EPiC Series in Built Environment

Volume 7, 2026, Pages 1192–1201

Proceedings of Associated Schools of Construction 62nd Annual International Conference

Cognitive Workload in Human-Robot Collaboration in Construction: A Systematic Review

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The growing integration of robotic technologies into construction operations has created new opportunities to enhance safety, precision, and productivity. However, as robots increasingly share workspaces with human collaborators, understanding the cognitive demands imposed on construction individuals becomes critical to ensuring efficient and safe human-robot collaboration (HRC). As such, this study systematically reviews existing body of research on cognitive workload in HRC within the construction domain. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, this study systematically reviews empirical evidence from 32 peer-reviewed studies published across Scopus and Web of Science (WOS) databases. The review examines cognitive workload under three identified key themes: (1) robot control and communication, (2) task sharing and delegation, as well as (3) work and environment conditions. It synthesizes the measurement approaches employed across the studies, including subjective, physiological, and behavioral indicators, identifies research gaps, and proposes future directions. By integrating insights from empirical studies, this review establishes a conceptual foundation for human-centered robot design and provides practical guidance for developing human-centered and cognitively aware collaborative environments.

Keywords: Collaborative Robot, Workload, Human Factors, Human-Robot Collaboration

Introduction

Construction is one of the most hazardous industries to work in. In 2023 alone, the construction sector suffered 1,075 worker fatalities, accounting for nearly one in five of all workplace deaths in the United States (*BLS, 2024*). These statistics underscore the industry's inherently volatile and hazardous nature, characterized by intense physical exertion, continuously shifting work environments, densely populated worksites, and frequent interaction with heavy, mobile machinery. At the same time, the construction industry continues to struggle with meeting productivity demands. In fact, construction labor productivity has fallen by about 40% since 1970, equating to a 1% annual decline over fifty years (Goolsbee & Syverson, 2023). In response to these enduring safety and productivity setbacks, the integration of robotic and automation technologies has emerged as a promising strategy to enhance efficiency and worker safety on jobsites.

While robots may improve productivity and safety, their integration introduces new worker interactions and additional safety dimensions that have not yet been explored. Specifically, cognitive factors have been identified as one of the most critical determinants underlying unsafe behaviors of construction workers (Hu et al. 2023). As workers increasingly engage with robots and share workspaces with them, the cognitive demand on workers evolves in complex ways (Okonkwo et al. 2024). HRC often requires construction individuals to divide cognitive resources between their own tasks, the robots and their surroundings. This multiple engagement heightens cognitive effort and can overload human information-processing capacity, particularly in poorly designed HRC systems. Therefore, understanding and regulating cognitive workload in HRC is essential for implementing safe and efficient collaborative environments. As such, cognitive workload in HRC has garnered growing scholarly attention in the construction domain, as researchers seek to understand the impact these robotic systems have on construction individuals' cognitive workload.

Literature reviews regarding HRC in construction have been conducted, with some focusing on barriers to robotic integration, auxiliary technologies, and existing applications (Chen 2022; Tomori et al. 2024; Wu et al. 2025). However, no prior work has solely focused on the cognitive workload in HRC. Addressing this gap is critical, as cognitive workload represents a central determinant of worker safety. Without a clear understanding of cognitive workload dynamics in HRC, the design of effective and human-centered collaborative systems in construction remains unattainable. Hence, the goal of this paper is to systematically review peer-reviewed studies that investigate cognitive workload in HRC in the construction domain. Specifically, this study aims to achieve the following research objectives: (1) Identify key factors that influence cognitive workload in HRC; (2) Examine measurement approaches employed in assessing cognitive workload in HRC studies; and (3) Identify limitations and proposed future research directions. The contribution of this study lies in offering a comprehensive mapping of existing empirical efforts and laying a foundation to guide researchers and practitioners in advancing human-centered and cognitively aware HRC in construction.

Methodology

To achieve these objectives, this study performed a systematic review of extant literature. A systematic review provides a rigorous and reproducible approach for identifying, evaluating, and synthesizing relevant studies, ensuring that evidence is reported in a transparent, objective, and comprehensive manner (Denyer and Tranfield 2009). The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, which establish a standardized framework to enhance transparency, accuracy, and completeness (Page et al. 2021). The PRISMA protocol comprises three steps including: (1) Identification; (2) Screening; and (3) Inclusion. In the initial (1) Identification phase, two widely recognized databases, Scopus and Web of Science, were queried to retrieve potentially relevant peer-reviewed articles. To ensure comprehensive coverage, the following keywords were used in both databases: ("built environment" OR "construction" OR "AEC") AND ("human-robot collaboration" OR "human-robot interaction" OR "cobot" OR "collaborative robot" OR "human-robot" OR "teleoperation") AND ("cognitive workload" OR "mental workload" OR "workload" OR "mental load" OR "perceived workload" OR "cognitive load"). The search yielded a total of 101 records, including 7 records found through manual search (Figure 1). The second (2) Screening phase encompassed the removal of duplicates (N=37), and a screening of article titles and abstracts based on the following criteria: (1) peer-reviewed journal or conference papers; other publication types such as literature reviews, book chapters, theses, dissertations, and technical reports were excluded and (2) written in English, resulting in the exclusion of three additional records (Figure 1). In the final (3) Inclusion phase, a full-text review was conducted on the remaining 61 articles to determine their eligibility based on the established inclusion criteria. Studies were included if they empirically investigated cognitive workload in HRC within the construction domain, focusing exclusively on collaborative robots (Figure 1). For the scope of this review, HRC is conceptualized as task-oriented interaction scenarios in which humans and robots work toward shared construction objectives. Additionally, cognitive workload is treated as a multidimensional construct, reflecting mental demand, effort, and related information-processing requirements imposed on individuals during such interactions (Hart and Staveland 1988). A total of 32 empirical studies met the eligibility criteria and were retained for further analysis.

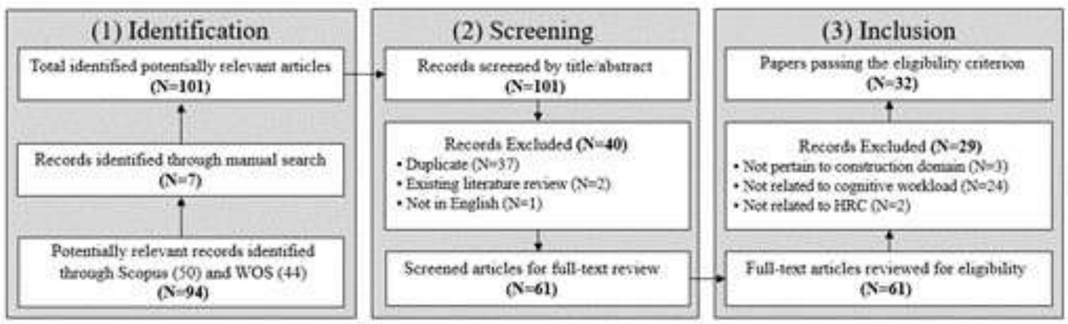

Figure 1. PRISMA protocol

Results and Discussion

This systematic review identified three main themes under which cognitive workload in HRC has been investigated in the construction domain, including: (1) Control and Communication; (2) Task Sharing and Delegation; and (3) Work and Environment Conditions. These themes were identified through an iterative content analysis of the included empirical studies during full-text review, by grouping studies based on recurring contextual factors influencing cognitive workload in HRC. Regarding robot type, most studies relied on Mobile ground robot (MG) (17, 53%), followed by Aerial robots (AR) (7, 22%) and Robotic Arms (RA) (5, 16%). Notably, three studies (9%) employed both mobile ground robots and aerial robots. Table 1 describes contextual definitions along with the focus areas of the studies within each theme together with corresponding robot types.

Table 1. Cognitive Workload Themes

Theme	Definition	Focus Areas	Study Count	MG	AR	RA
Control and Communication	Cognitive demands associated with operating, directing, and exchanging information with robots.	• Interfaces and Visual Support • Communication Modality • Human Attributes • Communication Delay	16	8	7	4
Task Sharing and Delegation	Cognitive demands associated with distribution of task responsibility between humans and robots	• Level of Collaboration and Autonomy • Training	12	8	3	1
Work and Environment Conditions	Cognitive demands associated with factors beyond the direct control of the human or robot within the construction setting.	• Jobsite Dynamism • Time critical conditions	4	4	-	-

Control and Communication

The successful implementation of HRC largely depends on effective control and communication dynamics, which was found to directly impact the cognitive workload experienced by construction individuals (Zhu et al. 2024).

Interfaces and Visual Support: Research consistently demonstrated that the design of interfaces and visual support in HRC plays a crucial role in shaping cognitive workload. In fact, the implementation of multi-view interfaces and Augmented Reality-based visual cues was found to significantly reduce individuals' cognitive workload compared to single-view interfaces (Park and Ji 2025). Moreover, employing multi-flying camera systems as operator visual support has been shown to induce less cognitive workload than conventional ground camera systems especially when the flying cameras' viewpoints dynamically adjusted to the operator's task (Ikeda et al. 2021; Kamezaki et al. 2024; Yamada et al. 2018).

Communication Modality: The mode of communication between robots and humans has been found to also influence cognitive workload. Investigations comparing gesture and speech-based communication modalities with robots revealed that, unlike gesture-based communication, speech modalities induced significantly higher cognitive workload among construction individuals (Hu et al. 2025; Liu and Ham 2024; Zhu et al. 2024). However, a comparison between speech communication and multimodal (i.e., speech coupled with controllers) showed that both modes induced comparable cognitive workload (Park et al. 2025). During teleoperation tasks, attenuating force feedback was found to significantly reduce cognitive workload compared with realistic force feedback (Zhu et al. 2021). Similarly, visual coupled with and haptic feedback resulted in lower cognitive workload than relying on visual or haptic cues alone (Uthai et al. 2025; Zhou et al. 2023). Even under time-critical tasks, electro-tactile feedback tended to impose less workload than non-electro-tactile alternatives (Lee et al. 2025). Furthermore, construction individuals experienced higher cognitive workload during the response phase of communication cycles compared to the information decoding phase (Chang and Hasanzadeh 2025).

Human Attributes. Evidence showed that human background characteristics also influenced cognitive workload during HRC. Experimental results indicated that mental workload was generally lower among older participants, while male operators tended to report higher workload than their female counterparts. Among female participants, workload increased with age, whereas among male participants it decreased (Kim and Irizarry 2019).

Communication Delay. Evidence from the literature demonstrated that delays in communication between construction individuals and robot partners significantly impacted cognitive workload. In fact, teleoperation tasks were found to induce high cognitive workload as communication delay increases (Kim et al. 2021; Seo et al. 2024a; b).

Task Sharing and Delegation

The cognitive workload experienced by construction individuals was found to be influenced by the degree of task sharing and delegation between humans and robots during HRC (Nassar et al. 2024). The subsequent subsections review the reported effects on individuals' cognitive workload.

Level of collaboration and autonomy. Research consistently demonstrated that the level of collaboration and robot autonomy influence construction individuals' cognitive workload. Cognitive workload was found to decrease as the extent of collaboration between humans and robots increases (Nassar et al. 2024). Similarly, autonomous robots have been shown to impose higher workload than semi-autonomous ones (Shayesteh and Jebelli, 2021). Construction individuals working alone or with other human partners generally experience greater cognitive workload than those collaborating with robot partners (Lee and Lee, 2025; Okonkwo et al., 2024). Extending on this concept, Artificial Intelligence (AI) models have been developed to enable robots to automatically adjust their action in response to individuals' cognitive workload during HRC (Liu et al. 2021, 2023; Liu and Jebelli 2022).

Training. Training methods have also been found to impact cognitive workload. Conventional HRC training has been found to induce higher workload than immersive virtual-reality (VR) training environments, though the difference was not statistically significant (Adami et al. 2022). In fact, recent VR-based training frameworks have evolved to dynamically adapt content complexity in real time based on individuals' cognitive workload (Shayesteh et al. 2023; Zhang and Jebelli 2025).

Work Environment Conditions

The cognitive workload experienced by construction individuals is not only influenced by direct interactions with robots but also by the work environment conditions. The construction industry in inherently high-pressure, complex and unpredictable, and these contextual actors contribute to cognitive workload levels during HRC (Liu and Ham 2024).

Jobsite Dynamism. The extent of construction site dynamism has been found to influence cognitive workload during HRC. Complex and challenging jobsites were found to impose significantly higher cognitive workload compared to simpler and static jobsites (Liu and Ham 2024). However, varying sound conditions were found not to be associated with significant cognitive workload changes during teleoperation (Rodrigues et al. 2025).

Time-Critical Conditions. Time-critical activities are common in the construction industry and play a role in cognitive workload levels during HRC. Cognitive workload has been found to increase significantly under high time pressure and decrease under reasonable time conditions (Lee and Ham 2024, 2025).

Cognitive Workload Measurement Approaches

Across the 32 empirical studies reviewed, 15 studies relied on subjective measures, 5 used objective measures, and 12 employed a combination of both. Two subjective measures were used including: (1) National Aeronautics and Space Administration-Task Load Index (NASA-TLX) (N=27; 84.4%) ; and (2) Mental Effort Rating Scale (N=1; 3.1%). In terms of objective measures, five categories of psychophysiological data were reported to be used, including: (1) Electroencephalography (EEG) (N=6; 18.8%); (2) Eye activity (N=5; 15.6%); (3) Electrodermal Activity (EDA) (N=4; 12.5%); (4) Photoplethysmography (PPG) (N=4; 12.5%); and (5) Functional Near-Infrared Spectroscopy (fNIRS) (N=1; 3.1%).

Table 2. Cognitive Workload Themes and Measures in Construction HRC

Theme	Studies	NASA-TLX	Mental Effort Rating	EEG	Eye-Activity	EDA	PPG	fNIRS

Control and Communication	16	88%	-	-	25%	6%	-	6%
Task Sharing and Delegation	12	67%	8%	50%	-	17%	33%	-
Work and Environment Conditions	4	100%	-	-	50%	-	-	-

Subjective Measures. Twenty-seven studies assessed cognitive workload using subjective measures. NASA-TLX was employed in all the 27 studies, reflecting its acceptance and dominance in cognitive workload assessment. This instrument evaluates cognitive workload through six dimensions: mental demand, physical demand, temporal demand, performance, effort and frustration (Hart and Staveland 1988). In one case, NASA-TLX was supplemented with the Mental Effort Rating Scale, which, unlike NASA-TLX, assesses only the mental resources expended during an activity (Paas 1992).

Objective Measures. Seventeen studies assessed cognitive workload using objective measures, among which EEG was the most frequently used objective measure, reported in 6 studies. EEG signals were reported to be collected through electrodes attached to the scalp, capturing electrical activity from specific brain regions related to information processing and perception (primarily prefrontal cortex), thereby providing direct insight into the activity of these cortices. Collected EEG signals were reported to be preprocessed for quality improvements using the following: bandpass filtering; adaptive predictor filtering; or independent component analysis. After preprocessing, the EEG signals were postprocessed to extract features across time, frequency, and spatial–temporal domains, providing complementary representations of neural activity for cognitive workload assessment (Shayesteh and Jebelli 2021; Liu et al. 2021, 2022, 2023; Liu and Jebelli 2022; Shayesteh et al. 2023).

Eye activity metrics were reported in 5 studies as indicators of cognitive workload. Eye activity was reported to be recorded using wearable eye trackers either embedded within VR headsets or as standalone devices. Pupil size was the most frequently used eye activity metric for cognitive workload, as reported in three studies. The other two studies, reported using gaze movement metrics; blink rate, dwell time and run count, to infer visual cognitive demand (Chang and Hasanzadeh 2025; Lee and Ham 2024, 2025; Liu and Ham 2024; Seo et al. 2024a).

EDA was also reported in 4 studies as measures of cognitive workload. EDA data were reported to be collected using electrodes attached to either the wrist or fingertips to capture changes in skin conductance. Noise was reported to be removed using Butterworth low-pass filtering, high-pass filtering, or moving-average filtering. After preprocessing, the EDA signals were further decomposed into tonic and phasic components to reveal long-term and instantaneous conductance change, thereby offering insights into variations in cognitive demand (Chang and Hasanzadeh 2025; Lee and Lee 2025; Seo et al. 2024b; Zhang and Jebelli 2025).

PPG was also reported in 4 studies as cognitive workload indicators. PPG data were reported to be collected through biosensors attached to the wrist to capture blood volume changes. The raw data were reported to be preprocessed by filtering out noise using bandpass filter. Following preprocessing, PPG data were postprocessed as cardiovascular activity metrics. Three of the four studies reported using one of the following cardiovascular activity metrics: heart rate (HR), heart rate reserve (HRR), and heart rate variability (HRV) to infer cognitive workload (Liang et al. 2024; Okonkwo et al. 2024; Shayesteh et al. 2023; Zhang and Jebelli 2025).

fNIRS was reported in only one study as an indicator of cognitive workload. fNIRS data were reported to be collected using optodes placed on the scalp to capture hemodynamic changes in the brain surface as indicator of activation within specific cortex. The signals were reported to be preprocessed by using a bandpass to remove artifacts, and the resulting data were reported to be used for extracting time-domain features to infer cognitive workload (Chang and Hasanzadeh 2025).

Future Research Directions

The synthesis of the 32 empirical studies reviewed revealed that, although cognitive workload in HRC has attracted increasing scholarly interest within the construction domain, further theoretical consolidation is needed to advance the field. While these studies collectively advance understanding of how robots influence human cognitive workload during HRC in construction, most remain constrained by limited environmental realism, and a predominant reliance on subjective measurement approaches. Moreover, existing investigations tend to focus on isolated contextual factors, providing only a partial representation of the complex, multidimensional nature of cognitive workload in real-world construction operations. From a control and communication perspective, most studies exploring cognitive demands associated with operating, directing, and exchanging information with robots remain static and predefined rather than adapting to real-time fluctuations in human cognitive workload. Notably, none of the studies under this theme incorporated feedback loops that modulate robot communication behavior based on physiological indicators. As such, future research should therefore focus on developing adaptive communication frameworks capable of modulating information density, feedback type, and communication modality in real time according to the cognitive workload levels. The development of such frameworks could significantly reduce cognitive workload; ultimately promoting safety on jobsites. From a task sharing and delegation perspective, research demonstrates advances in exploring different levels of collaboration and developing robot behaviors that adapt in response to human cognitive workload. However, the adaptive approaches remain short-term in nature, focusing primarily on immediate workload fluctuations and overlooking long-term cognitive adaptation. Furthermore, studies identified under this theme remain largely unidirectional, focusing mainly on robots' influence and adaptation to humans; while the reciprocal process, in which humans adapt their actions to regulate their own cognitive workload remains largely neglected. This asymmetry limits a deeper understanding of how task sharing and delegation evolves in the construction domain. Therefore, future investigations should focus on understanding how cognitive workload accumulates, stabilizes, and dissipates across repeated work cycles. Moreover, research should advance toward bidirectional, co-adaptive collaboration frameworks that enable humans and robots to jointly refine task distribution strategies over extended interactions. Finally, from a work and environmental conditions perspective, most experiments reviewed were conducted under simplified or static conditions. Specifically, only 1 study used an active jobsite while 21 (65.63%) used VR environments and 10 (31.25%) used controlled real environments. Moreover, the cognitive workloads associated with real construction stressors such as multitasking, task complexity, spatial constraints, and coordination with multiple agents were largely absent in the reviewed studies. This lack of ecological realism limits the generalizability of findings and constrains understanding of cognitive workload in HRC. Therefore, future investigations should incorporate experimental environments that closely replicate jobsite dynamics, to expand the understanding of external conditions' impact on cognitive workload in HRC.

Conclusion

This study conducted a systematic review of 32 empirical studies investigating cognitive workload during HRC in construction. The findings from this review were synthesized under three emerging themes: (1) Control and Communication; (2) Task Sharing and Delegation; and (3) Work and

Environment Conditions. The review identified two subjective measurement approaches: (1) NASA-TLX; and (2) The Mental Effort Rating Scale as well as five psychophysiological objective approaches: (1) EEG; (2) EDA; (3) Eye activity; (4) PPG; and (5) fNIRS. Despite the growing scholarly attention to this topic, three main research gaps were identified: (1) the scarcity of adaptive, real-time, cognitively aware communication frameworks; (2) the lack of long-term, bidirectional collaborative frameworks; and (3) the limited ecological realism in existing studies that capture real jobsite conditions. Addressing these gaps is essential to advancing the understanding of cognitive workload in HRC. The contribution of this study lies in offering a comprehensive mapping of existing empirical efforts and laying a foundation to guide researchers and practitioners in advancing human-centered and cognitively aware HRC in construction. This review is not without limitations; notably, wearable robots were excluded from the scope of this study, and their inclusion should be considered in future investigations to provide a more comprehensive understanding of cognitive workload in HRC.

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