



Competencies for human–robot collaboration in the construction industry: perspectives from academia and industry

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Abstract

Robotic automation in construction has created the need for new competencies that will enable the workforce to engage with robots safely and effectively. However, differing perceptions between industry professionals and academia make aligning academic programs with industry needs challenging. This study evaluates these perceptions to guide the design of HRC training programs. A three-round Delphi study was conducted separately with panels of industry professionals and academic experts to assess their views on HRC competencies in construction. The findings revealed that both panels identified human–robot interfaces, HRC safety and standards, robot control systems, and construction robot applications as the top five HRC knowledge areas. Industry professionals also emphasized task planning knowledge, while academic experts focused on HRC ethics. Key HRC skills include effective communication, safety management, technical proficiency, and compliance with regulations and standards, with industry professionals prioritizing proficiency in task planning and academics emphasizing human–robot interface proficiency. Both expert panels prioritized teamwork, continuous learning, problem-solving, communication, and adaptability as top-rated HRC abilities. This study contributes to knowledge by defining key HRC competencies and identifying differences in priorities between industry and academia. These insights can guide the development of academic curricula that better align with industry needs, supporting the creation of training programs that equip the workforce with the competencies required for safe and effective robotic collaboration. The study also promotes collaboration between industry and academia, fostering innovation in HRC and robotics in construction. Future research directions are proposed to explore innovative training methods to equip the future workforce with HRC competencies.

Keywords Industry perception · Academic perception · Competencies · Human–robot collaboration · Construction industry · Delphi study

1 Introduction

The construction industry aligns with the Fourth Industrial Revolution (Industry 4.0), adopted as Construction 4.0 in construction, emphasizing the necessity and significance of technological advancements in construction automation and robotics (Lee 2023). Human–robot collaboration (HRC) is a critical paradigm in the transformation process, offering enhanced efficiency, safety, and productivity (Zhang et al. 2018). HRC, which refers to the symbiotic interaction between humans and robots in shared workspaces, has necessitated a reevaluation of traditional roles, skill sets, and competencies of the construction workforce (Adepoju 2022). Despite the potential benefits of HRC, its successful implementation in the construction industry depends on many factors, including a comprehensive understanding of the competencies necessary for effective collaboration

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between humans and robots (Adepoju 2022). Defining these competencies, which encompass a wide range of knowledge, skills, and abilities essential for safe and efficient collaboration with robots, involves understanding the perceptions of industry and academia directly involved in implementing HRC in construction.

Researchers in academia recognized the need to define the multifaceted competencies essential for innovative and emerging technologies in construction (McCord et al. 2023). This endeavor has yielded valuable insights, often grounded in theoretical frameworks and empirical studies (Sergeeva and Liu 2020). The perspectives of industry professionals at the forefront of adopting and integrating robotic technologies into construction practices are equally indispensable (Vora et al. 2024). However, the perceptions of construction industry professionals and academic experts concerning the competencies for HRC vary significantly due to differences in their focus (McCord et al. 2023; Perera et al. 2017). Therefore, it is essential to understand the perceptions of both industry and academia concerning the competencies to facilitate the implementation of HRC in construction. This will assist in developing a competency framework that will meet each category of professionals' expectations and support the full integration of HRC in construction. Consequently, this study aims to address the following research question (RQ):

RQ: What are the areas of perceptual consensus and differences between industry and academia concerning the competencies for HRC in the construction industry?

Understanding the perceptions of these stakeholders in construction would help bridge the gap between industry and academia in terms of the competencies essential for implementing HRC in construction. It will also inform training programs and the improvements in the Construction Engineering and Management (CEM) curriculum to better prepare the workforce for integrating and collaborating with robots in the construction industry.

The remaining section of this paper is structured as follows: relevant literature on HRC in the construction industry was reviewed in the next section to provide background for the study, followed by the methodology section comprising the Delphi survey design and analysis. Results and findings of this research are presented after the methodology, followed by a discussion of the findings section. The last section contains the conclusion, limitations, and recommendations for future research. This study contributes to the body of knowledge by defining the competencies for HRC in construction and establishing areas of perceptual consensus and differences between construction industry professionals and academic experts concerning the competencies. It provides a template for establishing training programs to equip the current and future construction workforce with the necessary competencies to collaborate efficiently with

robotic technologies, ensuring they meet industry needs when implementing HRC in construction. It established the competency framework for hiring workers and managing robotic technologies. It also creates the basis for collaboration between industry and academia to innovate with robotic technology and HRC in construction.

2 Background

2.1 Overview of human–robot collaboration in construction

In recent times, the inclusion of robots in construction operations, working alongside human labor, has brought about notable improvements in productivity and efficiency (Wu et al. 2022), quality delivery (Brosque and Fischer 2022), safety (Brosque and Fischer 2022; Chen et al. 2023a), and project timelines and costs (Chen et al. 2023a; Brosque and Fischer 2022b). This inclusion is interesting for both industry professionals and academics; thus, the applications of robots in construction operations should be observed from the perspectives of industry and academia. Robots are transforming various processes within the construction industry. For instance, bricklaying robots, such as semi-automated masons (SAM), can lay bricks faster than humans, enhancing speed and precision while reducing physical strain on workers (Sklar 2015). Demolition robots are used for demolition tasks that are hazardous for humans, increasing safety by removing workers from dangerous environments and allowing for precise demolition in tight or complex spaces (Ghodsian 2024). In addition, unmanned aerial vehicles such as inspection and surveillance drones equipped with cameras and sensors can monitor construction sites for safety, progress, and quality control, improving site monitoring and early detection of potential issues (Gross 2023). Finally, automated construction vehicles, such as autonomous dump trucks and bulldozers, are being deployed in large-scale construction sites to enable continuous operation without breaks, increased efficiency, and reduced human labor costs (Alderton 2021).

Conversely, in academia, research into robotic applications in construction drives technological advancements and prepares future industry leaders (Bademosi et al. 2019). For instance, research in construction robotics focuses on developing new technologies and systems, such as advanced robotic control and coordination algorithms, which are crucial for creating innovative industry tools and methods (Chang et al. 2022). It also focuses on enhancing collaboration on construction sites by developing intuitive interfaces (Ravi et al. 2021). Furthermore, academics are developing innovative construction techniques (Jang et al. 2021), including robotic 3D printing of structures (Bazli et al.

2023), modular construction using robots for assembling prefabricated modules (Fu et al. 2024), and autonomous machinery like excavators and bulldozers for site preparation and earthmoving tasks with minimal human intervention (Moud et al. 2020). Moreover, academic researchers utilize robotic simulations and modeling for prototyping and testing new methods, assessing the feasibility, durability, and performance of new designs (Pereira da Silva et al. 2022; Zhu et al. 2023). Finally, academics engage in interdisciplinary collaboration in construction robotics, which involves joint research projects across engineering, computer science, architecture, and environmental science, as well as partnerships between academic institutions and construction companies, facilitating technology transfer and innovation (Badawi and Abdullah 2021).

2.2 Competencies for human–robot collaboration in construction

Competencies are an integration of knowledge, skills, and abilities needed for performance in specific job roles and domains (Helmold 2021; Hlavac 2023). According to Hlavac (2023), knowledge encompasses cognitive attributes, the recognition or understanding of objects or concepts, and knowing how to do something without necessarily requiring tangible or observable application (Helmold 2021; Pereira et al. 2023; Hlavac 2023). Skills represent the capability to demonstrate procedural knowledge, typically acquired through training or self-directed learning (Hlavac 2023). Skills are observable and measurable, involve interaction with stimuli or others, and are developed through structured processes, including formal instruction and experiential learning (Hlavac 2023). Finally, abilities refer to the inherent power or capacity to perform tasks or act in a particular way (Hlavac 2023). While similar to skills, abilities may not necessarily result from formal training; they include both learned and innate capabilities and encompass broader attributes beyond direct procedural knowledge application (Hlavac 2023). Based on the above definitions, HRC knowledge can be defined as the theoretical and domain-specific understanding of the principles, systems, and technologies that enable collaboration between humans and robotic systems in construction. It includes foundational concepts and procedural guidelines essential for managing HRC processes in the industry. HRC skills are the measurable capabilities or proficiencies needed to apply procedural knowledge in real or simulated construction scenarios involving robots. They are demonstrated through interaction, operation, and coordination with robotic systems during task execution. HRC abilities refer to the innate or acquired capacities to perform tasks and adapt within collaborative environments involving humans and robots. They encompass cognitive, problem-solving, and adaptability traits essential for navigating the

complexities of HRC in construction. Hence, the competencies for HRC in construction are integrated knowledge, skills, and abilities that enable construction workers to safely and efficiently collaborate with robots in executing construction tasks. To effectively develop and apply HRC competencies, it is essential to establish a structured framework that categorizes them based on their distinct yet interconnected functions in HRC.

Table 1 presents the competencies required for HRC in construction, including twenty knowledge areas (K1–K20), ten skills (S1–S10), and twelve abilities (A1–A12). These competencies were identified through a literature review and content analysis of published articles and case studies that provided evidence of HRC task applications, robotic technologies, and implementation strategies of HRC for executing construction tasks. This process involved analyzing the technical and operational requirements of HRC, considering the context-specific and implementation needs of construction robotics, and accounting for relevant human characteristics to ensure a comprehensive classification. The identification of the elements of the HRC competencies and the categorization of competencies into HRC knowledge areas, skills, and abilities was guided by the established definition of HRC competencies and its components presented above. Creating an identification schedule that outlines the categories and themes based on the established definition during content analysis ensures consistency and accuracy in recognizing components and enables a systematic and precise identification process (Hsieh and Shannon 2005). For instance, the painting robot (Pictobot) application case study designed and implemented by Asadi et al. (2018) informs the knowledge of system integration for incorporating six subsystems of a painting robot, knowledge of robot anatomy and technical specifications to understand the Pictobot payload, degree of freedom, and the type of actuators the spray gun uses. Knowledge of flight cameras and other sensors used by the Pictobot, understanding of the overall architecture of the control system, and task planning are also required for implementing Pictobot. Skills informed by this application include technical skills in setting the painting requirement, selecting the proper nozzle, and adjusting parameters such as spraying pressure or paint thickness. Other skills include human–robot interface proficiency, which enables the operator to teleoperate the Pictobot’s navigation between adjacent workstations and adapt to changing work environments, task planning, and safety management during the painting operation. Abilities required for implementing Pictobot include teamwork with robots, where humans paint at low heights or finish details close to the edges of windows or doors simultaneously, and the robot performs work on high walls. Other abilities include safety management and adaptability. Likewise, the 3D printing robot application by Zhang et al. (2018) needs the knowledge of system integration

Table 1 Knowledge, skills, and abilities for human–robot collaboration in construction

Competency components	Code	HRC competencies	Descriptions	References
Knowledge	K1	Types of robots	Understanding the different categories and functions of robots used in construction	Attalla et al. (2023)
	K2	Construction robot applications	Knowledge of how robots are applied in construction tasks and environments	Liu et al. (2024)
	K3	Robot anatomy and technical specifications	Understanding of the physical structure and technical specifications of robots	Asadi et al. (2018)
	K4	Sensors	Knowledge of the various sensors used by robots for perception and interaction	Zhang et al. (2018) and Asadi et al. (2018)
	K5	Task planning principles	Understanding the principles involved in planning tasks for HRC in construction	Asadi et al. (2018)
	K6	HRC ethics and regulation	Knowledge of ethical considerations and regulatory standards in HRC	Leenes et al. (2017)
	K7	HRC safety and standards	Knowledge of safety protocols and standards for HRC in construction	Rosenstrauch et al. (2017)
	K8	HRC evaluation	Understanding methods for evaluating HRC performance	Spatola et al. (2021)
	K9	HRC-related fields	Basic understanding in the fields of study such as Psychology, Ergonomics, Cognitive Science and cybersecurity, related to HRC	Giallanza et al. (2024) and Gualtieri et al. (2022)
	K10	Immersive virtual environments	Understanding the use of virtual environments for training or simulating HRC scenarios	Shen and Hsu (2023) and Xiang et al. (2021)
	K11	Communication modes and technologies	Knowledge of communication methods and technologies used in HRC systems	Zhang et al. (2018) and Chen et al. (2023b)
	K12	Human–robot interface	Understanding the interface through which humans interact with robots	Zhang and Wang (2021)
	K13	Robot control system	Knowledge of systems that allow humans to control and interact with robots	Asadi et al. (2018)
	K14	System integration	Familiarity with integrating robots and systems into existing workflows	Zhang et al. (2018) and Asadi et al. (2018)
	K15	Robot programming principles	Understanding the core principles for programming robots for specific tasks	Shen and Hsu (2023) and Xiang et al. (2021)
	K16	Modeling and simulation	Knowledge of using models and simulations to plan and test HRC scenarios	Zhang et al. (2018)
	K17	Data analytics and machine learning	Understanding the use of data analytics and machine learning in HRC systems	Rathore et al. (2021)
	K18	Robot learning methods	Familiarity with the methods through which robots learn and adapt to tasks	Chetouani (2023) and Kober (2020)
	K19	Computation design	Knowledge of computational methods used in designing robotic systems	Bächer et al. (2021) and Sung et al. (2023)
	K20	Robot operating system	Understanding the operating systems that manage and control robots	Zhang et al. (2018)

Table 1 (continued)

Competency components	Code	HRC competencies	Descriptions	References
Skills	S1	Effective communication skill	Proficiency in conveying and interpreting information clearly in HRC contexts	Bonarini (2020)
	S2	Task planning skills	Expertise in planning and organizing tasks effectively for HRC	Asadi et al. (2018)
	S3	Regulation standard compliance	Skill in adhering to relevant regulatory standards in HRC operations	Valori et al. (2021)
	S4	Safety management	Proficiency in implementing and managing safety protocols in human–robot interaction	Asadi et al. (2018) and Rosenstrauch et al. (2017)
	S5	Technical skill	Expertise in using technical tools and systems within the HRC environment	Asadi et al. (2018)
	S6	Programming skill	Proficiency in writing and adapting code to control and program robots for different tasks	Zhang et al. (2018)
	S7	Data analytics and management	Skill in analyzing and managing data to optimize robot performance	Rathore et al. (2021)
	S8	Human–robot interface proficiency	Expertise in operating and interacting with robots through different interfaces effectively	Zhang et al. (2018) and Asadi et al. (2018)
	S9	Application of Machine Learning Algorithms	Proficiency in applying Machine Learning techniques to improve robotic tasks	Zhang and Wang (2021) and Rathore et al. (2021)
	S10	Simulation and modeling	Skill in using simulations and models to design and test HRC systems and scenarios	Bächer et al. (2021)
Abilities	A1	Teamwork	Ability to collaborate effectively with others human and robots in a human–robot team setting	Asadi et al. (2018)
	A2	Communication	Capability to understand and adapt communication styles in HRC environments	Bonarini (2020)
	A3	Continuous learning	Ability to engage in ongoing learning to improve skills and knowledge in HRC	Shen and Hsu (2023)
	A4	Problem-solving	Ability to identify issues and find effective solutions within HRC contexts	Kimaporn and Nunkaew (2024)
	A5	Adaptability	Capacity to adjust to changing environments and tasks in HRC situations	Asadi et al. (2018)
	A6	Attention to detail	Capability identify and managing the finer aspects of HRC tasks and operations	Zhang et al. (2018)
	A7	Analytical aptitude	Ability to think critically and analyze data to make informed decisions in HRC	Zhang et al. (2018)
	A8	Decision-making	Ability to make informed and effective decisions in human–robot interactions	Leonard (2009) and Ren et al. (2023)
	A9	Critical thinking	Capacity to evaluate complex situations and think logically in problem resolution	Ren et al. (2023)

Table 1 (continued)

Competency components	Code	HRC competencies	Descriptions	References
	A10	Spatial awareness	Ability to perceive and understand spatial relationships in the environment for HRC tasks	Morando and Loianno (2024)
	A11	Cultural and social awareness	Sensitivity to diverse cultural and social contexts affecting HRC interactions	Lim et al. (2021) and Müller et al. (2023)
	A12	Safety awareness	Ability to proactively ensure safety in human–robot interactions and manage potential risks	Asadi et al. (2018) and Leenes et al. (2017)

to combine the holonomic mobile platform, print nozzle, robotic arm, pump, and mixer. It also requires knowledge of sensors such as inertial measurement units (IMUs), 2D laser scanners for localization and odometry, robot operating systems (ROS) for device control, and 3D modeling and simulation. Skills such as programming, human–robot interface proficiency, and technical proficiency are required for the application. Finally, abilities needed in this application include analytical aptitude to design cementitious materials to meet rheological requirements (yield stress and viscosity) for printing and attention to detail during the printing operation.

The distinctions between HRC knowledge, skills, and abilities are dynamic, reflecting differences in their definitions and applications. For instance, knowledge of communication modes and technologies (K11) is different from effective communication (S1) skill and communication ability (A2) in HRC contexts. While K11 refers to understanding various communication methods and tools used in HRC, S1 involves the learned proficiency to apply this knowledge, such as leveraging these tools to communicate effectively and provide clear feedback to robots and other team members during HRC. In contrast, A2 represents the inherent or developed capacity to adapt communication styles and interpret information accurately in diverse HRC environments. Similarly, S2 (task planning skills) is classified as a skill because it involves a learned ability to organize and execute tasks, rather than an innate capacity. Likewise, S7 (data analytics and management) is categorized as a skill because it requires training and proficiency in handling and interpreting data, rather than being an inherent ability. These distinctions highlight that competencies evolve from fundamental understanding (knowledge) to practical application (skills) and, ultimately, to the capability to apply and adapt these skills effectively in complex HRC environments (abilities).

2.3 Industry and academia perception of competencies in construction

Industry and academia's perceptions of competencies in the construction industry vary significantly (Simons et al. 2023). Industry professionals prioritize competencies like technical skills and hands-on experience that directly enhance productivity and profitability. Academic experts prioritize scientific and theoretical understanding and intellectual development to promote innovation through research and education. This divergence in perspectives often leads to a gap between the skills employers seek and those that graduates possess (Strain and Marshall 2023). Studies attest to variances in perceptions of competencies by academic and industry practitioners. For instance, Li et al. (2022) found that instructors' and practitioners' priorities concerning scheduling topics and learning outcomes are not in sync. Recent research by McCord et al. (2023) also established that the industry values personal attributes, while academia emphasizes sustainability learning through experiential learning and software competencies. Simons, Redden (Simons et al. 2023) reported a significant difference in the expectations of academic and industry professionals regarding site work knowledge for entry-level construction professionals. A study by Farooqui and Ahmed (2009) investigating industry and academic perspectives of key skills for graduating construction management students reveals that educators give skills ranked high by the industry professionals a lesser significance. Therefore, it is important to investigate the perceptions of industry and academia regarding the competencies for HRC in the construction industry.

2.4 Research gap

The roboticization of construction activities requires the current and future construction workforce to be equipped with the necessary competencies to engage with robots in the industry (Bademosi et al. 2019). There has been considerable research into the technological aspects of HRC in

construction, such as communication (Stumm et al. 2018), control systems (Liu and Jebelli 2021), integration with immersive technologies and digital twins (Wang et al. 2021), and brainwave-driven HRC (Liu et al. 2021). In addition, much of the existing literature has concentrated on robot performance (Simone et al. 2022), task-specific applications (Zhang et al. 2018), robotic integration in construction (Martinez et al. 2020), and robot task learning through human demonstration (Liang et al. 2020). Finally, studies have also focused on the cost assessment of construction robots (Sun et al. 2024), robotic automation adoption and acceptance (Law et al. 2022; Park et al. 2023), classification of HRC and research trends (Liang et al. 2021), safety in HRC (Okpala et al. 2023), stakeholders' perception of robotization (Kim et al. 2022), and ethical regulation of HRC in construction (Wynsberghe et al. 2022). However, a critical aspect that remains underexplored is the human side of collaboration, particularly the competencies required for safe and effective HRC. Most current research assumes that human workers can quickly adapt to working with robots once the technology is deployed (Weiss et al. 2021), an assumption that overlooks the specific knowledge, skills, and abilities needed to interact with robotic systems confidently and safely. Neglecting the focus on competencies may lead to safety risks and hinder productivity, as workers may lack the preparation to navigate the complex requirements of HRC effectively.

Moreover, research focusing on identifying competencies for HRC in construction is scarce, and few attempts that have been made to approach it lack input from industry and academia to better align the competencies. For example, Kim et al. (2024) explored the use of immersive technology to train students for HRC in construction. However, the study lacks a competency framework identified through a literature review of HRC applications and implementations in construction. In addition, recent studies have advocated for examining competencies in construction from both industry and academic perspectives (Simons et al. 2023; Chileshe and Haupt 2007), emphasizing that a dual perspective is essential for aligning educational programs with real-world demands (Aljohani et al. 2022). In earlier work, Olukanni et al. (2024) identified key competencies for HRC in construction from an academic perspective, offering initial insights into how academia perceives the competencies required for preparing the construction workforce. However, that study did not incorporate industry perspectives, whose practical insights are essential for workforce readiness. This study builds on that foundation by expanding the scope to include industry viewpoints, enabling a comparative analysis that responds to calls for a more comprehensive and balanced understanding of HRC competencies in construction.

To address this gap, the present study aims to evaluate and compare the perspectives of construction industry professionals and academic experts regarding the competencies

(i.e., knowledge, skills, and abilities) required for HRC in construction. Understanding these diverse perspectives is crucial, as it will highlight areas where academic programs can be enhanced to meet industry needs while also identifying the industry's expectations for HRC to enhance safety and productivity. It will enable the full implementation of robotic technologies in construction. Finally, it will facilitate the alignment of industry and academia's perceptions of HRC competencies, which can support the development of a training program that can be incorporated into construction engineering and management (CEM) education to prepare the future construction workforce with the necessary competencies for successful HRC.

3 Methodology

This study seeks to understand the industry and academia perceptions regarding important competencies necessary for successful HRC in the construction industry. The methodology includes identifying HRC competencies in the form of knowledge, skills, and abilities through a literature review and content analysis (see Sect. 2.2), the Delphi survey design, questionnaire development and validation, and selection of experts adapted from an initial study by Olukanni et al. (2024), which measured the academic perceptions of competencies for HRC in construction and data analysis. The study was approved by the Institutional Review Board (IRB) at Virginia Tech. Figure 1 presents an overview of the methodology, which is discussed in subsequent sections.

3.1 Delphi survey design

The Delphi method, developed by the Rand Corporation in the 1950s for the U.S. defense industry (Landeta and Lertxundi 2023), has been widely adapted across fields to collect expert insights and achieve consensus in a field without agreement or incomplete knowledge (Attanasio et al. 2021). Its iterative nature and anonymity foster unbiased feedback, enhancing reliability (Alomari et al. 2020) and reaching a consensus in the second or third round, depending on the study objectives and predefined criteria (Mansilla et al. 2024; Boel et al. 2021). The Delphi method has been adopted in CEM research (Hallowell and Gambatese 2010), including construction safety (Alomari et al. 2020), managerial strategies (Tummalapudi et al. 2021), technology adoption (Okunola et al. 2024), and competency identification (Simmons et al. 2020). This study employed separate three-round Delphi surveys for industry and academia, involving participant recruitment, assessment of experts' perceptions of the identified HRC competencies, and iterative refinements to achieve consensus on HRC competencies.

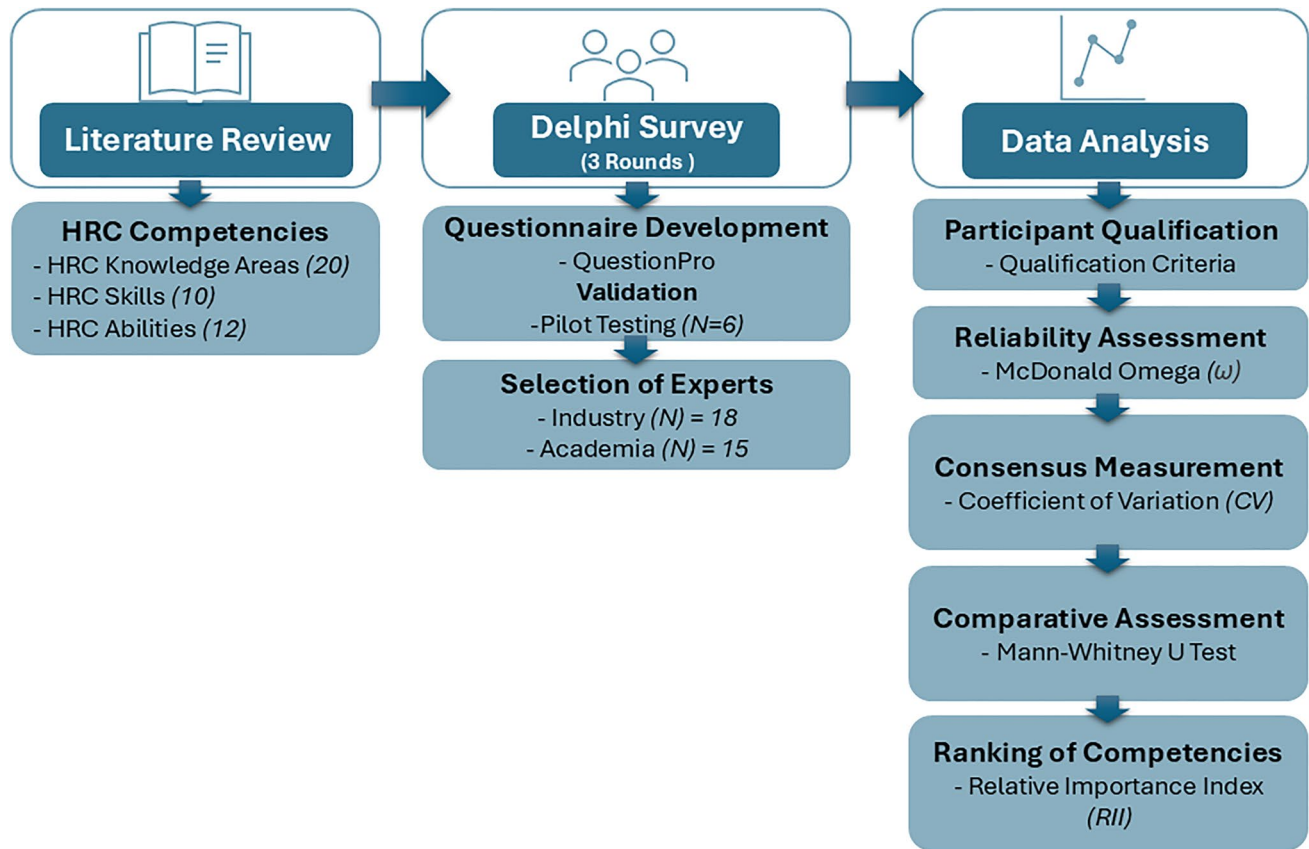


Fig. 1 Overview of research method

3.2 Questionnaire development and validation

The questions were designed based on a literature review of HRC competencies and refined through pilot testing with six industry and academic experts, aligning with questionnaire development, reliability, and validity testing (Sanda et al. 2021). In addition, an external evaluation of the questionnaire was conducted to ensure that the questions effectively measure the intended constructs and are easily understood and interpreted as intended by the participants. The questionnaire, which followed a structure similar to that used in the study by Olukanni et al. (2024), was shared with the participants on QuestionPro, a flexible web-based survey data collection and reporting platform (Rea et al. 2022). The first-round questions consist of two sections designed to collect data to determine the eligibility of the participants for the Delphi survey. The first section was designed to collect demographic data through open-ended questions, and the second section was designed to gather information on participants' educational backgrounds, professional experience, robotic technology expertise, and industry prominence. The second-round questions were designed for experts to rate the HRC competencies on a 5-point Likert scale

(5 = Extremely Significant, 4 = Very Significant, 3 = Moderately Significant, 2 = Slightly Significant, and 1 = Not Significant) to determine their relative significance and provide additional knowledge, skills, and abilities that are relevant for HRC in construction. The third-round questions presented the rankings of HRC competencies, calculated from the second-round ratings, for refinement. McDonald's Omega was calculated to evaluate the internal consistency of the expert panel's Likert scale ratings (Hayes and Coutts 2020), ensuring a reliable measurement of the relative significance of HRC knowledge, skills, and abilities. The high omega coefficients of 0.90, 0.78, and 0.85 for HRC knowledge, skills, and abilities in the industry panel and 0.94, 0.92, and 0.97 for the same constructs in the academia panel indicate strong internal consistency of the ratings (Hayes and Coutts 2020).

3.3 Selection of experts

The panels of experts for the industry and academia Delphi surveys were comprised of construction professionals and academics in construction-related departments from universities across the United States. Participants were contacted via LinkedIn, Myers-Lawson School of Construction

industry advisory board, and the American Society of Civil Engineers Construction Research Council (ASCE-CRC) listserv to target industry professionals and academics with expertise in construction robotics and HRC. The flexible point-grading system proposed by Hallowell and Gambatese (2010) was adapted to select participants for this study (see Table 2).

The eligibility criteria were adapted to assess participants' expertise in construction robotics and HRC, focusing on their educational qualifications, professional experience, contributions to the field, and experience with robotic technologies in construction (the most important criterion). For educational qualifications (C1), a Bachelor of Science (BS) is weighted higher (4 points) than a Master of Science (MS) (2 points) because the BS typically marks entry into the construction workforce. However, educational qualifications (C1) were not considered for academic participants, who are expected to have a PhD, ensuring stricter selection criteria for academics. Professional experience (C2) includes 3 points for faculty or industry roles and 1 point per year of relevant experience (C3). Professional prominence (C4–C10) evaluates credentials, such as professional registration (C4, 3 points), committee roles (C5–C6), and publications (C7–C10), reflecting leadership and contributions to the field. Experience with robotic technology (C11–C13), including years of experience with robotic technology (C11, 2 points per year), usage or research involving robotics (C12, 1 point), and patents (C13, 5 points). To qualify as an expert panel member, Hallowell and Gambatese (2010) recommended that participants score at least 1 point in four categories and a total of 11 points for eligibility. However, to recruit highly competent and experienced participants, we raised the requirement to a minimum of 1 point in each category and at least 20 points to qualify for the subsequent rounds based on the minimum obtainable scores in each qualification criterion. This criterion ensures that selected participants have a minimum level of qualification across all relevant criteria, preventing the inclusion of those without experience in critical aspects. It also guarantees that only participants capable of providing reliable feedback are selected. Table 3 presents the scores and credentials of eighteen industry professionals selected for the survey. Similarly, Table 4, adapted from Olukanni et al. (2024), presents the scores and credentials of 15 academic experts who participated in the survey. However, attrition reduced the number of participants in the subsequent rounds, with sixteen industry and fifteen academic experts in the second round and thirteen industry and fourteen academic experts in the third round. However, the final sample size remains adequate for a Delphi survey (Khodyakov et al. 2023).

The industry and academia expert panels relevant qualifications, from BS to Ph.D. in Civil Engineering, Structural Engineering, and CEM. Their professional affiliations

include the American Society of Civil Engineers (ASCE), the American Society of Safety Engineers (ASSE), the American Concrete Institute (ACI), the National Council of Examiners for Engineering and Surveying (NCEES), Association for Uncrewed Vehicle Systems International (AVUSI), Institute of Electrical and Electronics Engineers (IEEE), Leadership in Energy and Environmental Design Accredited Professional (LEED AP), American Welding Society (AWS), and Design-Build Institute of America (DBIA). Certifications held by the members of the expert panel include Professional Engineer (PE), Project Management Institute (PMI), American Welding Society Certified Robotic Arc Welding (AWS-CRAW), Evidence-Based Design Accreditation and Certification (EDAC), ASEA Brown Boveri Certification Program for Robotic Arc Welding (ABB-CRAW), and Federal Aviation Association Small Unmanned Aircraft System (FAA-Small UAS). This highlights their strong qualifications and extensive experience with robotic technologies currently utilized in the construction industry.

3.4 Data analysis

Statistical tests, including the coefficient of variation (CV) and the Mann–Whitney *U* test (a nonparametric statistic), were used to analyze the data collected. The consensus of experts' opinions was measured with a CV obtained by dividing the standard deviation by the mean of the rating data (Bhagat and Jha 2024). The CV value ranges between 0 and 1.0, where a CV below 0.5 indicates consensus, while a CV between 0.51 and 1.0 suggests a lack of consensus (Bedeian and Mossholder 2000; Pélabon et al. 2020). Given the study's sample size of 13 industry participants and 14 academic participants, the Mann–Whitney *U* nonparametric test was conducted to compare the industry professionals mean ratings and academic experts mean ratings adapted from in Olukanni et al. (2024) of HRC knowledge, skills, and abilities for agreement and differences at a confidence interval (CI) of 95%. This sample size is appropriate for a nonparametric test like the Mann–Whitney *U* test due to its robustness in handling small sample sizes (Vermeulen et al. 2015). Previous studies have adopted the nonparametric statistical method to compare two groups when the number of Delphi respondents is less than 30 (Gunduz et al. 2024; Kalaian and Kasim 2012). Rank biserial correlation was adopted to compute the effect size to understand the magnitude of the statistical results (Kerby 2014). The limits of biserial rank correlation range from -1.0 to 1.0 . The ranking of the competencies to determine HRC knowledge, skills, and abilities prioritized by industry and academia for HRC was computed using the relative importance index (RII) (see Eq. 1). RII values of 0.8 – 1.0 are considered highly important, and RII values of 0.6 – 0.79 are considered of

Table 2 Point grading for participants' qualification

Qualification criteria	Code	Experience/achievement	Points (each)	Minimum qualification criteria	Maximum possible points
Educational qualification	C1	BS	4	4	10
		MS	2		
		PhD	4		
Professional experience	C2	A faculty member at an accredited university/work in a relevant industry	3	3	3
	C3	Year of professional experience in the construction industry/academia	1		
Professional prominence	C4	Professional registration	3	3	3*Number of professional registrations
	C5	Membership of a committee	1		1*Number of committee
	C6	Chair of a committee	3		3
	C7	Peer-reviewed journal/technical article/technical report publication	2		2*Number of publications
	C8	Conference papers publication	1		1*Number of conference paper publications
	C9	Book publication	2		2*Number of book publications
	C10	Conference presentation	1		1*Number of conference presentations
Experience with robotic technology	C11	Years of experience with robotic technology	2	2	2*Years of experience with robotic technology
	C12	Use of robotic technology/research with robotic technology	1		1*Number of robotic technologies used in organization or research with
	C13	Patents	5		5*Number of patents
Total				20	

high-medium importance. A similar method was adopted by Okunola et al. (2024) to rank facilitators and barriers to adopting active exoskeletons in the construction industry.

$$RII = \frac{\sum W}{(A*N)} \quad (1)$$

where W is the weight assigned to each response, A is the highest weight (i.e., 5 for a 5-point Likert scale), and N is the total number of participants. Microsoft Excel and Jamovi (2.4.8) were used for quantitative data analyses.

4 Results

4.1 Measurement of consensus

The CV values used to calculate each expert panel's consensus are presented in Figs. 2 and 3. For the industry panel of experts, the CV for knowledge is between 0.22 to 0.40, skills from 0.14 to 0.48, and abilities from 0.20

to 0.46 (see Fig. 2). Similarly, for the academic panel of experts, the analysis reveals that CV for knowledge ranges from 0.10 to 0.35, skills from 0.14 to 0.34, and abilities from 0.14 to 0.37 (see Fig. 3). The box and violin plots in Figs. 2 and 3 visualize the distribution, central tendency, and variability of the CV of industry professionals' and academic experts' consensus measurements. The violin plot revealed that most CV values are concentrated around the median with fewer CV values at the whiskers (though still within the limit of consensus criteria), thus indicating strong consensus among each expert panel.

4.2 Comparative assessment of industry and academia perceptions of HRC knowledge

As stated in Sect. 3.4, the comparison of industry professional panels' mean ratings and academia expert panels' mean ratings [adapted from Olukanni, Akanmu (Olukanni et al. 2024)] of HRC knowledge areas is presented in Fig. 4. The findings indicate that academic experts generally assigned higher mean ratings across most knowledge

Table 3 Credentials and scores assigned to industry participants

Industry participant (IP)	Role	C1	C2	C3	C4	C5	C6	C7	C8	C10	C11	C12	Total points
1	Robotics innovation leader	10	3	8	0	1	0	2	8	2	10	9	53
2	Virtual construction manager	4	3	18	0	0	0	0	0	0	22	2	49
3	Executive vice president	4	3	28	6	1	0	0	0	0	4	3	49
4	Structural engineer	6	3	28	12	0	0	0	0	0	4	1	54
5	Director of innovation	4	3	28	0	1	0	0	0	0	10	11	57
6	Robotics lead, research and development	10	3	3	3	0	0	6	12	6	14	6	63
7	Construction manager	6	3	28	6	1	0	0	0	0	8	5	57
8	Project manager	4	3	28	0	0	0	0	0	0	10	2	47
9	Vice president, construction	4	3	28	3	0	0	0	0	0	10	2	50
10	President	4	3	28	9	0	0	0	0	0	14	6	64
11	Construction manager	4	3	28	9	1	0	1	0	1	14	2	63
12	Analyst	10	3	3	3	0	0	8	6	1	4	2	40
13	Executive	6	3	28	0	0	0	0	0	0	4	4	45
14	Site supervisor	4	3	13	0	0	0	0	0	0	4	2	26
15	Division leader	4	3	28	0	2	0	0	0	0	16	1	54
16	Construction inspector	2	3	8	6	0	0	0	0	0	4	1	24
17	Construction manager	10	3	13	3	0	0	0	0	0	4	2	35
18	Project manager	4	3	8	3	0	0	0	0	0	4	3	25

Table 4 Credentials and scores assigned to academic participants

Academic participant (AP)	Role	C2	C3	C4	C5	C6	C7	C8	C9	C10	C12	C13	Total points
1	Assistant professor	3	3	3	0	0	12	3	4	3	3	0	34
2	Assistant professor	3	3	0	0	0	30	8	3	8	2	0	57
3	Assistant professor	3	8	6	2	0	6	2	0	2	1	0	30
4	Assistant professor	3	3	3	2	0	6	2	0	2	2	0	23
5	Assistant professor	3	3	3	0	0	16	8	0	8	2	0	43
6	Assistant professor	3	3	12	3	0	4	3	0	3	6	0	37
7	Professor	3	13	3	2	0	80	30	0	30	4	20	185
8	Associate professor	3	13	3	2	0	6	12	0	12	2	0	53
9	Assistant professor	3	8	6	0	0	12	3	2	3	5	0	42
10	Associate professor	3	13	3	1	3	4	3	2	3	2	5	42
11	Professor	3	18	3	1	0	65	20	10	20	6	25	171
12	Associate professor	3	13	3	0	0	4	3	0	3	2	0	31
13	Professor	3	13	3	0	0	50	25	0	25	2	0	121
14	Professor	3	18	3	0	0	20	8	0	8	1	1	62
15	Associate professor	3	13	3	0	0	22	10	4	10	1	0	66

areas, except for HRC modeling and simulation (K16), which showed the smallest mean rating difference between the two groups. The largest mean rating difference was observed in HRC ethics and regulation (K6). The results of the Mann–Whitney *U* test, presented in Table 5, indicate significant differences in the ratings of HRC ethics and regulation (p value < 0.001, effect size = 0.6750), signifying

a strong disagreement between industry and academia. Significant differences in the mean ratings of both panels were also observed for knowledge of the robot control system (p value = 0.036, effect size of 0.4125) and communication modes and technologies (p value = 0.044, effect size of 0.4083), suggesting a moderate disagreement. Furthermore, while the knowledge of robot anatomy and technical

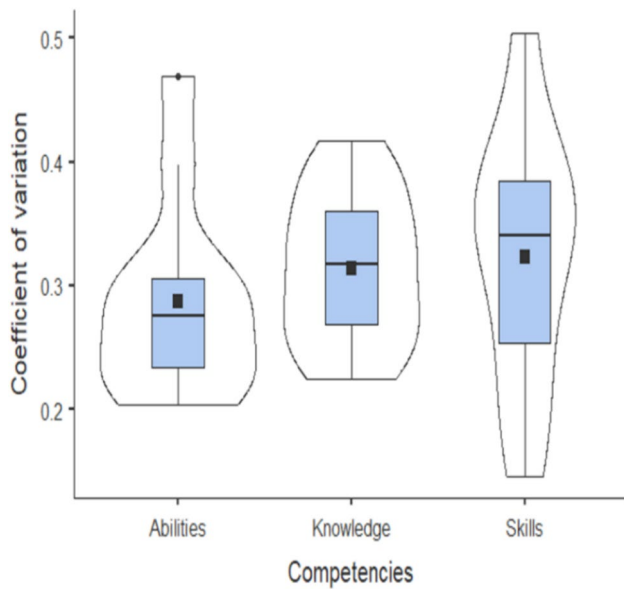


Fig. 2 Industry professionals' coefficient of variation consensus measurements

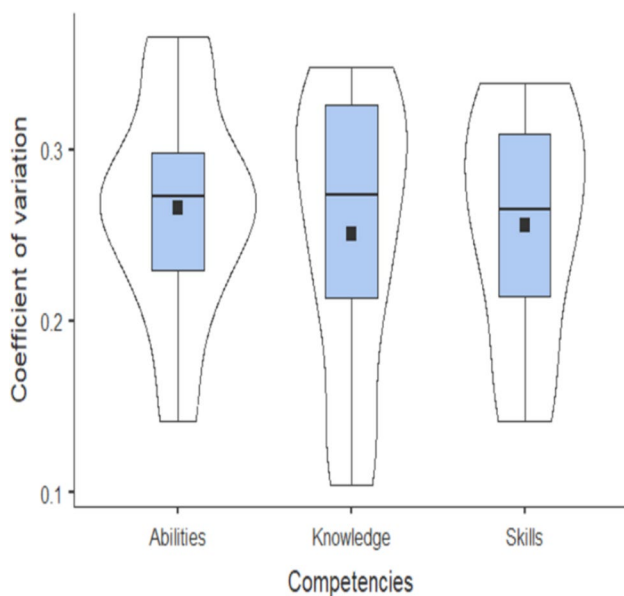


Fig. 3 Academic experts' coefficient of variation consensus measurements

specifications and HRC evaluation did not show statistically significant differences, their p values (0.083 and 0.072) and their associated moderate effect sizes (0.3583 and 0.3708) suggest trends toward disagreement between the expert panels. Conversely, several HRC knowledge areas exhibited high p values and small effect sizes, indicating weak or no meaningful differences between the industry and academia. These include types of robots ($p=0.604$, effect size=0.1083), construction robot applications ($p=0.641$, effect size=0.0958),

task planning ($p=0.706$, effect size=0.0792), immersive virtual environments ($p=0.600$, effect size=0.1083), programming ($p=0.870$, effect size=0.0375), and modeling and simulation ($p=0.900$, effect size=0.0292).

4.3 Comparative assessment of industry and academia perceptions of HRC skills

The result of the comparison between industry and academia's expert panels' mean ratings of HRC skills presented in Fig. 5 reveals that academic experts constantly provide higher ratings for all the skills. The highest mean difference was observed in regulation standard compliance (S3), while the lowest mean rating difference was observed in task planning (S2). The results of the Mann–Whitney U test in Table 6 indicate significant differences in specific HRC skills. Notably, human–robot interface proficiency demonstrates a significant difference, with a Mann–Whitney U value of 63.0, a p value of 0.017, and a rank biserial correlation of 0.4750, indicating moderate disagreement between industry and academia. Similarly, the Mann–Whitney U value of 65.5 for regulation standard compliance, with a p value of 0.026 and an effect size of 0.4542, suggests a moderate disparity between industry and academia. While not statistically significant, certain HRC skills display p values near the threshold and moderate effect sizes, hinting at potential trends toward disagreement. For instance, technical skill exhibits a Mann–Whitney U value of 79.5, a p value of 0.082, and an effect size of 0.3375. Effective communication similarly shows a near-significant difference, with a Mann–Whitney U value of 83.0, a p value of 0.127, and an effect size of 0.3083. In contrast, some HRC skills such as task planning ($p=0.743$, effect size=0.0667), simulation and modeling ($p=0.695$, effect size=0.0833), programming ($p=0.278$, effect size=0.2250), and data analytics and management ($p=0.216$, effect size=0.2542) have high p value and small effect sizes that suggest weak or no meaningful differences between industry and academia.

4.4 Comparative assessment of industry and academia perceptions of HRC abilities

A comparison between the mean ratings of HRC abilities of industry and academia shows that academic expert panel ratings of HRC skills are constantly high compared to industry expert panel ratings, as evidenced in the mean rating presented in Fig. 6. The highest mean difference was observed in cultural and social awareness (A11), while the lowest mean difference was seen in continuous learning (A3). The results of the Mann–Whitney U test shown in Table 7, show a significant difference in cultural and social awareness, with a Mann–Whitney U value of 58.0, a p value

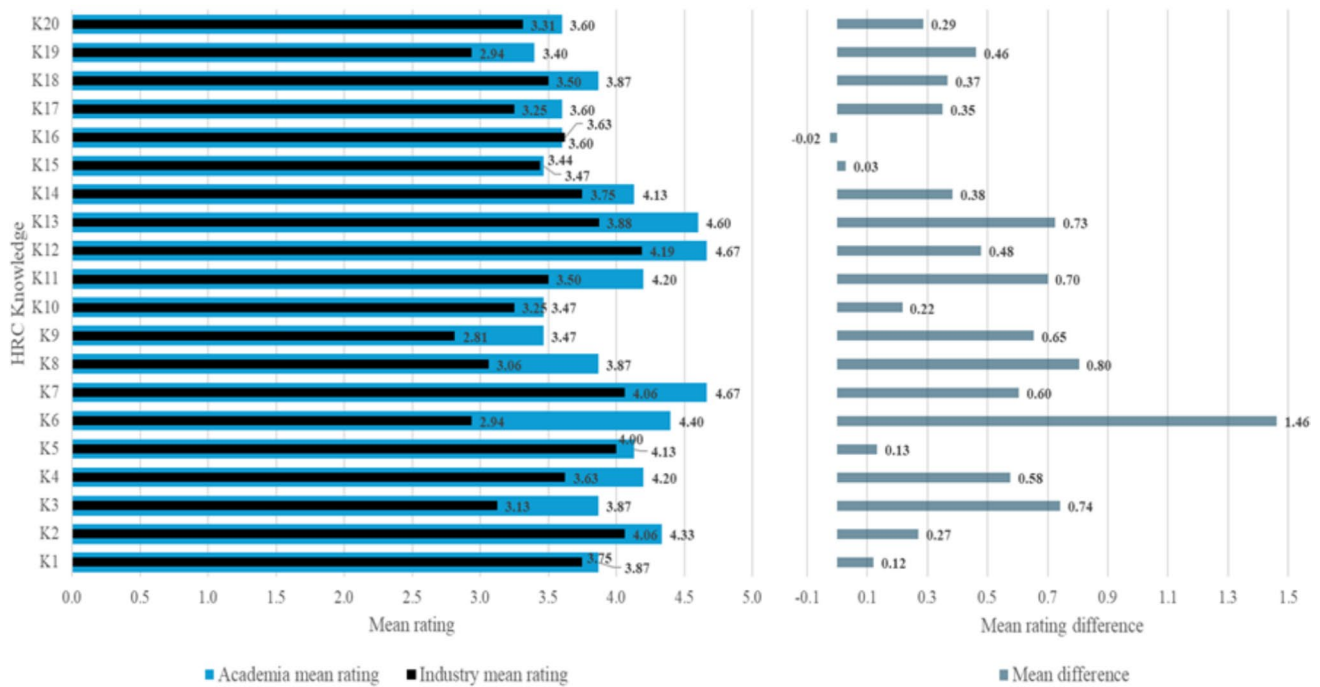


Fig. 4 Industry and academia's mean ratings of HRC knowledge

Table 5 Comparative analysis of industry and academia ratings of HRC knowledge (bolded*: statistical significance at p value < 0.05)

Code	HRC knowledge	Mann–Whitney U	p value	Effect size (rank biserial correlation)
K6	HRC ethics and regulation	39.0	<0.001*	0.6750
K13	Robot control system	70.5	0.036*	0.4125
K11	Communication modes and technologies	71.0	0.044*	0.4083
K8	HRC evaluation	75.5	0.072	0.3708
K3	Robot anatomy and technical specifications	77.0	0.083	0.3583
K4	Sensors	83.0	0.129	0.3083
K9	HRC related fields	87.0	0.17	0.2750
K12	Human–robot interface	90.0	0.187	0.2500
K7	HRC safety and standards	92.0	0.202	0.2333
K18	Robot learning methods	92.5	0.269	0.2292
K19	Computation design	93.5	0.287	0.2208
K17	Data analytics and machine learning	97.5	0.371	0.1875
K14	System integration	99.5	0.407	0.1708
K20	Robot operating system (ROS)	103.0	0.5	0.1417
K10	Immersive virtual environments	107.0	0.6	0.1083
K1	Types of robots	107.0	0.604	0.1083
K2	Construction robot applications	108.5	0.641	0.0958
K5	Task planning	110.5	0.706	0.0792
K15	Programming	115.5	0.87	0.0375
K16	Modeling and simulation	116.5	0.9	0.0292

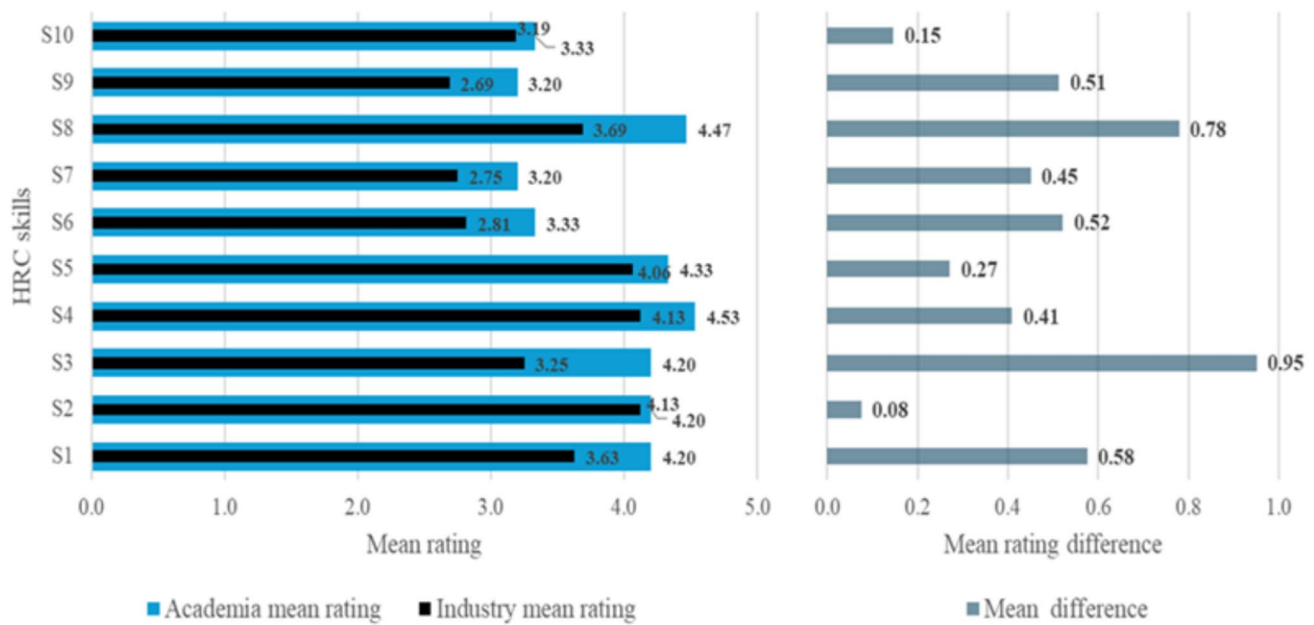


Fig. 5 Industry and academia's mean ratings of HRC skills

Table 6 Comparative analysis of industry and academia ratings of HRC skills (bolded*: statistical significance at p value < 0.05)

Code	HRC skills	Mann–Whitney U	p value	Effect size (rank biserial correlation)
S8	Human–robot interface proficiency	63	0.017*	0.475
S3	Regulation standard compliance	65.5	0.026*	0.4542
S5	Technical skill	79.5	0.082	0.3375
S1	Effective communication	83	0.127	0.3083
S4	Safety management	86	0.148	0.2833
S9	Application of machine learning algorithms	86	0.169	0.2833
S7	Data analytics and management	89.5	0.216	0.2542
S6	Programming	93	0.278	0.225
S10	Simulation and modeling	110	0.695	0.0833
S2	Task planning	112	0.743	0.0667

of 0.013, and a rank biserial correlation of 0.517, suggesting a strong disagreement between the groups. In addition, several HRC abilities exhibit p values near the 0.05 confidence interval and moderate effect sizes, suggesting potential trends toward disagreement. For instance, communication has a Mann–Whitney U value of 74.0, a p value of 0.053, and an effect size of 0.383. At the same time, adaptability shows a Mann–Whitney U value of 79.5, a p value of 0.094, and an effect size of 0.338. Although these categories are not statistically significant, the near-threshold p values and moderate effect sizes suggest notable trends. However, HRC abilities such as teamwork ($p = 0.203$, effect size = 0.254), continuous learning ($p = 0.566$, effect size = 0.117), problem-solving ($p = 0.234$, effect size = 0.238), attention to

detail ($p = 0.409$, effect size = 0.171), analytical aptitude ($p = 0.120$, effect size = 0.324), decision making ($p = 0.205$, effect size = 0.258), critical thinking ($p = 0.219$, effect size = 0.246), spatial awareness ($p = 0.599$, effect size = 0.108), and safety awareness ($p = 0.355$, effect size = 0.179) exhibit high p values and small effect sizes, indicating weak or no meaningful differences between the industry and academia ratings of HRC abilities.

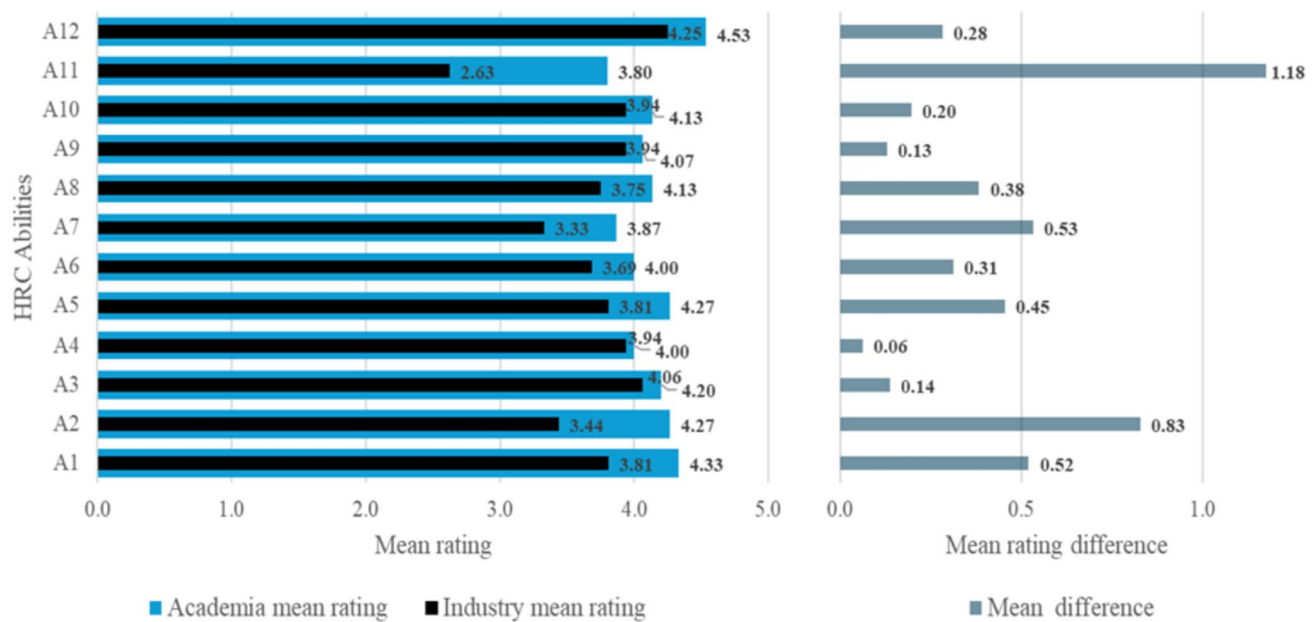


Fig. 6 Industry and academia's mean ratings of HRC abilities

Table 7 Comparative analysis of industry and academia ratings of HRC abilities (bolded*: statistical significance at p value < 0.05)

Code	HRC abilities	Mann–Whitney U	p value	Effect size (rank biserial correlation)
A11	Cultural and social awareness	58	0.013*	0.517
A2	Communication	74	0.053	0.383
A5	Adaptability	79.5	0.094	0.338
A7	Analytical aptitude	76	0.12	0.324
A1	Teamwork	89.5	0.203	0.254
A8	Decision making	89	0.205	0.258
A9	Critical thinking	90.5	0.219	0.246
A4	Problem-solving	91.5	0.234	0.238
A12	Safety awareness	98.5	0.355	0.179
A6	Attention to detail	99.5	0.409	0.171
A3	Continuous learning	106	0.566	0.117
A10	Spatial awareness	107	0.599	0.108

4.5 HRC competencies prioritized by industry and academia

4.5.1 HRC knowledge areas prioritized by industry and academia

Table 8 compares the RII rankings computed for HRC knowledge areas prioritized by industry and academia. In the industry, four HRC knowledge areas, including human–robot interface—K12 (RII 0.84, Rank 1), HRC safety and standards—K7 (RII 0.81, Rank 2), construction robot applications—K2 (RII 0.81, Rank 2), task

planning—K5 (RII 0.80, Rank 4) are in the high importance category. However, in academia, nine HRC knowledge areas in the high importance category include human–robot interface—K12 (RII 0.93, Rank 1), HRC safety and standards—K7 (RII 0.93, Rank 1), robot control system—K13 (RII 0.92, Rank 3), HRC ethics and regulation—K6 (RII 0.88, Rank 4), construction robot applications—K2 (RII 0.87, Rank 5), sensors—K4 (RII 0.84, Rank 6), communication modes and technologies—K11 (RII 0.84, Rank 6), task planning—K5 (RII 0.83, Rank 8), and system integration—K14 (RII 0.83, Rank 8). Other competencies are either high-medium important

Table 8 Industry and academia prioritized HRC knowledge areas (bolded*: highly important and prioritized HRC knowledge ($0.80 \leq \text{RII} \leq 1.0$))

Industry				Academia			
Code	HRC knowledge	RII	Rank	Rank	RII	HRC knowledge	Code
K12	Human–robot interface	0.84*	1	1	0.93*	Human–robot interface	K12
K7	HRC safety and standards	0.81*	2	1	0.93*	HRC safety and standards	K7
K2	Construction robot applications	0.81*	2	3	0.92*	Robot control system	K13
K5	Task planning	0.80*	4	4	0.88*	HRC ethics and regulation	K6
K13	Robot control system	0.78	5	5	0.87*	Construction robot applications	K2
K1	Types of robots	0.75	6	6	0.84*	Sensors	K4
K14	System integration	0.75	6	6	0.84*	Communication modes and technologies	K11
K4	Sensors	0.73	8	8	0.83*	Task planning	K5
K16	Modeling and simulation	0.73	8	8	0.83*	System integration	K14
K11	Communication modes and technologies	0.70	10	10	0.77	Types of robots	K1
K18	Robot learning methods	0.70	10	10	0.77	Robot learning methods	K18
K15	Programming	0.69	12	10	0.77	HRC evaluation	K8
K20	Robot operating system (ROS)	0.66	13	10	0.77	Robot anatomy and technical specifications	K3
K10	Immersive virtual environments	0.65	14	14	0.72	Modeling and simulation	K16
K17	Data analytics and machine learning	0.65	14	14	0.72	Data analytics and machine learning	K17
K3	Robot anatomy and technical specifications	0.63	16	14	0.72	Robot operating system (ROS)	K20
K8	HRC evaluation	0.61	17	17	0.69	HRC related fields	K9
K6	HRC ethics and regulation	0.59	18	17	0.69	Immersive virtual environments	K10
K19	Computation design	0.59	18	17	0.69	Programming	K15
K9	HRC related fields	0.56	20	20	0.68	Computation design	K19

or below. It is evident that both sectors highly prioritize human–robot interface (K12) and HRC safety and standards (K7) in the highly important HRC knowledge category. Other knowledge areas recognized as highly important by both sectors are robot control systems (K13) and task planning (K5). Both industry and academia prioritize human–robot interface (K12), HRC safety and standards (K7), construction robot applications (K2), and task planning (K5) as highly important, with RII values above 0.8. Robot control system (K13), although slightly below 0.8 for industry, is highly prioritized by academia. Sensors (K4), system integration (K14), and communication modes and technologies (K11) are considered high by academia and high-medium by industry, showing their significant importance in the construction industry and academia.

4.5.2 HRC skills prioritized by industry and academia

The comparison of HRC skills prioritized by industry and academia is presented in Table 9. The industry has no HRC skills, with an RII above 0.80 in the highly important category. However, the industry's top prioritized HRC skills in the high-medium importance category include task planning—S2 (RII 0.78, Rank 1), effective communication—S1 (RII 0.73, Rank 2), safety management—S4 (RII 0.69, Rank 3), and technical skill—S5 (RII 0.65,

Rank 4). In academia, the top prioritized HRC skills in the highly important category are safety management—S4 (RII 0.91, Rank 1), human–robot interface proficiency—S8 (RII 0.89, Rank 2), technical skill—S5 (RII 0.87, Rank 3), with effective communication—S1 (RII 0.84, Rank 4), regulation standard compliance—S3 (RII 0.84, Rank 4), and task planning—S2 (RII 0.84, Rank 4) sharing the fourth position. Both expert panels prioritize task planning (S2), effective communication (S1), safety management (S4), and technical skills, which are highly prioritized by academia and fall within the high-medium category for industry.

4.5.3 HRC abilities prioritized by industry and academia

The HRC abilities prioritized by both expert panels are presented in Table 10. The result reveals that the industry has no HRC abilities, with an RII score above 0.800 in the high-importance category. However, the industry's prioritized HRC abilities in the high-medium importance category are teamwork—A1 (RII 0.76, Rank 1), continuous learning—A3 (RII 0.72, Rank 3), problem-solving—A4 (RII 0.66, Rank 4), communication—A2 (RII 0.65, Rank 2) and adaptability—A5 (RII 0.61, Rank 5). HRC abilities in the high-importance category prioritized by academia include teamwork—A1 (RII 0.87, Rank 1) and communication—A2 (RII 0.80, Rank 2). Other HRC abilities prioritized by academia

Table 9 Industry and academia prioritized HRC skills (bolded*: highly important and prioritized HRC skills— $0.80 \leq \text{RII} \leq 1.0$, bolded**: high-medium important and prioritized HRC skills— $0.6 \leq \text{RII} \leq 0.8$)

Industry				Academia			
Code	HRC skills	RII	Rank	Rank	RII	HRC skills	Code
S2	Task planning	0.78**	1	1	0.91*	Safety management	S4
S1	Effective communication	0.73**	2	2	0.89*	Human–robot interface proficiency	S8
S4	Safety management	0.69**	3	3	0.87*	Technical skill	S5
S5	Technical skill	0.65**	4	4	0.84*	Effective communication	S1
S3	Regulation standard compliance	0.58	5	4	0.84*	Regulation standard compliance	S3
S8	Human–robot interface proficiency	0.51	6	4	0.84*	Task planning	S2
S6	Programming	0.43	7	7	0.67	Programming	S6
S10	Simulation and modeling	0.41	8	7	0.67	Simulation and modeling	S10
S7	Data analytics and management	0.40	9	9	0.64	Data analytics and management	S7
S9	Application of machine learning algorithms	0.36	10	9	0.64	Application of machine learning algorithms	S9

Table 10 Industry and academia prioritized HRC abilities (bolded*: highly important and prioritized HRC abilities— $0.80 \leq \text{RII} \leq 1.0$, bolded**: high-medium important and prioritized HRC abilities— $0.6 \leq \text{RII} \leq 0.8$)

Industry				Academia			
Code	HRC abilities	RII	Rank	Rank	RII	HRC abilities	Code
A1	Teamwork	0.76**	1	1	0.87*	Teamwork	A1
A3	Continuous learning	0.72**	2	2	0.80*	Communication	A2
A4	Problem-solving	0.66**	3	3	0.74**	Continuous learning	A3
A2	Communication	0.65**	4	4	0.67**	Problem-solving	A4
A5	Adaptability	0.61**	5	4	0.67**	Adaptability	A5
A6	Attention to detail	0.56	6	6	0.60**	Attention to detail	A6
A9	Critical thinking	0.53	7	7	0.56	Decision making	A8
A8	Decision making	0.52	8	8	0.55	Analytical aptitude	A7
A10	Spatial awareness	0.50	9	9	0.53	Critical thinking	A9
A12	Safety awareness	0.50	9	10	0.52	Safety awareness	A12
A7	Analytical aptitude	0.45	11	10	0.52	Spatial awareness	A10
A11	Cultural and social awareness	0.32	12	12	0.46	Cultural and social awareness	A11

in the high-medium importance category include continuous learning—A3 (RII 0.74, Rank 3), adaptability—A5 (RII 0.67, Rank 4), problem-solving—A4 (RII 0.67, Rank 4), and attention to detail—A6 (RII 0.60, Rank 6). Both industry and academia prioritized teamwork (A1) and communication, though highly prioritized by academia and the high-medium category for industry. Continuous learning (A3), problem-solving (A4), and adaptability (A5), ranked within the high-medium category, are prioritized by both industry and academia, highlighting their mutual importance.

5 Discussion

The perceptions of industry professionals and academia concerning the competencies for implementing HRC in construction vary significantly. This study revealed the perceptions of industry professionals and academic experts concerning the competencies for implementing HRC in

the construction industry. It further emphasizes the area of perceptual consensus and differences between the two stakeholders regarding HRC competencies. This research finding reinforces the previous works of Bademosi and Issa (2022) and ElZomor et al. (2020), highlighting the importance of equipping current and future workers in construction-related departments with the competencies required to implement advanced automation and robotics technologies in construction. Understanding the perceptions of industry and academia, especially areas of consensus and dissent, regarding HRC's core competencies holds immense implications for industry and academia. These implications are discussed below.

5.1 HRC knowledge

This study showed that the most prioritized HRC knowledge is the human–robot interface (K12) by industry and academia for implementing HRC in construction. Previous

studies have established that user-friendly human–robot interfaces are critical for the increased adoption of robots, acceptance of robots by workers, advancing HRC in construction, and enhancing intuitive communication between construction workers and robots (Burden et al. 2022; Park et al. 2025; Wang et al. 2022). These interfaces include immersive virtual reality and brain–computer interfaces (Zhang et al. 2018), graphical user interfaces (GUIs) (Das et al. 2019; Gross and Krenn 2023), intuitive human–robot interaction interfaces (e.g., gesture, voice, gaze, bio-signal, and vision-based) (Zhang et al. 2018), and virtual human–drones interaction interfaces (Onososen et al. 2022). Both expert panels prioritized the knowledge of HRC safety and standards (K7) in the second position. This is not surprising because safety has always been a significant concern for the stakeholders in the construction industry (Benny and Jaishree 2017). Similar to these findings, previous studies (Okpala et al. 2023; Sun et al. 2023; Tehrani and Alwisy 2023) have established that safety is crucial in HRC. The primary concern is that human–robot interaction could introduce new hazards or worsen existing risk levels (Okpala et al. 2023). As such, there is a need for knowledge of HRC safety and standards. In addition, knowledge of construction robot applications (K2) and task planning (K5) are prioritized by industry and academia, highlighting the need to understand various applications of robots and operational efficiency in the construction industry. The identification of these areas of agreement in this research provides a foundation for developing standardized training programs that address both interface design and safety protocols, which can be uniformly applied across the construction industry.

There are notable differences in the ranking of HRC knowledge between industry and academia. Academia places a significantly higher priority on knowledge areas such as HRC ethics and regulation (K6), ranked fourth compared to eighteenth in industry, highlighting its importance in academic discussions. Similarly, knowledge of communication modes and technologies (K11) and sensors (K4) are also ranked higher by academia (sixth) than by industry (tenth and eighth, respectively), suggesting a greater focus on technological frameworks for interaction and perception in academic circles. In addition, knowledge of HRC evaluation (K8) and robot anatomy and technical specifications (K3) are seen as more important in academia, reflecting its broader interest in the foundational and evaluative aspects of HRC. In contrast, the industry gives more importance to the knowledge of types of robots (K1), ranked sixth, while academia ranks it lower at the tenth position. This divergence suggests that while industry focuses on operational realities and technology implementation, academia emphasizes research, innovation, and the broader societal implications

of robotics. These differences indicate a need for collaborative efforts to align educational frameworks with industry requirements and ensure that robotic technologies can be effectively integrated into practical applications, aligning with Rossoni, de Vasconcellos (Rossoni et al. 2024), who emphasized industry and academia collaboration to drive the implementation of research and drive innovation. In return, this would facilitate the establishment of standardized educational frameworks and training programs, enhancing efficiency and effectiveness in preparing construction workers for HRC roles (Ras et al. 2017) and increasing productivity and efficiency in the industry (Wu et al. 2022).

5.2 HRC skills

The findings from the ranking of HRC skills by industry and academia revealed that both expert panels prioritize effective communication (S1), safety management (S4), technical (S5), and regulation standard compliance (S3) HRC skills, indicating the essential roles of these skills in facilitating successful HRC in construction. Previous studies emphasized the importance of effective communication to ensure that humans can effectively instruct, monitor, and collaborate with robots (Liang et al. 2024; Park et al. 2024), minimizing errors and improving productivity using different communication modes (Gross and Krenn 2023). Safety management is crucial in human–robot work environments. Its prioritization by industry and academia highlights its commitment to minimizing risks and ensuring workers have the skills to follow safety protocols and conduct risk assessments. Technical skills are essential for workers to understand and operate robotic systems effectively (Shmatko and Volkova 2020). Emphasizing technical skills ensures that workers can leverage robotic technologies to enhance productivity and efficiency (Dungrani et al. 2023). Regulation standard compliance underscores the importance of adhering to safety and operational standards specific to HRC. It includes compliance with guidelines that govern the use of robots in construction, ensuring that all activities are legally compliant and that robots are used safely and effectively (Richter et al. 2023). These prioritized HRC skills reflect areas where industry and academia could collaborate to develop training programs to train the current workforce and CEM students to develop the prioritized skills. This would also help construction industries planning to integrate robotic automation into their operations understand the critical HRC skills needed to successfully implement HRC in construction.

Significant differences between industry and academia characterize the HRC skills rankings. The industry prioritizes task planning (S2) and effective communication (S1) in the first and second positions as essential HRC skills

for ensuring efficient workflows and coordinating teams in practical applications. Conversely, academia ranks safety management (S4) as the top HRC skill due to its focus on developing comprehensive safety protocols and addressing ethical implications. Human–robot interface proficiency (S8) is ranked second, emphasizing research and development in interaction technologies. This divergence further confirms that industry is concerned with skills that will meet the immediate operational needs, while academia prioritizes foundational knowledge and theoretical constructs. These differences also highlight the necessity for collaboration between both stakeholders to align educational frameworks with industry demands, ensuring that critical HRC skills are effectively integrated into real-world practices.

5.3 HRC abilities

Teamwork (A1) was given the top priority in the HRC abilities ranking by industry and academia. Previous studies have highlighted the importance of integrating robots with human teams, leveraging the strengths of robots' precision and humans' cognitive skills in industrial settings (Mingyue Ma et al. 2018; Onososen and Musonda 2023). The consensus on teamwork ranking highlights its crucial role in HRC, as it enables seamless interaction, enhances efficiency, and ensures safety in robot-assisted construction tasks. Furthermore, continuous learning (A3) is prioritized by industry and academia, reflecting the importance of keeping pace with the construction industry's rapidly evolving robotic technologies and methodologies. In addition, problem-solving (A4) is prioritized by industry and academia, highlighting the need for effective troubleshooting and innovative thinking to address challenges in human–robot collaborative scenarios in construction operations. Communication (A2) and adaptability (A5), ranked in the top five HRC abilities by industry and academia, underscore the necessity of ensuring clear and efficient interactions between human workers and robots and flexibility in adapting to new technologies and changing project requirements. These prioritized HRC abilities highlight the need for a construction environment where workers continuously adapt to new technologies, solve complex HRC problems, and maintain clear communication with robotic systems to enhance workflow efficiency, improve adaptability to changing demands, and ensure more innovative and resilient human–robot teams.

However, it is noteworthy that there are differences in the ranking categories of the top five HRC abilities and the remaining HRC abilities. For example, while the industry expert panel ranked critical thinking (A9) and decision-making (A8) in the seventh and eighth positions, the academia expert panel ranked decision-making ability (A8) and analytical aptitude (A7) in these positions. This difference in ranking by both expert panels suggests that the construction

industry prioritizes quick, adaptive problem resolution during HRC scenarios, whereas academics emphasize structured decision-making and data-driven analysis to improve HRC efficiency. In addition, spatial awareness (A10), ranked ninth, holds slightly more importance for industry experts than academia, reflecting the industry's emphasis on ensuring safe and efficient robot navigation in dynamic construction environments. These discrepancies highlight the fundamental differences in perspective between academia and industry, while industry prioritizes immediate practical implementation and real-time adaptability in HRC, academia focuses on long-term optimization and systematic decision frameworks.

Therefore, given the differences in priorities for HRC knowledge, skills, and abilities between industry and academia, collaboration is essential to bridging this gap. Such collaboration can help prioritize the most essential competencies and address the broader competencies necessary for effective HRC implementation. This collaboration can create a framework that integrates both practical industry needs and academic objectives.

6 Conclusion

This study analyzed the perceptions of industry professionals and academics regarding the competencies for HRC in the construction industry, establishing that their HRC competency priorities are not totally in sync. It highlights HRC knowledge, skills, and abilities that the industry and academia prioritize for implementing HRC in construction. It also establishes their areas of perceptual agreement and disparity regarding HRC competencies. These differences in prioritization highlight a balance between immediate industry needs and a broader, perhaps more theoretically informed academic perspective on the fundamentals of HRC in construction. These perceptual disparities in competencies for HRC in construction suggest that collaboration between industry and academia is essential for creating standardized educational frameworks that balance both practical skills and theoretical knowledge. The consensus on the significance of specific HRC competencies suggests areas where training programs can be universally focused.

This study contributes to knowledge by identifying the essential competencies for implementing HRC in construction. It also outlined the specific knowledge and technical skills prioritized by both construction industry professionals and academic experts as critical for successful HRC integration. In addition, this study highlighted managerial abilities such as teamwork, communication, problem-solving, decision-making, which are critical thinking, and cultural and social awareness crucial for managing the collaborative dynamics between human and robotic resources in

construction. Finally, by establishing areas of consensus and divergence between industry and academia, the study fosters collaborative innovation in construction robotics.

The limitation of this study is the reduction or loss of participants due to dropouts and withdrawals from the study. However, this attrition has been carefully handled by selecting highly competent industry and academic panel members to participate in the study. Furthermore, the reliability assessment and consensus measurements of the panel of experts' feedback data revealed a high level of agreement among the participants, indicating that the results are valid and reliable. This strengthens the credibility of the study's findings and recommendations. Future research could aim to refine these competencies as construction robotic technologies evolve and more experts emerge in the field, exploring distinctions between various groups (e.g., practitioners and academics), different experience and expertise levels, and types of robots. In addition, future research can focus on implementing these findings in designing training programs for the current workforce and incorporating them into the CEM curricula to train the future workforce. Finally, research on developing collaborative training platforms for industry and academia to exchange information about industry HRC needs and train the future workforce to acquire the relevant competencies could be explored.

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Data availability All data, models, and code generated or used during the study appear in the submitted article.

Declarations

Conflict of interest The authors declare no conflict of interest.

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