPro, an online survey platform, was shared via a social media post on LinkedIn and via emails sent to the Myers-Lawson School of Construction industry advisory board to recruit industry professionals across the US. The call for participation includes questions designed to gather participants' demographic, educational, and professional information, construction industry experience, years with robotic technology, professional licensure, publications, and robotic technology use within their organizations. Eighteen industry professionals responded to the call for participation in this study. A flexible point-based grading system, proposed by Hallowell and Gambatese (2010) in the Delphi method guidelines for construction engineering and management (CEM) research, was adapted to select expert panel members for this Delphi survey, as shown in Table 3.

The criteria were tailored to recruit highly qualified industry professionals by assigning points to their educational qualifications (QC1), professional experience (QC2), construction industry prominence (QC3), and experience with robotic technology (QC4). Points are awarded for academic achievements (e.g., a BS earns 4 points), professional experience (e.g., each year of expe-

Table 3 Modified point grading system for participants' qualification (Hallowell and Gambatese, 2010)

Qualification Codes	Experience /Achievement	Points (Each)	Minimum qualification criteria
QC1	Educational qualification		
QC1-A	Associate degree	2	4
	BS	4	
	MS	2	
	PhD	4	
QC2	Professional experience		
QC2-A	Faculty member at an accredited university/work in a relevant industry	3	3
QC2-B	Year of professional experience in the construction industry	1	1
QC3	Professional prominence		
QC3-A	Professional registration	3	3
QC3-B	Membership of a committee	1	
QC3-C	Chair of a committee	3	
QC3-D	Peer-reviewed journal /technical article/technical report publication	2	2
QC3-E	Conference papers publication	1	1
QC3-F	Book publication	2	2
QC3-G	Conference presentation	1	1
QC4	Experience with robotic technology		
QC4-A	Years of experience with robotic technology	2	2
QC4-B	Use of robotic technology/research with robotic technology	1	1
QC4-C	Patents	5	
Total			20

rience in the construction industry adds 1 point), and professional prominence (e.g., publishing peer-reviewed journal articles earns 2 points per article). Additionally, expertise in robotic technology is important, with points given for each of the years of experience with robotic technology and the use of robots in the participant's organization. To qualify as an expert panel member, each participant must earn at least one point in each category and accumulate a minimum of 20 points across these categories. By requiring participants to earn at least one point in each category, the process guarantees that every expert has experience across all key areas, avoiding bias from specialists who might have a narrow focus. Additionally, the minimum threshold of 20 points ensures that each panel member has substantial expertise. This structured and measurable approach helps ensure that the panel represents a broad and balanced set of perspectives, leading to more reliable, well-rounded, and credible findings in the research. Eighteen experts who responded to the call for participation qualified and were selected for the study after applying the qualification criteria. The number of participants in this study is consistent with recommended sizes for achieving a balance between diversity and manageability of Delphi surveys (Bakhshi et al., 2024; Kermanshachi et al., 2023; Pamidimukkala and Kermanshachi, 2022). Additionally, the point grading selection criteria guarantee the inclusion of highly qualified experts with substantial experience and relevant knowledge in the panel. By systematically assessing candidates using objective metrics such as years of experience, publication records, and professional roles, the criteria strengthen the credibility of the findings and minimize selection bias.

3.1.2 First round

Experts selected for the survey were asked to rate the identified competencies (i.e., knowledge, skills, and abilities) in Table 2 on a 5-point Likert scale (where 5 = extremely significant, 4 = very significant, 3 = moderately significant, 2 = slightly significant, and 1 = not significant). Additionally, each expert was asked to provide more relevant competencies for HRC based on their experience and rank the top five HRC knowledge, skills, and abilities they consider crucial for implementing HRC in the construction industry. However, the competencies provided by the participants are already included in the initially identified competencies.

3.1.3 Second round

The rating of the HRC competencies and the top five relevant competencies for implementing HRC in construction data collected in the first round were analyzed and ranked. These rankings and the aggregated top five HRC competencies were returned to the experts for review in the second round. Additionally, experts who disagreed with the rankings and the aggregated top five HRC competencies were allowed to provide a new ranking and select a new top five competencies. Finally, each expert panel member was asked to explain reasons for their agreement or disagreement with the ranking. This provides a qualitative means of measuring consensus, supporting the quantitative consensus measurement and justifying why some HRC knowledge, skills, and abilities were ranked higher than others.

3.2 Data analysis

In the first round, Cronbach's alpha (α) was employed to evaluate the internal consistency and reliability of the rating data collected from the experts, as shown in Eq. (1) (Cronbach, 1951; Forero, 2023; Josa and Aguado, 2024).

$$\alpha = \left(\frac{k}{k-1}\right)\left(\frac{\sigma^2 y - \sum_{i=1}^{K} \sigma^2 i}{\sigma^2 y}\right), \tag{1}$$

where k is the number of items, $\sigma^2 i$ is the variance of the ith item, and $\sigma^2 y$ is the variance of the total score. Cronbach's alpha ranges between 0 and 1.0, with values closer to 1 indicating higher reliability and internal consistency (Cronbach, 1951; Forero, 2023; Josa and Aguado, 2024). Cronbach's alpha values for HRC knowledge, skills, and ability are 0.89, 0.76, and 0.82, respectively. Ideally, a Cronbach's alpha higher than 0.7 indicates an acceptable level of reliability (Forero, 2023). These alpha values underscore the internal consistency of the survey data, indicating that the items constituting the knowledge, skills, and abilities are closely related and reliably capture the intended constructs.

The consensus of experts' opinion regarding the competencies for HRC in construction on a 5-point Likert scale was measured using the coefficient of variation (CV) as presented in Eq. (2) (Bhagat and Jha, 2024; Ghosh et al., 2023; Meyer et al., 2022). CV provides a standardized measure of dispersion relative to the mean, allowing for a clear comparison across diverse metrics (Xu et al., 2020). The consensus criteria established in literature indicate that consensus is reached when the CV is less than 0.5 (Bhagat and Jha, 2024; Meyer et al., 2022; Von Der Gracht, 2012).

$$CV = \frac{Standard\ Deviation\ (SD)}{Mean}, \tag{2}$$

A multicriteria decision-making aggregation method using the weighted rank sum (WRS) (Gunduz et al., 2024; Taherdoost and Madanchian, 2023) was employed to determine the relative significance (ranking) of the items in HRC knowledge, skills, and abilities as well as the five most important competencies for implementing HRC in the construction industry, as defined in Eq. (3)

$$WRS = \sum_{i=1}^{n} w_i \times r_i, \tag{3}$$

where n is the number of items, w_i is the weight (frequency) of the ith item, and r_i is the rank of the ith item. Manual in vivo coding was used to analyze the qualitative data collected in the second round (Gupta, 2023) due to the small size of the qualitative feedback collected from the experts. The quantitative results were analyzed using Microsoft Excel and Jamovi (version 2.4.8), a graphical user interface for the R programming language.

4 Results

This section describes the results of the analysis conducted to assess industry practitioners' perspectives on the competencies required for HRC in the construction industry.

4.1 Demographics of panel of experts

The credentials and total points outlined in Table 4 indicate that the participants in this study have diverse educational backgrounds, ranging from associate degrees to PhD. Their years of experience with robotic technology vary significantly, from 1 to over 13 years. Professionally, many participants are registered with organizations such as the American Society of Civil Engineers (ASCE), the National Council of Examiners for Engineering and Surveying (NCEES), and the Institute of Electrical and Electronics Engineers (IEEE). Some participants hold specific licensures like Professional Engineers (PE), AWS Certified Robotic Arc Welding (AWS-CRAW), and FAA Small UAS certifications. The roles of the participants in their organization range from managerial to technical. Managerial positions like Executive Vice

Table 4 Credentials of participants

Industry participant ID	QC1	QC2		QC3					QC4		Total points
	A	A	B	A	B	D	E	G	A	B	
IP1	4	3	8	0	1	2	8	2	10	9 - (UAVs, exoskeletons, robotic demolition equipment, robotic surveying and layout tools, overhead drilling robots, drywall finishing robots, autonomous reality capture robots, crane load stabilization robots, and robotic solutions research and development)	47
IP2	4	3	18	0	0	0	0	0	22	2 - (UAVs, and robotic surveying and layout tools)	49
IP3	4	3	28	6	1	0	0	0	4	3 - (UAVs, construction 3D printers, and autonomous construction equipment)	49
IP4	6	3	28	12	0	0	0	0	4	1 - (UAVs)	54
IP5	4	3	28	0	1	0	0	0	10	11 - (UAVs, exoskeletons, construction 3D printers, autonomous construction equipment, robotic demolition equipment, robotic surveying and layout tools, robotic rebar tying machines, robotic layout printers, robotic pallet handlers, robotic drywall finishers, and robotic overhead drillers)	57
IP6	10	3	3	3	0	6	12	6	14	6 - (UAVs, construction 3D printers, autonomous construction equipment, robotic surveying and layout tools, autonomous reality capture, and remote safety inspection)	63
IP7	6	3	28	6	1	0	0	0	8	5 - (Bricklaying robots, UAVs, exoskeletons, construction 3D printers, and robotic surveying and layout tools)	57
IP8	4	3	28	0	0	0	0	0	10	2 – (UAVs and exoskeletons)	47
IP9	4	3	28	3	0	0	0	0	10	2 - Robotic demolition equipment and robotic surveying and layout tools	50
IP10	4	3	28	9	0	0	0	0	14	6 - (UAVs, exoskeletons, construction 3D printers, autonomous construction equipment, robotic demolition equipment, and robotic surveying and layout tools)	64
IP11	4	3	28	9	1	1	0	1	14	2 - (Construction 3D printers and autonomous construction equipment)	63
IP12	10	3	3	3	0	8	6	1	4	2 - (UAVs and exoskeletons)	40
IP13	6	3	28	0	0	0	0	0	4	4 - (UAVs, exoskeletons, construction 3D printers, and robotic surveying and layout tools)	45
IP14	4	3	13	0	0	0	0	0	4	2 - (UAVs and robotic surveying and layout tools)	26
IP15	4	3	28	0	2	0	0	0	16	1 - (Robotic welding machine)	54
IP16	2	3	8	6	0	0	0	0	4	1 - (UAVS)	24
IP17	10	3	13	3	0	0	0	0	4	2 - (UAVs and 3D printers)	35
IP18	4	3	8	3	0	0	0	0	4	3 - (Bricklaying robots, UAVs, and construction 3D printers)	25

President, President, and Project Manager focus on strategy, innovation, and overseeing construction projects, ensuring the integration of robotics aligns with business goals. Technical roles, including Structural Engineers, Robotics Leads, and Analysts, provide specialized knowledge on engineering, technology development, and performance evaluation, offering critical insights into the effectiveness and challenges of robotics in construction. Operational roles, such as construction managers and site supervisors, represent the frontline construction workers handling day-to-day management and ensuring effective robotic implementation on the ground. Some participants have published journal articles and conference papers, further strengthening their credibility and expertise in the field, providing them with a deep understanding of both the theoretical and practical aspects of robotics in construction and allowing them to offer informed, evidence-based feedback in the study.

Finally, participants have implemented and interacted with construction robots ranging from UAVs, exoskeletons, robotic surveying and layout tools, construction 3D printers, autonomous construction equipment, robotic demolition equipment, robotic welding machines, robotic rebar tying machines, robotic layout printers, robotic pallet handlers, robotic drywall finishers, robotic overhead drillers, bricklaying robots. Thus, the participants are well-positioned to provide valuable, firsthand feedback on the essential competencies critical for HRC in the industry. The total points scored by participants range from 24 to 64, reflecting varying levels of engagement and expertise in robotic technologies within the construction industry. The 18 experts selected for the study brought diverse backgrounds and extensive experience with various construction robots, contributing to a rich array of perspectives and ensuring the reliability of the feedback provided.

However, some participants withdrew after the first round of the survey due to tight schedules. Table 5 presents the number of experts that participated in each survey round.

4.2 Consensus of experts' opinion

The coefficient of variation (CV) adopted to measure consensus in this study ranged between 0.22 and 0.40 for HRC knowledge, 0.14 and 0.48 for skills, and 0.20 and 0.46 for abilities, as shown in Table 6. These values below the threshold of 0.50 indicate that the desired consensus was achieved (Bhagat and Jha, 2024; Meyer et al., 2022; Von Der Gracht, 2012).

4.3 Industry perception of competencies for HRC

The perception of construction industry professionals concerning the competencies for HRC was assessed by asking the panel of experts to rate various components of

Table 5 Number of participants in Delphi rounds

Participant's ID	Participant selected	Round 1	Round 2
IP1	√	√	×
IP2	√	√	√
IP3	√	√	√
IP4	√	√	×
IP5	√	√	√
IP6	√	√	√
IP7	√	×	×
IP8	√	√	√
IP9	√	√	√
IP10	√	√	√
IP11	√	√	√
IP12	√	√	√
IP13	√	√	√
IP14	√	√	√
IP15	√	√	√
IP16	√	√	√
IP 17	√	√	×
IP 18	√	×	×
Total	18	16	13

HRC knowledge, skills, and abilities on a five-point Likert scale and providing qualitative feedback to support their decision. The analysis of the WRS of these competencies presented in the sections below provides insights into how industry professionals rank and prioritize these competencies.

4.3.1 Industry perception of knowledge for HRC

4.3.1.1 Knowledge for HRC

Figure 2 presents the relative significance (ranking) based on the WRS of various HRC knowledge areas as perceived by industry professionals. The result revealed that the most prioritized HRC knowledge areas are human–robot interface (K-12), with a WRS of 67, followed by HRC safety and standards (K-7) and construction robot applications (K-2), both with a WRS of 65. Task planning (K-5) and robot control systems (K-13) also received considerable attention, with WRS values of 64 and 62, respectively. Other notable HRC knowledge areas include types of robots (K-1) and system integration (K-14), each with a WRS of 60. Sensors (K-4) and modeling and simulation (K-16) rank slightly lower, with WRS values of 58. Communication modes and technologies (K-11) and robot learning methods (K-18) are somewhat less prioritized, with a WRS of 56. The knowledge areas with the lowest rankings are computation design (K-19) and HRC ethics and regulation

Table 6 HRC knowledge, skills, and abilities mean, standard deviation, and coefficient of variation

HRC Knowledge	Mean	SD	CV	HRC Skills	Mean	SD	CV	HRC Skills	Mean	SD	CV
K-1	3.75	1.00	0.27	S-1	3.63	1.15	0.32	A-1	3.81	1.22	0.32
K-2	4.06	1.06	0.26	S-2	4.13	0.96	0.23	A-2	3.44	1.31	0.38
K-3	3.13	1.26	0.40	S-3	3.25	1.24	0.38	A-3	4.06	1.00	0.25
K-4	3.63	1.15	0.32	S-4	4.13	0.81	0.20	A-4	3.94	0.77	0.20
K-5	4.00	0.89	0.22	S-5	4.06	0.57	0.14	A-5	3.81	0.91	0.24
K-6	2.94	1.12	0.38	S-6	2.81	1.05	0.37	A-6	3.69	1.08	0.29
K-7	4.06	1.29	0.32	S-7	2.75	0.93	0.34	A-7	3.33	0.98	0.29
K-8	3.06	1.12	0.37	S-8	3.69	1.08	0.29	A-8	3.75	1.00	0.27
K-9	2.81	0.91	0.32	S-9	2.69	1.30	0.48	A-9	3.94	0.85	0.22
K-10	3.25	0.93	0.29	S-10	3.19	1.17	0.37	A-10	3.94	1.12	0.29
K-11	3.50	0.97	0.28					A-11	2.63	1.20	0.46
K-12	4.19	0.98	0.23					A-12	4.25	0.86	0.20
K-13	3.88	1.02	0.26								
K-14	3.75	1.18	0.32								
K-15	3.44	1.15	0.34								
K-16	3.63	0.96	0.26								
K-17	3.25	1.18	0.36								
K-18	3.50	0.97	0.28								
K-19	2.94	1.18	0.40								
K-20	3.31	1.14	0.34								

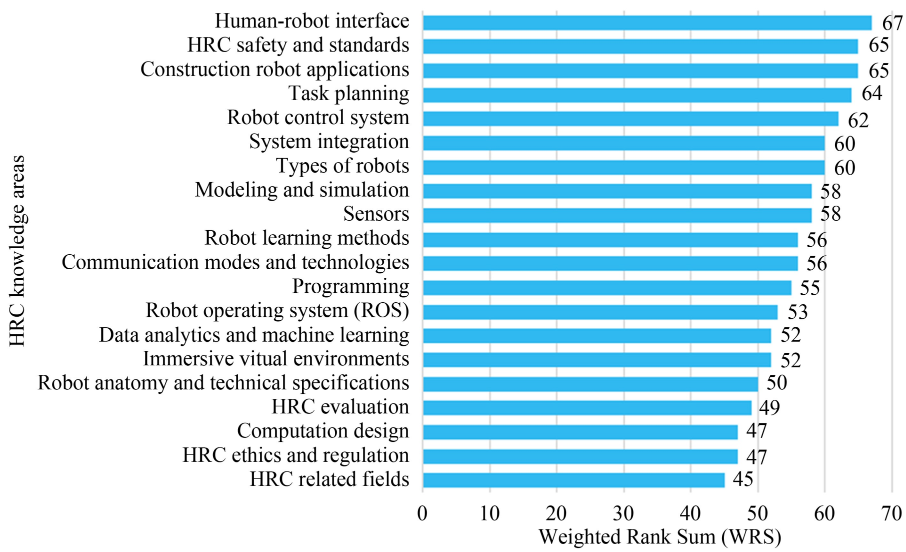

Fig. 2 Relative significance (ranking) of knowledge for HRC.

(K-6), both having a WRS of 47, and HRC-related fields (K-9) with a WRS of 45, indicating they are viewed as less critical for HRC by industry professionals.

4.3.1.2 Opinions of industry professionals on the ranking of HRC knowledge

The qualitative feedback from the industry experts provides valuable insights into their perceptions of the competencies required for HRC in construction, particularly regarding their relative significance, thereby justifying why certain knowledge areas are considered more important than others. An expert highlighted the initial oversight of safety considerations by stating *"that HRC ethics and regulations was ranked in the lower half. I did not think about safety at first,"* this assertion was supported by another expert who noted that *"application should be the most important, safety issues should be addressed once application is determined."* This justifies the rating of HRC safety in the second position. The experts also emphasized ethical considerations. One expert stated, *"I think ethics should be higher,"* indicating a recognition of the ethical implications of HRC in construction. Additionally, experts acknowledged the current developmental stage of HRC technologies and their limited utilization in the industry. One expert highlighted that those robots *"are not widely utilized in the industry due to the cost and unpredictability in outcome at the moment."* Furthermore, gaps in knowledge and awareness were recognized, particularly regarding specific HRC knowledge like modeling and simulation. One expert said, *"I am surprised that modeling and simulation was ranked the least important."* Finally, experts noted discrepancies between their expectations and rankings, indicating potential mismatches between industry perceptions and empirical findings. One participant remarked, *"I felt that the HRC evaluation and robot anatomy and technical specification would be above immersive virtual environments. But overall, I agree with the ranking."* This qualitative feedback from industry professionals highlights why specific HRC knowledge are rated higher than others, with safety being prioritized due to its importance, while other areas, such as modeling and simulation, are seen as less critical at this stage of technological development, reflecting both the current limitations of HRC technologies and the evolving needs of the construction industry.

4.3.2 Industry perception of skills for HRC

4.3.2.1 Skills for HRC

Figure 3 presents the ranking of HRC skills based on their WRS, indicating their relative significance in the industry. The highest-ranked HRC skills are safety management (S-4) and task planning (S-2), with a WRS of 66. Other highly prioritized skills include technical skills (S-5), which received a WRS of 65, and human–robot interface proficiency (S-8), with a WRS of 59. Effective communication (S-2) follows closely with a WRS of 58. On the other hand, HRC skills perceived as less critical include programming (S-7) with a WRS of 45, data analytics and management (S-7) with a WRS of 44, and application of machine learning algorithms (S-9) with the lowest WRS of 43.

4.3.2.2 Opinions of industry professionals on the ranking of HRC skills

Reactions to the HRC skill rankings varied among industry expert panels. Some experts found the rankings unsurprising and aligned with their expectations, while others noted unexpected placements, particularly for programming and data analytics and management. One expert remarked, *"I was surprised that programming and data analytics were ranked low,"* suggesting potential discrepancies between expectations and the actual rankings. Effective communication emerged as a skill that some participants found unexpected but relevant for HRC. One expert mentioned, *"I agree with the ranking but was surprised that effective communication was part of the skill for human–robot collaboration,"* implying that the expert may not consider effective communication between humans and robots significant for HRC in construction. Moreover, the high ranking of safety management reflects experts' recognition of the significant risk and liability associated with artificial intelligence (AI) and robotic production systems. One expert noted, *"There is risk and liability regarding AI and robotic production systems, and the application can have major safety implications on different augmented tasks. This needs to be fully understood by the industry."* This

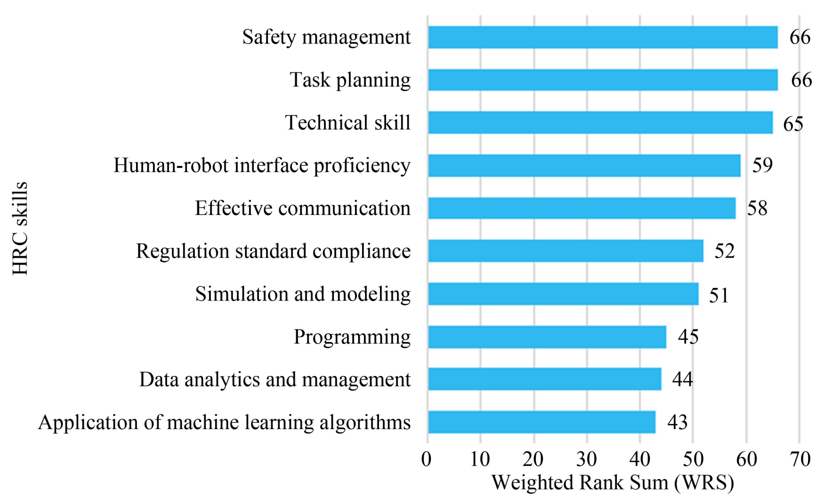

Fig. 3 Relative significance (ranking) of skills for HRC.

emphasizes the critical importance of prioritizing safety considerations in HRC efforts. The ranking of HRC skills reflects the industry's prioritization of safety management due to the significant risks and liabilities associated with robotic technologies, while skills like programming and data analytics were ranked lower, due to their perceived complexity or less immediate relevance in the current stage of HRC implementation in construction. Additionally, the inclusion of effective communication, though unexpected to some participants, underscores its importance in ensuring seamless interaction between humans and robots in the construction environment.

4.3.3 Industry perception of abilities for HRC

4.3.3.1 Abilities for HRC

The WRS of HRC abilities, indicating their relative significance, is presented in Fig. 4. The top-ranked HRC ability is safety awareness (A-12), with a WRS of 68. Continuous learning (A-3) with a WRS of 65 and problem-solving (A-4), critical thinking (A-9), and spatial awareness (A-10) with a WRS of 63 follow closely. In contrast, HRC abilities perceived as less significant include communication (A-2) with a WRS of 55, analytical aptitude (A-7) with a WRS of 50, and cultural and social awareness (A-11) with a WRS of 42.

4.3.3.2 Opinions of industry professionals on the ranking of HRC abilities

Similarly, the experts' reactions concerning the relative significance of the abilities for HRC in construction vary. While some experts found the rankings unsurprising or aligned with their expectations, others noted surprises, particularly regarding the placement of safety awareness and certain abilities like decision-making and communication. One expert remarked, *"I am surprised that decision-making and communications ranked low on this list,"* suggesting potential discrepancies between expectations and the actual rankings. Communication emerged as a skill that some experts emphasized as crucial for HRC. An industry expert stated that *"communication is going to be a key part of this process,"* highlighting the importance of clear communication in facilitating collaboration between humans and robots in construction tasks, despite receiving a low rating from the experts. Furthermore, there were differing perspectives on some abilities and their importance. Some experts expressed surprise at the high ranking of continuous learning, while others felt that specific abilities, such as analytical aptitude, should be ranked higher. One expert noted, "*I agree with the ranking*; *however*, *I felt that analytical aptitude should be higher on the list. Maybe even above teamwork*," indicating varying opinions on the relative importance of different abilities in the context of HRC in the construction industry. The varying expert reactions to the ranking of HRC abilities highlight the complexity of determining which abilities are most critical in construction. While safety awareness and continuous learning were prioritized, the lower ranking of decision-making and communication raised concerns for some experts, suggesting that these abilities might be more important than initially perceived. Additionally, the differing views on abilities like analytical aptitude and teamwork reflect the ongoing debate over the competencies necessary for effective HRC, emphasizing the need for further exploration, refining and consensus on the most essential abilities for HRC in construction. These differences also underscore the evolving nature of HRC in construction, where the importance of certain abilities shifts as robotic technologies and industry practices continue to develop.

4.4 Top five competencies for implementing HRC in construction

Implementing HRC in construction requires some basic

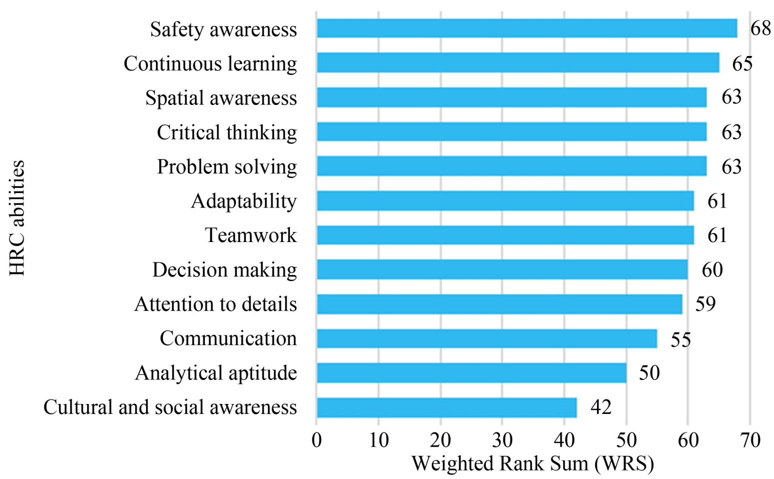

Fig. 4 Relative significance (ranking) of abilities for HRC.

understanding of fundamental knowledge, basic proficiencies, and specific attributes that could guarantee seamless interaction between humans and robots. The construction industry experts' perceptions of these basic competencies are reflected in the top five competencies for implementing HRC in construction presented in Table 7. The experts emphasize the importance of understanding robot anatomy and technical specifications (K-3), ethics and regulations guiding robots (K-6), task planning (K-5), types of robots (K-1), and robot control systems (K-13) for the successful implementation of HRC in the industry. Moreover, industry professionals also emphasize the significance of human–robot interface proficiency (S-8), application of machine learning (S-9), and effective communication (S-1) skills for seamless interaction between humans and robots and enhancing collaboration efficiency. Finally, industry professionals underscore abilities such as problem-solving (A-4), continuous learning (A-3), and safety awareness (A-12) to adapt to evolving HRC within the construction sector. Communication (A-2) and teamwork (A-1) were also highlighted as vital for fostering safe and productive collaboration between humans and robots in executing construction tasks.

5 Discussion

This section discusses the implications of the practitioners' views of the competencies for implementing HRC in construction.

5.1 Knowledge for implementing HRC in construction

The findings reveal that key knowledge areas for implementing HRC in construction include the human–robot interface, HRC safety and standards, and construction robot applications. These areas are crucial for ensuring effective communication between humans and robots, maintaining safety, and understanding how robots can enhance construction workflows. The prioritization of human–robot interfaces suggests that practitioners recognize the importance of intuitive and adaptable interaction methods to enhance efficiency and reduce errors. One possible reason human–robot interface was ranked highly is its direct impact on ensuring effective communication and collaboration between humans and robots. For example, in robotic bricklaying, operators must use an intuitive interface to adjust robotic movements in real time to align with manual masonry work. With the increasing use of AI in robotics, more sophisticated human–robot interfaces, such as those based on machine learning and natural language processing, are emerging (Giachos et al., 2020; Solanes et al., 2024). These techniques could enable robots to better understand and interpret human intentions, improving interaction fluidity and safety (Giachos et al., 2020). Similarly, HRC safety and standards ranked high because construction sites are inherently hazardous, and integrating robots introduces additional risks. For instance, robotic rebar-tying machines require strict adherence to safety protocols to prevent unexpected movements that could endanger human workers. These priorities align with prior research that underscores the importance of understanding robot reliability and fail-safe mechanisms for successful HRC implementation (Chen et al., 2023b).

Additionally, knowledge of robot anatomy and technical specifications (e.g., robotic arms, end effectors, actuators) was highly ranked. This knowledge is critical for ensuring proper selection and deployment of robots. For example, selecting an articulated robotic arm with sufficient degrees of freedom is necessary for tasks such as plastering curved surfaces, where rigid robots would be ineffective. Similarly, understanding payload capacity is essential when deploying robots for lifting heavy materials like prefabricated concrete panels. This insight mirrors findings from Chen et al. (2023a), which emphasize the need for robust technical knowledge to ensure the reliability of robotic systems in HRC settings. Further highlighting the practical orientation of industry professionals, task planning, robot control systems, and robot types were also highly prioritized. Task planning is crucial for coordinating human–robot interactions and ensuring safety. Meanwhile, knowledge of control systems and robot types enables more tailored robot deployment across a variety of construction tasks. These results are consistent with previous research on the importance of task planning (Ren et al., 2023), robot types (Liang et al., 2021), and control systems (Oyediran et al., 2024) in optimizing HRC.

Conversely, some HRC knowledge areas were ranked lower, such as ethics and regulations, and modeling and

Table 7 Top five competencies for implementing HRC in construction

Code	HRC knowledge	Code	HRC skills	Code	HRC abilities	Ranks
K-3	Robot anatomy and technical specifications	S-8	human–robot interface proficiency	A-4	Problem-solving	1
K-6	HRC ethics and regulations	S-9	Application of machine learning algorithms	A-3	Continuous learning	2
K-5	Task planning	S-1	Effective communication	A-12	Safety awareness	3
K-1	Types of robots	S-6	Programming	A-2	Communication	4
K-13	Robot control system	S-2	Task planning	A-1	Teamwork	5

simulation. This suggests that industry professionals may currently prioritize immediate operational concerns over long-term ethical considerations in HRC, such as the ethical implications of AI decision-making in construction. For example, while AI-driven robotic inspectors can autonomously assess structural integrity, concerns about liability and job displacement have not yet become pressing regulatory issues (Liang et al., 2024). However, as AI-based safety monitoring and autonomous decision-making in HRC evolve, ethical considerations such as data privacy and algorithmic bias in robot task allocation will become more relevant. This could also be attributed to the current technological landscape in construction, where robotics is still emerging, and its implementation is limited. Industry professionals may be more focused on practical applications and immediate technical concerns. One expert's feedback supports this view, stating that these issues should be addressed once the application of robots is clearly determined. However, ethical considerations will become more significant as robotic technologies evolve and are widely deployed in construction environments. Literature in high-risk industries already emphasizes the need for ethical frameworks in robotics (van Wynsberghe et al., 2022). Although ethics ranked low, addressing these concerns early could mitigate negative emotional impacts and foster greater acceptance of robotics. The emergence of AI-enabled techniques, such as machine learning algorithms, will further drive the need for strong ethical guidelines in HRC applications, as AI systems gain the capability to make autonomous decisions, raising new challenges in accountability and fairness (Liang et al., 2024).

Similarly, modeling and simulation, sensors, and robot learning methods were ranked lower, which may reflect the industry's current emphasis on direct applications over digital simulation-based planning. For instance, despite the advantages of digital twins in simulating construction workflows before deployment, their use in HRC remains limited (Ye et al., 2022). Some experts expressed surprise at the low ranking of modeling and simulation, indicating the need for greater awareness of their value in improving the reliability and predictability of HRC outcomes. These advanced technologies were expected to have a higher ranking due to their potential to enhance HRC outcomes by enabling pre-implementation testing, improving reliability, and ensuring the predictability of HRC outcomes. This highlights the need for increased industry awareness of machine learning techniques, such as reinforcement learning, which enable robots to optimize their movements in constrained spaces, such as assembling precast concrete components in tight areas. Moreover, AI-driven simulation models could play an important role in evolving construction practices, allowing for more sophisticated training systems and predictive models for HRC (Shayesteh and Jebelli, 2022). One possible reason for this discrepancy is industry familiarity. Practitioners may be more comfortable with traditional construction methods and less aware of the advantages of modeling and simulation for pre-deployment testing. Additionally, cost concerns may play a role, as implementing digital twin technology and AI-driven simulations requires significant investment in software and workforce training. Experts who work closely with cutting-edge technologies may underestimate these barriers. Another factor could be the perceived technical complexity associated with advanced HRC applications. Practitioners may view machine learning-based robot learning methods as challenging to implement without specialized expertise, leading to their lower ranking. Addressing these barriers through targeted training and industry awareness initiatives could help bridge the gap between expert expectations and industry priorities.

5.2 Skills for implementing HRC in construction

The prioritization of safety management, task planning, technical expertise, human–robot interface proficiency, and effective communication reflects the industry's recognition of the complex requirements for working alongside robotic systems. The high ranking of safety management aligns with the construction industry's inherently hazardous nature, underscoring the importance of risk mitigation in HRC. For example, robotic arms must be monitored in demolition projects to ensure safe deconstruction without unintended structural collapses. This finding aligns with Brosque et al. (2021), who stress the importance of human–robot interfaces that provide real-time haptic feedback to support safe and intuitive collaboration. This is also reflected in the results, as human–robot interface proficiency emerged as another critical skill. This highlights the necessity of skilled operators who can effectively manage the interaction between humans and robots, ensuring smooth operation in high-risk environments. Studies by Brosque et al. (2021) and Wang et al. (2024a) confirm that user-friendly interfaces are essential for seamless collaboration, improving HRC efficiency, and encouraging the broader adoption of robotics in construction. Similarly, task planning was ranked highly, as construction sites require meticulous coordination. For instance, in robotic concrete printing, workers must schedule material supply, curing time, and robot nozzle paths to avoid collisions and inefficiencies. Likewise, technical expertise is essential for troubleshooting robotic welding defects, adjusting control parameters in autonomous excavators, or calibrating LiDAR-based navigation in mobile construction robots. The rankings of both task planning and technical expertise highlight the need to effectively coordinate human–robot activities and ensure robots are integrated into workflows without disruptions (Alami et al., 2005).

Surprisingly, effective communication was ranked lower in the quantitative analysis, though qualitative feedback from industry experts highlights its importance. For instance, in robotic crane operations, workers and load-balancing systems must exchange clear commands to prevent load swings. This suggests that while communication is inherently necessary, it may be taken for granted rather than explicitly acknowledged as a top skill. As Brunckhorst and Dasgupta (2021) highlighted, communication is essential for coordinating human and robotic teams, especially in complex construction environments. The high priority placed on communication by experts suggests the growing importance of clear communication channels between humans and robots to avoid errors and improve collaboration, and that interpersonal and team communication skills will be crucial for enhancing HRC safety and efficiency. As AI-based communication tools like voice assistants (Fernandes et al., 2024) and natural language processing techniques (Mohana et al., 2022) continue to evolve, they will play a more significant role in facilitating seamless communication between humans and robots. These technologies enable clearer instructions and feedback to be exchanged between human workers and robots, minimizing errors and improving collaboration (Gustavsson et al., 2018).

Programming and data analytics and management skills received lower rankings, likely due to their perceived complexity and specialization. Most construction workers do not directly engage in robot programming. However, these skills are critical for developing and fine-tuning AI-driven construction robots. Furthermore, expert feedback suggests that while programming and data analytics are important, their application may not be as widespread or urgent during the early stages of HRC integration in construction. Nevertheless, their significance should not be underestimated. Programming enables workers to modify robot behaviors for specific tasks, a foundational skill emphasized by Dombrowski et al. (2018). Additionally, the relatively lower rating of machine learning algorithms reflects the current limitations of AI and machine learning applications within the construction sector. The complexity and cost concerns associated with these technologies likely explain why industry professionals do not prioritize them at this stage (Semeraro et al., 2023). However, as robots gain the ability to adapt to changing environments and tasks, these skills will become increasingly vital. Training programs must evolve to address these future needs. The lower ranking of programming, data analytics, and machine learning skills may also be linked to industry familiarity and resource constraints. Researchers may expect these competencies to be crucial due to their role in optimizing HRC. However, construction practitioners likely prioritize immediate, hands-on technical skills over programming due to the current workforce's limited exposure to coding and AI-driven analytics. Additionally, companies may be hesitant to invest in programming training due to cost concerns and the perception that such skills are not yet essential for on-site operations. As HRC adoption grows, structured upskilling initiatives will be crucial to overcoming these barriers and aligning industry competencies with expert expectations.

5.3 Abilities for implementing HRC in construction

Problem-solving was ranked as a top priority, emphasizing its crucial role in addressing real-time challenges during HRC. The complexity of integrating robots into dynamic construction environments necessitates strong problem-solving skills to adapt to unforeseen issues. Construction sites are dynamic, requiring workers to adapt to unforeseen challenges. For example, if an autonomous bricklaying robot malfunctions mid-task, workers must quickly diagnose whether the issue stems from a mechanical failure, sensor misalignment, or software error. The high ranking of problem-solving reinforces the importance of human cognitive flexibility in ensuring smooth HRC operations. Human workers contribute cognitive flexibility, allowing them to identify and resolve problems that may arise in dynamic construction environments, complementing robots' strengths in repetitive tasks (Chacón et al., 2021). This finding emphasizes the value of human judgment in ensuring effective collaboration.

The study also highlights the importance of continuous learning in the rapidly changing field of HRC. Workers must stay updated on the latest advancements in robotic technologies and safety protocols to remain effective collaborators. In addition, as robotic technologies evolve, construction workers must continuously update their knowledge on emerging AI techniques such as generative adversarial networks, which can be used for generating synthetic structural failure scenarios for training AI models. This adaptability aligns with industry trends toward more technologically advanced construction environments, where upskilling will be essential to maintain productivity and safety. The ranking of safety awareness as the most critical ability further reinforces the industry's commitment to risk mitigation. As robots become more integrated into construction tasks, understanding and addressing the hazards they introduce is crucial for maintaining a safe working environment (Nnaji et al., 2021; Nnaji et al., 2023). This ability requires a proactive approach to safety, where workers are trained to recognize potential risks and implement adequate controls.

Interestingly, decision-making and communication ranked lower than expected. One expert expressed surprise at the low ranking of decision-making, considering it a critical ability for HRC. This discrepancy could stem from the fact that, at present, much of the decision-making in HRC is still based on established protocols and technologies. More advanced decision-making abilities will become essential as robots take on increasingly autonomous roles in construction tasks. For example, most of the current commercially available exoskeletons used in heavy lifting still operate based on preset movement patterns rather than AI-driven adaptive responses to worker fatigue. However, as AI-driven robotics advances, decision-making will likely become more crucial. Furthermore, expert feedback suggests that communication is equally indispensable for HRC, as it facilitates the conveyance of instructions to robots and ensures coordination among human teams (Nikolaidis et al., 2018). Alongside communication, teamwork was also identified as a fundamental HRC ability, enabling efficient human–robot interactions and ensuring tasks are completed safely and effectively (Ma et al., 2022). The lower-than-expected ranking of decision-making and communication abilities may be due to practitioners perceiving these as implicit competencies rather than specialized skills requiring deliberate development. Experts, who may have a broader perspective on interdisciplinary collaboration, likely anticipated a higher ranking based on their experiences in research and development settings. Additionally, practitioners may view decision-making in HRC as primarily dictated by established safety protocols and workflow constraints rather than a dynamic and evolving skill. Bridging this gap through targeted training and awareness programs could help practitioners better understand the strategic importance of communication and decision-making in optimizing HRC outcomes.

Similarly, the lower ranking of analytical aptitude suggests an industry focus on hands-on execution rather than data interpretation. This is particularly surprising, given the importance of data in making informed decisions about robot performance. Experts noted that this ability might be underappreciated, indicating the need for educational programs to emphasize developing workers' analytical skills. However, with the rise of AI-based construction monitoring systems, the ability to analyze sensor data, such as detecting anomalies in robotic excavation patterns using machine learning algorithms like support vector machines, will become more important. Lastly, cultural and social awareness received one of the lowest rankings, possibly because industry professionals view technical proficiency as more critical than interpersonal factors. However, as cobots become commonplace, understanding how different cultural perspectives influence HRC acceptance could improve adoption rates. For example, in Japan, construction companies have embraced humanoid robots for customer-facing tasks (Bogue, 2020), while Western countries tend to deploy industrial robots for back-end automation (Faria et al., 2020).

5.4 Recommendations for construction industry stakeholders

Based on this study's findings, several recommendations are provided below for policymakers, educators, employers, and professionals to facilitate the formalization, adoption, and continuous improvement of competencies required for HRC in the construction industry. A strategic, multi-stakeholder approach is essential to ensure that workers, employers, and educational institutions are adequately prepared for the increasing integration of robotic technologies in the workplace (Sankar et al., 2024).

5.4.1 Policymakers

Policymakers play a crucial role in creating an enabling environment for the adoption of technologies (Januar Mahardhani, 2023) such as robotic technologies and the development of competencies for effective HRC. To support a structured industry-wide transition to HRC, it is recommended that policymakers establish regulatory guidelines that define competency requirements, ethical considerations, and safety protocols for human–robot interactions in construction. These standardized frameworks should be developed in collaboration with industry stakeholders, academic institutions, and professional associations to ensure alignment with current and future industry needs. Furthermore, financial incentives such as grants or tax breaks should be introduced to encourage construction firms to invest in robotics technologies and HRC. These incentives would help alleviate initial cost barriers (Svensson, 2024; Tafazzoli et al., 2024), promote the widespread adoption of robotic systems (Tafazzoli et al., 2024), and ensure that workers receive necessary training. Additionally, funding should be allocated to research initiatives that explore best practices for HRC integration, safety enhancements, and workforce adaptability in automated construction environments.

5.4.2 Educators

Educational institutions are critical to preparing the next generation of construction professionals. To address the industry's evolving needs, the CEM and other construction-related curricula should be updated to accommodate specialized courses on robotic operation, programming, and HRC principles. These courses should include hands-on training (Betti et al., 2024), virtual simulations (Onososen and Musonda, 2024), and interdisciplinary learning approaches (Albeaino et al., 2023) to help students develop both technical and cognitive skills necessary for human–robot teamwork. Moreover, continuous collaboration with industry professionals is vital to ensure that educational programs remain relevant and aligned with industry needs (Sarwar et al., 2015). Regular feedback from construction firms, technology developers, and robotics experts can help educational institutions refine their programs and teaching methodologies (Sarwar et al., 2015), ensuring that graduates are equipped with the skills demanded by the industry.

Offering industry-sponsored internships, cooperative education programs, and on-site robotics training will provide students with real-world experience and facilitate a smoother transition into the workforce (Al-Atroush and Ibrahim, 2022). Furthermore, with the rapid pace of technological advancements, educational institutions must offer professional development programs for current workers. These professional development programs should include certification courses, micro-credentialing, and modular training formats to accommodate working professionals (Barrows et al., 2020) seeking to enhance their competencies in robotic operations and HRC. Online and hybrid learning options (Adlemo et al., 2023) should also be explored to ensure accessibility for a broader audience.

5.4.3 Employers and industry professionals

Employers must actively invest in their workforce and create an environment conducive to HRC on the construction job site. Employers should prioritize training programs that focus on both the technical and soft skills required for HRC (Kaur and Singh, 2024). Offering certifications in robotic operation and HRC integration will equip workers with the necessary qualifications to perform effectively in an increasingly automated environment (Delgado et al., 2019). Additionally, safety is a top priority when integrating robots into construction workflows. Employers must establish safety protocols and conduct regular safety training to mitigate risks associated with human–robot interaction (Shayesteh et al., 2023). The implementation of standardized safety checklists, emergency response procedures, and ergonomic assessments will further enhance workplace safety and operational efficiency. Finally, stakeholders in the construction industry must adopt data-driven approaches when evaluating robotic technologies and HRC (Schmailzl et al., 2024). Employers and policymakers should invest in systematic data collection, performance monitoring, and feedback mechanisms to assess the effectiveness of HRC integration (Baratta et al., 2023; Mehak et al., 2024). This data should be leveraged to refine training methodologies, optimize workflow processes, and guide future policy and investment decisions in construction automation.

6 Conclusions, limitations, and future research

The adoption of robotic technologies in the construction industry has provided an alternative and sustainable solution to the problems of safety, productivity, and efficiency. However, little is known about the competencies required for HRC in the construction industry owing to the lack of research in this area. This study evaluated the perceptions of construction industry professionals concerning the competencies for HRC in construction. It establishes the competencies in the form of knowledge, skills, and abilities that industry professionals deem significant for HRC in the industry. It also uncovers the top five competencies that construction industry professionals consider fundamental for implementing HRC in construction. These findings could help facilitate the implementation of HRC, safe and effective collaboration between humans and robotic agents, and address the issues of productivity and efficiency in the industry. It could also facilitate collaboration between industry and academia, where the construction industry would invest in training programs and professional development opportunities focusing on these critical areas to ensure workers have the necessary knowledge to operate and interact with robotic systems efficiently and safely. Academia could develop training programs to prepare students from construction-related disciplines for HRC to meet the industry’s expectations.

One limitation of this study is the issue of attrition of the expert panel, which is familiar with Delphi studies and has prevented the collection of more qualitative and quantitative data that would have added more insights into the study. However, the credentials of the remaining expert panel members and the reliability assessment justify the correctness of the feedback provided by the remaining members of the panel. Additionally, the size of the panel of experts provides a robust foundation for exploring the competencies required for HRC in the construction industry. While the size aligns with the recommended ranges for Delphi studies, typically between 10 and 30, it may not fully capture the extensive diversity of the broader construction industry. The panel’ s composition, however, mitigates this limitation, as the experts were carefully selected based on their diverse backgrounds and substantial experience with construction robotics. This selection process enhances the reliability of the insights, though generalizing the results to the entire industry should be approached with caution, as the findings are more indicative of expert consensus rather than a comprehensive representation of all stakeholders in the field.

Future research could investigate the perceptions of construction workers directly interacting with robots to gain deeper insights into the implementation of HRC in construction and to develop a comprehensive framework for HRC competencies in the industry. Considering that robotic technologies continuously evolve and become more integrated into the sector, future studies could also focus on refining these HRC competencies for different robotic technologies and their applications, using more participants. Investigating the impact of these competencies on job performance and productivity in construction projects and how they can be effectively taught and implemented within construction organizations could also be explored in future research. Finally, examining the potential challenges and barriers to adopting these competencies in the construction industry could provide valuable insights for industry professionals and instructors.

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