Routledge
Taylor & Francis Group

International Journal of Construction Education and Research

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/uice20

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To cite this article: Ebenezer Olukanni, Abiola Akanmu, Houtan Jebelli & Saratu Terreno (21 Sep 2024): Competencies for Human-Robot Collaboration in the Construction Industry – Academia's Perspective, International Journal of Construction Education and Research, DOI: 10.1080/15578771.2024.2405618

To link to this article: https://doi.org/10.1080/15578771.2024.2405618

Published online: 21 Sep 2024.

INTERNATIONAL JOURNAL OF CONSTRUCTION EDUCATION AND RESEARCH
https://doi.org/10.1080/15578771.2024.2405618

Competencies for Human-Robot Collaboration in the Construction Industry – Academia's Perspective

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ABSTRACT

This paper investigates the perceptions of Construction Engineering and Management instructors regarding the competencies for Human-Robot Collaboration (HRC) in construction to determine knowledge areas, skills, and abilities prioritized for facilitating effective collaboration between humans and robots in the industry. A two-round Delphi study was employed to evaluate the perceptions of construction instructors regarding HRC competencies. This study's findings revealed that human-robot collaboration knowledge areas prioritized by the instructors include HRC ethics and regulation, robot anatomy and technical specifications, construction robot applications, sensors, and task planning. The instructors prioritized skills such as task planning, application of machine learning algorithms, safety management, human-robot interface proficiency, and effective communication. HRC abilities prioritized include decision-making, continuous learning, critical thinking, attention to detail, analytical aptitude, and adaptability. This research established the competencies prioritized by the instructors for implementing HRC in the construction industry and recommended future research directions.

KEYWORDS
Instructors' perception; human-robot collaboration; competencies; construction; Delphi study

Introduction

The construction industry faces significant challenges impacting productivity, safety, and labor shortages (Tafazzoli et al., 2024). Robots are increasingly explored as potential solutions to these challenges (Pradhananga et al., 2021). These technologies can automate labor-intensive tasks in construction, enhancing efficiency and reducing reliance on human labor (Richter et al., 2023). They could also improve safety by performing dangerous tasks, thereby minimizing the risk of accidents and injuries (Okpala et al., 2023). Despite these benefits, the adoption of robots in the construction industry has not gained much traction compared to other sectors like logistics, manufacturing, and agriculture. This is due to reluctance to adopt new technologies, high initial cost, and limited understanding of how to safely and efficiently deploy robots on construction sites (Attalla et al., 2023). Additionally, the human-centric nature of construction work and the dynamics of construction sites further complicate robot integration (Ahiable & Banawi, 2021). This has led to recent explorations of human-robot collaboration (HRC) in the construction industry (Chen,

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2021) and, more importantly, how to train the workforce to collaborate with robots on construction sites.

Academic institutions play a crucial role in shaping the future workforce's skills (Pallathadka & Pallathadka, 2023). Researchers in these institutions are often at the forefront of exploring how new technologies like robots can be adopted and sustained in industry settings (Pradhananga et al., 2021). These advances could help drive how the future and current workforce should be trained to advance innovation with robots in the construction industry. Some construction engineering and management (CEM) programs have commenced incorporating robotic technologies into their curriculum to train the future construction workforce (ElZomor et al., 2020). Thus, academia's view on the competencies needed to facilitate HRC in construction is crucial.

Therefore, this research aims to investigate the perceptions of academia regarding competencies for HRC in construction, ultimately determining the core competencies in the form of knowledge, skills, and abilities that should be incorporated into CEM curricula to prepare current and future construction workers for successful collaboration with robots. The rest of this paper is structured as follows: First, the background section presents the extant literature on HRC in construction and academia's role in shaping the discourse on workforce competencies, followed by the methodology. The results and findings of the research are presented, followed by the discussion section. The conclusion, limitations, and future research recommendations are presented in the last section. This study contributes to the body of knowledge by establishing instructors' perceptions of the competencies for HRC in construction. It also established HRC knowledge areas, skills, and abilities prioritized by instructors.

Background

Overview of human-robot collaboration in the construction industry

Recently, various types of robots have been explored to support construction tasks (Saidi et al., 2016). These include semi-automatic masons for bricklaying, TyBOT for rebar tying, welding robots for fabrication and welding tasks, and exoskeletons for augmenting workers' bodies while executing construction tasks (Saidi et al., 2016). Others also include industrial robotic arms for modular construction and prefabrication (Fu et al., 2024) and onsite construction (Zhang et al., 2023), quadrupedal robots for automated on-site image capture for construction progress monitoring (Afsari et al., 2022), unmanned ground vehicles (UGVs) like excavators and bulldozers for autonomous operation without human operators (Fernandez et al., 2019), and unmanned aerial vehicles (UAVs) or drones for tasks such as aerial surveying and site monitoring (El Meouche et al., 2016).

These technologies have shown potential for improving efficiency and safety in the construction industry. For instance, rebar-tying robots can bind multiple rebar nodes simultaneously (Jin et al., 2021), enhancing efficiency. Additionally, robots are used for hazardous tasks in construction, minimizing fatalities and safety concerns (Sundara Mahalingam et al., 2019). Moreover, construction robots have helped address labor shortages by automating demanding, repetitive, and dangerous construction operations (Zhang et al., 2021). Despite these benefits, working with robots in the construction industry could present unintended consequences such as safety risks, efficiency concerns, and skill gaps. Improper interaction between humans and robots can lead to accidents (Okpala et al., 2023). Understanding how to coordinate tasks, communicate effectively, and manage issues when working alongside robots can significantly enhance productivity and safety on construction sites. The increased adoption of robots could result in skill gaps due to a shortage of skilled workers who can operate and integrate robots with other technologies. Thus, identifying and fostering the necessary competencies for interacting with robots is imperative to sustain the aforementioned benefits in the construction industry.

Academia's role and pedagogical approach in competency development

Academia plays a significant role in preparing future construction professionals to develop competencies for emerging technologies in the industry. Academic institutions develop competency frameworks that encompass knowledge, skills, and abilities relevant to various concepts and fields essential for education, certification, recruitment, and ongoing research (Batt et al., 2020). These institutions are hubs for research and innovation, encouraging students to engage in research projects and fostering critical thinking and problem-solving skills (Čajka et al., 2023). Active, experiential, and collaborative learning are the most effective pedagogical approaches supporting these roles (Ajani, 2023; Canada & Gayton, 2023; Nasr et al., 2016). These strategies ensure that students are well-prepared to meet the new demands of HRC in construction. Considering the crucial role of academia in competency development, it is essential to investigate what instructors in CEM and other construction-related disciplines believe the current and future workforce should know to facilitate safe and effective collaboration with robotic technologies in the construction industry.

Methodology

This section describes the methods adopted to achieve the study's objective of investigating academia's perception of HRC competencies in construction. As shown in Figure 1, the identified HRC competencies from literature were categorized as HRC knowledge, skills, and abilities, which are then incorporated into the Delphi technique adopted in this study. Finally, the methods used for analyzing the research data are explained.

Competencies for human-robot collaboration in construction

Competencies are a combination of knowledge, skills, and abilities that enable individuals to perform their roles effectively and achieve desired outcomes (Helmold, 2021). The author defines knowledge as theoretical understanding, skills as learned proficiencies, and abilities as innate or acquired attributes needed for task execution. Based on these definitions, literature review and content analysis of relevant peer-reviewed journals and conference papers were conducted to extract relevant information on HRC competencies. Indicators leading to knowledge identification include theoretical foundations and conceptual information, while skills indicators focus on technical and task-specific proficiencies. Abilities indicators encompass personal attributes and innate capabilities. These competencies are presented in Table 1 as HRC knowledge (K), HRC skills (S), and HRC abilities (A).

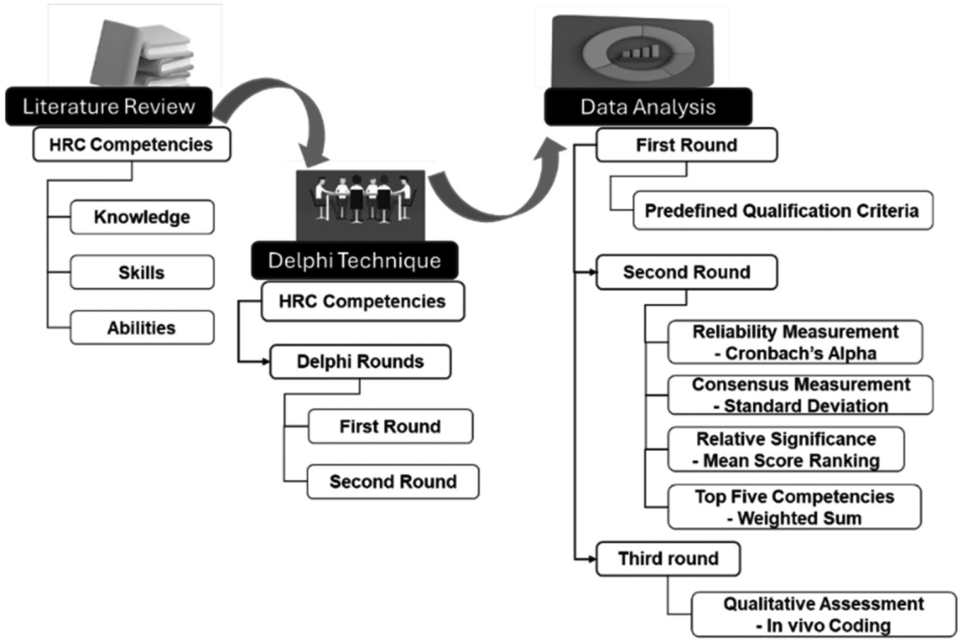

Figure 1. Overview of research method.

Delphi technique

The Delphi method, according to Hallowell and Gambatese (2010), was developed in the 1950s by the Rand Corporation as a structured communication method, conceived initially to forecast the impact of technology on warfare. It involves multiple rounds of questionnaires or surveys to gather expert opinions and feedback without face-to-face interaction (Tummalapudi et al., 2021). The anonymity of responses allows for honest and unbiased input, leading to more accurate results and decision-making (Alomari et al., 2020). Other characteristics of the techniques include an iterative process, including multiple rounds where experts can review their responses to achieve consensus, controlled feedback, and statistical group response (Tummalapudi et al., 2021). The Delphi study is widely used in CEM research areas (Hallowell & Gambatese, 2010) such as safety (Alomari et al., 2020), technology adoption (Okunola et al., 2024), and competency (F. M. Bademosi & Issa, 2022) due to its ability to reach a consensus among experts on complex or uncertain issues, especially when empirical data is scarce or when predicting future events, trends, or developments (Marchau & van de Linde, 2016). This study utilized Delphi study, as approved by Virginia Tech's Institutional Review Board (IRB), to collect instructors' opinions regarding the competencies for HRC in construction.

Expert panel selection

To recruit participants for this study, instructors with extensive experience in teaching and conducting research on robots and HRC in construction were deliberately targeted. Recruitment involved emailing the link to the survey designed on QuestionPro, an online survey software, to the American Society of Civil Engineers Construction Research Council

Table 1. Knowledge, skills, and abilities for HRC in construction

Code	HRC knowledge	Code	HRC skills	Code	HRC abilities
K-1	Types of robots (Zhang et al., 2023)	S-1	Effective communication with robots (Zhang et al., 2023)	A-1	Teamwork (Yang & Zhang, 2023)
K-2	Construction robot applications (Zhang et al., 2023)	S-2	Task planning (Yang & Zhang, 2023)	A-2	Communication (Zhang et al., 2023)
K-3	Robot anatomy and technical specifications (Yang & Zhang, 2023; Zhang et al., 2023)	S-3	Regulation standard compliance (Leenes et al., 2017)	A-3	Continuous learning (Sutikno, 2023)
K-4	Sensors (Fernandez et al., 2019; Yang & Zhang, 2023)	S-4	Safety management (Zhang et al., 2023)	A-4	Problem-solving (Tadesse et al., 2023)
K-5	Task planning (Yang & Zhang, 2023; Zhang et al., 2023)	S-5	Technical skill	A-5	Adaptability (Oliff et al., 2020)
K-6	HRC ethics and regulation (Leenes et al., 2017)	S-6	Programming (Yang & Zhang, 2023; Zhang et al., 2023)	A-6	Attention to detail (Stumm et al., 2017)
K-7	HRC safety and standards (Zhang et al., 2023)	S-7	Data analytics and management (El Meouche et al., 2016)	A-7	Analytical aptitude (Yang & Zhang, 2023)
K-8	HRC evaluation (Yang & Zhang, 2023)	S-8	Human-robot interface proficiency (Zhang et al., 2023)	A-8	Decision-making (Ren et al., 2023)
K-9	HRC-related fields (Zhang et al., 2023)	S-9	Application of machine learning algorithms (El Meouche et al., 2016)	A-9	Critical thinking (Ren et al., 2023)
K-10	Immersive virtual environments (Zhang et al., 2023)	S-10	Simulation and modeling (Yang & Zhang, 2023; Zhang et al., 2023)	A-10	Spatial awareness (Grushko et al., 2021)
K-11	Communication modes and technologies (Zhang et al., 2023)			A-11	Cultural and social awareness (M. Müller et al., 2023)
K-12	Human-robot interface (Zhang et al., 2023)			A-12	Safety awareness (Zhang et al., 2023)
K-13	Robot control system (Gustavsson et al., 2018)				
K-14	System integration (Yang & Zhang, 2023)				
K-15	Programming (Yang & Zhang, 2023)				
K-16	Modeling and simulation (Yang & Zhang, 2023)				
K-17	Data analytics and machine learning (El Meouche et al., 2016)				
K-18	Robot learning methods (Wang et al., 2023)				
K-19	Computation design (Sung et al., 2023)				
K-20	Robot operating system (ROS) (Wang et al., 2023)				

(ASCE-CRC) members. Additionally, postings were made on LinkedIn, a professional networking platform, to reach other qualified instructors across the United States. The questions were designed to collect information on participants' educational backgrounds, professional experience, and involvement with robotic technologies in the construction industry to assess their eligibility for the study. As a result, nineteen participants responded to the call for participation in the study.

Expert panel qualification criteria

The flexible point system proposed by Hallowell and Gambatese (2010) was adapted to qualify participants for the study, as shown in Table 2. Participants are scored based on four

Table 2. Flexible point grading for participants' qualification

Code	Experience/Achievement	Points (Each)	Minimum qualification criteria
A	Educational qualification		
A1	Associate degree	2	4
	BS	4	
	MS	2	
	PhD	4	
B	Professional experience		
B1	Faculty member at an accredited university/work in a relevant industry	3	3
B2	Year of professional experience in the construction industry	1	1
C	Professional prominence		
C1	Professional registration	3	3
C2	Membership of a committee	1	
C3	Chair of a committee	3	
C4	Peer-reviewed journal/technical article/technical report publication	2	2
C5	Conference papers publication	1	1
C6	Book publication	2	2
C7	Conference presentation	1	1
D	Experience with robotic technology		
D1	Use of robotic technology/research with robotic technology	1	1
D2	Patents	5	
	Minimum Total Score	**20**	

major categories: educational qualification, professional experience, professional prominence, and experience with robotic technology – the most important qualification criterion. Each participant must score at least one point in four criteria, including experience with robotic technology. Additionally, the minimum points each participant is expected to score to qualify as a member of the expert panel has been modified to 20 points compared to the 11 points suggested in the paper to ensure that highly experienced expert panel members are selected. To make the criteria more stringent, educational qualifications are not scored since all potential participants are university faculty members in the US and are presumed to hold a PhD.

To qualify participants for the study, the credentials of the participants were analyzed by first categorizing their qualifications into predefined criteria: Educational Qualification (A), Professional Experience (B), Professional Prominence (C), and Experience with Robotic Technology (D). Participants were then assessed based on their achievements and allocated corresponding points as outlined in Table 2. The total score for each participant was calculated by summing the points from all applicable criteria. Fifteen of the nineteen instructors who agreed to participate in the study met the predefined qualification criteria, scoring 20 points or more, and were therefore eligible to advance to the first round as expert panel members. In the second round, 14 expert panel members participated in the survey. The scores of qualified participants ranged from 23 to 185 points (see Table 3), highlighting substantial expertise and accomplishment, exceeding the basic eligibility requirements.

Credentials of experts

The instructors who participated in the study have various professional registrations, primarily with the American Society of Civil Engineers (ASCE). Some also hold memberships with other organizations, such as the American Society of Safety Engineers (ASSE)

Table 3. Credentials of participants

Academic participant ID	B1	B2	C1	C2	C3	C4	C5	C6	C7	D1	D2	Total points
AP1	3	3	3	0	0	12	3	4	3	3 - (Terrestrial robots, terrestrial rovers with manipulators, and laser scanners).	0	34
AP2	3	3	0	0	0	30	8	3	8	2 - (UAVs and exoskeletons).	0	57
AP3	3	8	6	2	0	6	2	0	2	1- (UAVs).	0	30
AP4	3	3	3	2	0	6	2	0	2	2 - (Construction 3D printers and industrial robot arm).	0	23
AP5	3	3	3	0	0	16	8	0	8	2 - (Bricklaying robots and robotic surveying and layout tools).	0	43
AP6	3	3	12	3	0	4	3	0	3	6 - (Bricklaying robots, UAVs, exoskeletons, construction 3D printers, autonomous construction equipment, and robotic surveying and layout tools).	0	37
AP7	3	13	3	2	0	80	30	0	30	4 - (UAVs, exoskeletons, autonomous construction equipment, and robot manipulators for assembly).	20	185
AP8	3	13	3	2	0	6	12	0	12	2 - (UAVs and robotic demolition equipment).	0	53
AP9	3	8	6	0	0	12	3	2	3	5 - (Bricklaying robots, UAVs, exoskeletons, robotic surveying and layout tools, and robotic rebar-tying machines).	0	42
AP10	3	13	3	1	3	4	3	2	3	2 - (UAVs and autonomous construction equipment).	5	42
AP11	3	18	3	1	0	65	20	10	20	6 - (Bricklaying robots, UAVs, construction 3D printers, autonomous construction equipment, robotic surveying and layout tools, and robotic arc welding machines).	25	171
AP12	3	13	3	0	0	4	3	0	3	2 - (UAVS and robotic surveying layout tools).	0	31
AP13	3	13	3	0	0	50	25	0	25	2 - (Construction 3D printers and cobots).	0	121
AP14	3	18	3	0	0	20	8	0	8	1- (Bricklaying robots).	5	66
AP15	3	13	3	0	0	22	10	4	10	1 - (UAVs).	0	66

and the Institute of Electrical and Electronics Engineers (IEEE), including certifications from the Project Management Institute (PMI). Their research involves diverse robotic technologies, including terrestrial robots, UAVs, exoskeletons, 3D printers, and autonomous construction equipment. Their scholarly contributions are documented through journal papers, technical reports, book or book chapters, conference papers publications, and patents. These contributions reflect their extensive research outputs and showcase a wide range of expertise and involvement in cutting-edge robotics research within the academic community.

Delphi survey rounds

To achieve the objective of this study, a two-round Delphi survey was conducted. In the first round, each expert panel member was sent the identified knowledge, skills, and abilities in Table 1 to rate based on their significance to HRC in construction on a 5-point Likert scale (5 = extremely significant, 4 = very significant, 3 = moderately significant, 2 = slightly significant, and 1 = not significant). Furthermore, each expert panel member was asked to provide additional knowledge, skills, and abilities deemed significant for HRC in construction that were not included on the list provided. This process ensured a comprehensive evaluation of the competencies needed for HRC in the construction industry. Finally, each expert panel member was asked to select the top five competencies from each of the knowledge areas, skills, and abilities essential for implementing HRC in the construction industry.

Finally, in the second round of the Delphi survey, the rating data collected in the first round was analyzed, converted into relative significance rankings of HRC knowledge areas, skills, and abilities, and sent back to the expert panel members to consider. The top five competencies for implementing HRC in construction selected by each expert were also aggregated and sent back for further experts' consideration. The experts were asked to provide qualitative responses to justify why they agreed or disagreed with the relative significance rankings of the competencies and the aggregated top five competencies for implementing HRC in construction.

Data analysis

Different statistical methods were adopted to analyze the data collected. The reliability of the 5-point Likert scale rating data collected in the first round was evaluated with Cronbach's alpha. High Cronbach alphas of 0.93, 0.91, and 0.96 obtained for HRC knowledge areas, skills, and abilities (respectively) underscore a high internal consistency and reliability (Taber, 2018). This indicates that the questionnaire is highly reliable in evaluating HRC competencies. Standard deviation (SD) was computed to determine if consensus existed among the expert panel on each item of knowledge, skills, and abilities because it provides information about how much an opinion (rating) deviates from the average opinion (mean rating) (Lee et al., 2015). This study adopts the consensus criteria that SD should be less than 1.5, suggested by Christie and Barela (2005) and Akhanova et al. (2019), for measuring consensus in a Delphi study. The rating data collected were analyzed using the mean score (Abdel-Hafez & Xu, 2015) to compute the relative importance of each item in HRC knowledge area, skills, and abilities. The mean scores are assessed using the Likert scale rating criteria outlined in Genc (2023), i.e., 1.00–1.79: Very low importance; 1.80–2.59: Low importance; 2.60–3.39: Medium importance; 3.40–4.19; High importance; and 4.20–5.00: Very high importance.

The weighted sum was adopted to aggregate the rankings of the top five HRC competencies that each expert panel member selected (Gunduz et al., 2024). The frequency of each rating was first calculated. Subsequently, weights were assigned to the ratings, with 1 corresponding to "not significant" and 5 to "extremely significant." The weighted sum was then calculated by multiplying these weights by the frequencies of each Likert scale rating and summing the results for each item. The weighted sum and the corresponding item were ranked from the highest to the smallest, reflecting the prioritized competencies. In the second round, manual in vivo coding was conducted on the qualitative feedback from the expert panel due to the small size of the data. This method utilized the participants' exact words or phrases as codes to preserve the meaning and context of their perspectives during data analysis (Gupta, 2023). The quantitative feedback was analyzed using Microsoft Excel and Jamovi (2.4.8), a graphical user interface for the R programming language.

Results

This section presents the results of the analysis conducted to determine instructors' perceptions of HRC competencies. It contains consensus measurements, relative significances of HRC knowledge, skills, and abilities, and the top-ranked competencies prioritized by instructors for implementing HRC in construction.

Consensus measurement

Figure 2 presents the bar plots of instructors' consensus measurement for HRC knowledge, skills, and abilities. The experts reached a consensus as the results indicated that SD for knowledge ranged between 0.49 and 1.30, skills ranged from 0.64 to 1.15, and abilities ranged from 0.64 to 1.46. According to Christie and Barela (2005) and Akhanova et al. (2019), these values are within the 0 to 1.5 condition for consensus using SD, as presented in Figure 2.

Instructors' perception of competencies for HRC in construction

The following sections discuss instructors' perceptions regarding HRC competencies, which are evaluated using mean scores to rank and categorize the competencies.

Instructors' perception of HRC knowledge areas

The mean score ranking of HRC knowledge areas in Figure 3 reveals predominantly high to very high-level rating categories. Instructors' mean score ranking categorizes HRC safety and standards (K-7), human-robot interface (K-12), robot control systems (K-13), HRC ethics and regulation (K-6), construction robot applications (K-2), sensors (K-4), communication modes and technologies (K-11) as very highly important with their mean scores ranging between 4.20 and 4.67, reflecting the knowledge areas instructors believe are critical for HRC in construction. Other HRC knowledge areas, such as task planning (K-5), system integration (K-14), types of robots (K-1), robot anatomy and technical specifications (K-3), HRC evaluation (K-8), robot learning methods (K-18), modeling and simulation (K-16), ROS (K-20), HRC-related fields (K-9), immersive virtual environments (K-10), and computation design (K-19) are all categorized as highly important with their mean scores ranging between 3.40 and 4.13. The mean score ranking of HRC knowledge areas reveals the comprehensive nature of important HRC knowledge areas required for effective HRC indicated in its high to very high-level rating and suggests that instructors prioritize knowledge of HRC safety, interfaces, control, and ethical aspects of HRC. In contrast, knowledge of ROS and computational design are considered less critical for HRC in construction.

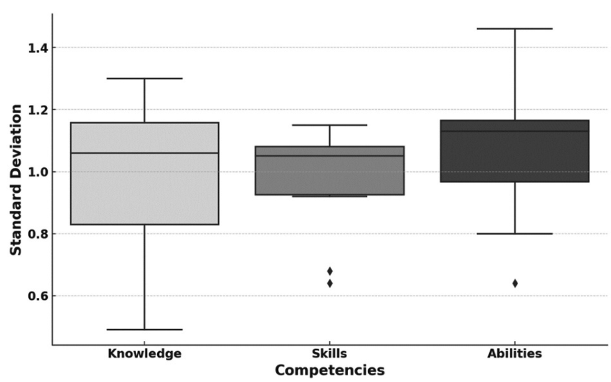

Figure 2. Distribution of standard deviation for consensus of expert panel.

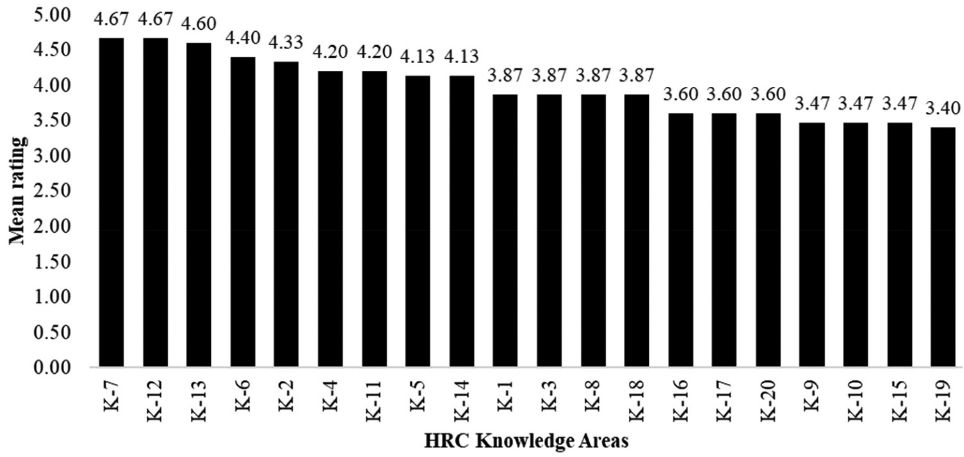

Figure 3. Mean rating of HRC knowledge areas.

Perception of HRC skills

The instructors' mean score ranking of HRC skills indicates the prioritization of specific skills presented in Figure 4. For instance, the mean scores of safety management (S-4), human-robot interface proficiency (S-8), technical skills (S-5), effective communication (S-1), task planning (S-2), and regulations and standards compliance (S-3) ranged between 4.20 and 4.53, categorizing these HRC skills as very highly important. This ranking underscores their critical roles in ensuring successful and safe interactions between humans and robots, emphasizing their necessity for HRC in the construction industry. The mean scores of programming (S-6), simulation and modeling (S-10), data analytics and management (S-7), and application of machine learning algorithms (S-9) ranged between 3.20 and 3.33, categorizing them at a medium level and suggesting that these HRC skills are necessary but not as critical as other HRC skills. The mean score ranking of HRC skills suggests that instructors prioritize safety, interface proficiency, technical skills, and regulatory compliance HRC skills. In contrast, programming and application of machine learning skills are deemed less essential.

Perception of HRC abilities

The mean score ranking of HRC abilities in Figure 5 reveals that safety awareness (A-12), teamwork (A-1), communication (A-2), adaptability (A-5), continuous learning (A-3) were ranked in the very high category with the mean scores rating between 4.20 and 4.53, indicating their crucial importance in ensuring effective and safe collaboration between humans and robots. Additionally, decision-making (A-8), spatial awareness (A-10), critical thinking (A-9), problem-solving (A-4), attention to detail (A-6), analytical aptitude (A-7), and cultural and social awareness (A-11) are ranked in the high-level category with their mean scores ranging between 3.80 and 4.13, highlighting the need for comprehensive abilities that includes spatial and

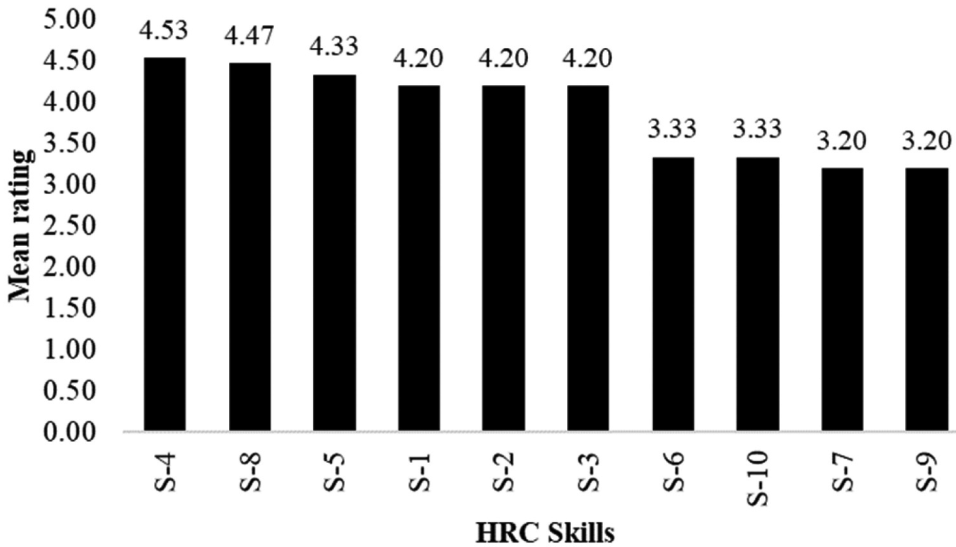

Figure 4. Mean rating of HRC skills.

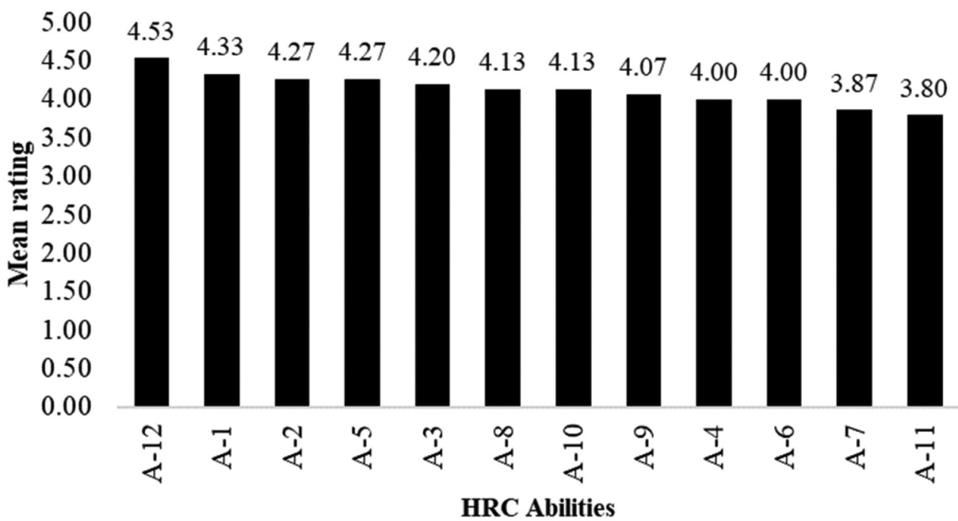

Figure 5. Mean rating of HRC abilities.

cultural awareness, and cognitive, abilities. The mean score ranking of HRC abilities highlights the emphasis on safety, teamwork, and effective communication abilities for HRC.

Competencies prioritized by instructors for implementing HRC in construction

The results of the weighted sum ranking adopted to aggregate the top five HRC competencies that instructors perceive as crucial for implementing HRC in the construction industry are presented below.

HRC knowledge areas prioritized by instructors for implementing HRC in construction

Table 4 presents the top-ranked HRC competencies instructors believe are essential for implementing HRC in construction. HRC ethics and regulation (K-6) knowledge is ranked highest with a weighted sum of 39, indicating that the instructors consider it the most important HRC knowledge. Following this, knowledge of robot anatomy and technical specifications (K-3) and construction robot applications (K-2) with weighted sums of 34 and 32 were ranked in the second and third positions, suggesting significant importance but slightly less than ethics and regulation. Knowledge of sensors (K-4) and task planning with weighted sums of 30 and 18 were in the fourth and fifth positions. This ranking highlights the relative emphasis instructors place on HRC knowledge areas.

Qualitative assessment of HRC knowledge areas prioritized by instructors

The qualitative feedback on the top HRC knowledge areas prioritized by instructors indicates a general agreement with the current ranking of HRC knowledge. Many instructors *"agree with the ranking,"* noting that there were *"no surprises"* and affirming that *"it looks good."* However, some instructors agree with the ranking, suggesting that *"communication and interface are more important than others," "construction robot applications can be in the fifth place,"* and *"moving task planning application above technical specification."* Finally, an instructor highlighted that *"based on the type of application/robot, you might need more knowledge in any of the above specific areas."* These suggestions indicate that instructors largely agree with the top five HRC knowledge areas, with minor revisions suggested.

HRC skills prioritized by instructors for implementing HRC in construction

The top HRC skills prioritized by instructors for implementing HRC in construction are presented in Table 5. The weighted sum ranking reveals that task planning (S-2) and application of machine learning algorithms (S-9) are tied in the first rank with weighted sums of 41, highlighting these skills as crucial for effective HRC. Safety management (S-4) and human-robot interface proficiency (S-8) are also tied in third rank with a weighted sum of 38, indicating these skills are also highly valued for HRC in construction, though below task planning and application of machine learning algorithms. Effective communication (S-1) is ranked fifth with a weighted sum of 26. This ranking underscore a strong emphasis on these skills for HRC in construction.

Table 4. Top HRC knowledge areas prioritized by instructors

Code	HRC knowledge areas	Weighted sum	Rank
K-6	HRC ethics and regulation	39	1
K-3	Robot anatomy and technical specifications	34	2
K-2	Construction robot applications	32	3
K-4	Sensors	30	4
K-5	Task planning	18	5

Table 5. Top HRC skills prioritized by instructors

Code	HRC skills	Weighted sum	Rank
S-2	Task planning	41	1
S-9	Application of machine learning algorithms	41	1
S-4	Safety management	38	3
S-8	Human-robot interface proficiency	38	3
S-1	Effective communication	26	5

Qualitative assessment of HRC skills prioritized by instructors

The qualitative feedback reveals a general agreement with the top-rated HRC skills and suggestions for minor improvements. Several instructors "*agree with the ranking*," emphasizing it is "*fine with me*" and "*no surprises and consistent with my previous comment*." Some found the ranking acceptable with minor adjustments, such as one instructor who noted that it "*looks good overall, just minor tweaks to the ranking*" would be needed. However, an instructor expressed concern about "*programming skill*" not included in the prioritized HRC skills, indicating its essential nature. Another instructor emphasized that human-robot interaction "*HRI should be no.1*." An instructor stated that "*machine learning should not rank that high. It is a ubiquitous knowledge nowadays*." Additionally, the importance of safety and practical robot usage was underscored by an instructor who stated, "*I believe safety and how to use robots are more important factors*."

HRC abilities prioritized by instructors for implementing HRC in construction

The top HRC abilities the instructors prioritized for implementing HRC in construction are presented in Table 6. The result showed that all the HRC abilities prioritized by instructors have weighted scores of 35. These abilities include decision-making (A-8), continuous learning (A-3), critical thinking (A-9), attention to detail (A-6), analytical aptitude (A-7), and adaptability (A-5). Given that each ability has the same weighted sum, they are all equally ranked in the first position in terms of importance according to the instructors' evaluations.

Qualitative assessment of HRC abilities prioritized by instructors

Instructors provided feedback reflecting general agreement with a few suggestions for improvement. Some instructors "*generally agree with the outcomes from the panel of experts*," emphasizing that it "*looks reasonable*" and "*fine*," while others expressed "*no*

Table 6. Top HRC abilities prioritized by instructors

Codes	Abilities	Weighted sum	Rank
A-8	Decision-making	35	1
A-3	Continuous learning	35	1
A-9	Critical thinking	35	1
A-6	Attention to detail	35	1
A-7	Analytical aptitude	35	1
A-5	Adaptability	35	1

surprises." Instructors highlighted that "*adaptability should be higher in ranking*." Additionally, an instructor affirmed "*decision-making*" as an important HRC ability to consider. Finally, an instructor was surprised that "*communication and safety awareness are not in the top five*."

Discussion

This study explores the perceptions of academia regarding the competencies necessary for HRC in construction. This study's findings highlight the relative importance of various HRC competencies and categorize them into different levels as perceived by instructors. Additionally, the study identifies the top-ranked HRC knowledge areas, skills, and abilities the instructors consider most important for implementing HRC in the construction industry. These findings align with and further confirm the previous research by F. Bademosi et al. (2018), which assessed skills for robotics in construction education. The findings of this study, discussed in the section below, provide insight into instructors' perceptions of HRC competencies, which have significant implications for shaping construction robotics education and industry practices.

Implications of instructors' perception of HRC knowledge areas

The top-ranked HRC knowledge areas prioritized by instructors have significant implications for construction robotics education and the industry. Firstly, integrating HRC ethics and regulation into the curriculum is essential for preparing future professionals to navigate legal and ethical boundaries, which corresponds to the findings of Casas-Roma et al. (2022). Furthermore, the focus on robot anatomy and technical specifications in construction education aligns with the findings of Lafhaj et al. (2022), as it enhances technical proficiency, prepares students, and enables construction workers to troubleshoot and maintain robotic systems effectively, thereby reducing downtime. Additionally, understanding construction robot applications through practical examples and case studies agrees with key recommendations from Prieto et al. (2024) for integrating robotic systems into construction workflows. Lastly, the prioritization of task planning in both education and industry aligns with the findings of Hamzeh (2009), which suggest that optimizing workflows and improving project management with robotic systems ensures efficient resource allocation and timely project completion.

Implications of instructors' perception of HRC skills

The prioritization of task planning skills in HRC underscores the need for comprehensive courses that teach students how to optimize the allocation of tasks between humans and robots. This aligns with the work of Kousi et al. (2022), who developed a contemporary method for human-robot task allocation. The focus on application of machine learning algorithmic skills reflects the findings of Xu et al. (2021), emphasizing the importance of advanced programming courses and hands-on experience with machine learning tools. This interdisciplinary approach fosters collaboration between computer science and CEM to effectively integrate intelligent systems into construction robotics. Safety management skills require strong training and regulatory knowledge, aligning with Rahman et al. (2022), who found that equipping safety professionals with the right competencies enhances their ability to improve occupational safety and health. Proficiency in human-robot interfaces necessitates focused coursework on interface design, practical workshops, and user experience, aligning with Shamonsky (2021), who emphasized the development of intuitive and effective systems. Effective communication skills are crucial in HRC, with training ensuring students can convey complex technical information and work effectively with robots, as highlighted by Gross and Krenn (2023).

Implications of instructors' perception of HRC abilities

Integrating decision-making, one of the top-ranked HRC abilities, into the CEM curriculum will prepare students to make informed choices when executing construction tasks with robots. Encouraging a culture of continuous learning is essential for keeping students and professionals updated with the latest advancements in construction robotics, fostering ongoing professional growth, and adapting swiftly to new tools and methods, as Brosque and Fischer (2022) emphasized. According to Akintewe and Sotillo (2022), critical thinking prioritized by the experts should be a core curriculum component facilitated through analytical courses and project-based learning. This ability enables students to evaluate information critically and develop innovative solutions to the complex challenges of integrating robots into construction workflows, ultimately supporting strategic planning and more effective project management. Attention to detail is crucial for the high-quality delivery of construction tasks executed by humans and robots, as Liang et al. (2024) noted. Training focusing on precision, accuracy, and quality control will reduce errors and reworking tasks jointly executed by humans and robots.

Conclusion

This study evaluated instructors' perceptions regarding HRC competencies (knowledge areas, skills, and abilities) in construction. The study identifies 20 knowledge areas, 10 skills, and 12 abilities essential for HRC in construction. It measures the consensus of the instructors' panel of experts on these competencies and examines the top-rated competencies prioritized by instructors for implementing HRC in the industry. The study's findings reveal that instructors rank the competencies for HRC, including knowledge areas, skills, and abilities, in the very high to high importance categories except for some HRC skills, including programming, simulation and modeling, data analytics and management, and application of machine learning algorithms, which are ranked in the medium importance category. Instructors prioritize the top-rated HRC knowledge areas, which include HRC ethics and regulation, robot anatomy and technical specifications, construction robot applications, sensors, and task planning. Additionally, HRC skills prioritized by instructors include task planning, application of machine learning algorithms, safety management, human-robot interface proficiency, and effective communication. Lastly, instructors prioritized decision-making, continuous learning, critical thinking, attention to detail, analytical aptitude, and adaptability, which are the top-rated HRC abilities.

These findings highlight the importance of revising the current CEM curriculum to incorporate the HRC competencies identified as crucial by the instructors. This adjustment will ensure that the future workforce has the necessary skills to work safely and effectively alongside robots in the construction industry. Additionally, it will enable the development of a training initiative for existing employees to gain the knowledge, expertise, and capabilities required to stay competitive in a rapidly evolving industry shaped by the integration of robotic technologies.

A limitation of this study is the sample size, which could affect the generalizability of the results. However, it is important to note that the potential attrition of the study was effectively managed by enlisting a reasonable number of highly competent instructors to participate. This, coupled with the reliability assessment and consensus measurements from the panel of experts' feedback data, has shown a high level of agreement among the participants, affirming the validity and reliability of the results. The rigorous methodology of this study significantly bolsters the credibility of its findings and recommendations. Further research could focus on evaluating the perceptions of construction industry practitioners regarding the competencies for HRC in construction. Additionally, various pedagogical training techniques, such as active, experiential, and collaborative teaching and learning, could be investigated to determine the most suitable method to equip students with these competencies.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by the National Science Foundation [grant numbers 2235375 and 2402008].

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