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The Effects of a Co-Worker's Cognitive Response on Human-Robot Team Productivity in Construction

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Abstract: Human-robot collaboration (HRC) is an emerging form of work anticipated to improve construction productivity by integrating robotic capabilities with human expertise. With the expected transition towards tasks that demand more cognitive efforts for human workers, considering the cognitive status of each co-worker, such as task engagement and vigilance, can become crucial to achieve high-quality human performance during HRC, potentially contributing to a more productive HRC in construction. However, the potential cognitive changes of each co-worker have remained unclear during HRC, as studies have primarily focused on identifying general trends from aggregated cognitive responses of people, in which an individual's response can be overlooked. In this study, we examine the cognitive response of each co-worker during HRC for a construction task. We observed the cognitive responses of 18 people while they were experiencing different collaborating conditions, such as the robot's different movement speed, during a bricklaying task with an arm-type collaborative robot. For each participant, we analyzed electroencephalogram (EEG) signals to identify the changes in cognitive status by using a wearable EEG headset. The results present that the cognitive responses of almost all the participants were significantly and differently affected during HRC, impacting the estimated productivity of their human-robot teams. The findings of the study present the importance of considering each co-worker's potentially unique cognitive response as a way to achieve cognitive well-being while pursuing high productivity within human-robot teams, potentially contributing to overall productive HRC in construction.

Key words: Human-Robot Collaboration, Cognition, Wearable Sensor

1. INTRODUCTION

The construction industry has suffered from stagnant productivity growth and high safety risk compared to other industries [1,2]. For the past two decades since 1995, the productivity (real gross value added per labor hour) of the construction industry has grown around 1%, while the average annual growth by the total global economy was 2.8% [3]. Additionally, the safety of construction workers is concerning, with a fatal work injury rate of 13.0 for 100,000 full-time workers in 2022, while that of all industries was 3.6 [2]. With other ongoing issues within the industry, such as the aging workforce and the labor shortage [4], stagnant productivity and high safety risk can become more critical challenges.

In response to these challenges, Human-Robot Collaboration (HRC) is envisioned as a promising paradigm shift toward co-robotic construction [5]. Collaborative robots, an evolved form of conventional industrial robots, are expected to combine the strength of humans and robots in the form of collaboration [6]. Robots can take over physically demanding, dangerous, and repetitive tasks to make room for human workers to focus on dexterous, problem-solving, and decision-making tasks [6]. The reduced dependence on workers' manual labor and increased level of robotic automation holds the potential to improve construction productivity and the safety of workers.

To realize its potential, efforts have been made with a primary focus on advancing robotic capabilities to ensure seamless and safe interactions between humans and robots. This involves equipping robots with sensors like cameras and microphones to interpret different signals from humans, such as hand gestures and gazes, for seamless collaboration [7,8]. Additionally, enabling robots to recognize their human co-workers has been another major focus to ensure safe HRC by preventing undesired physical contact like collisions [9]. This focus on the technical aspects of robots has served as a major driving factor toward productive and safe HRC in construction.

Recently, preliminary efforts have emerged that begin to highlight the potential importance of considering human responses for the success of HRC in construction. Particularly, the cognitive status of people—defined as the level of activation in mental processes for acquiring knowledge and understanding, such as engagement and attention—is expected to become increasingly important within the new co-robotic work environment [10,11]. As robots assume portions of the physical workload, the primary roles of human workers can shift toward tasks that demand greater cognitive effort, including decision-making, problem-solving, and supervising [6]. In preparation for this shift, an in-depth understanding of the cognitive responses of people during HRC can help lead to high-quality human performance, thereby contributing to better productivity of human-robot teams in construction.

To understand the cognitive responses of people during HRC, preliminary studies have been directed towards examining how different collaborating conditions, such as robot's autonomy levels, could cause cognitive changes in people, including cognitive load. For example, Shayesteh and Jebelli (2022) [11] demonstrated through an experiment in a virtual reality (VR) environment that working with an autonomous robot generally caused a higher cognitive load for people compared to a semi-autonomous robot. These findings can provide valuable insights for accommodating people's cognitive responses to the design and implementation of HRC, such as determining the robot's autonomy levels to reduce the cognitive load of people. Nevertheless, such insights may not accurately reflect every co-worker's cognitive response to HRC due to personal differences such as skill levels and experience [12]. Overlooking these potential individual variances among co-workers can lead to suboptimal cognitive states, such as cognitive overload, possibly hampering the anticipated productivity growth from HRC. This highlights the critical need for considering individual differences in cognitive responses to construct productive work environments for human-robot teams.

However, there exist notable gaps in our understanding of each co-worker's cognitive response during HRC. First, it remains unclear how collaborating conditions, such as robots' different movement speeds, can be influential to the cognitive responses of different co-workers, as previous studies have primarily focused on analyses that aggregate data, overlooking each co-worker's response [11,13]. Second, the potential similarity or difference between cognitive responses of different co-workers has not been uncovered, which can provide insight into the importance of focusing on individual differences in addition to identifying the generic responses in people. Third, it is unclear how cognitive responses of different co-workers can influence the productivity of human-robot teams. Although previous studies characterized cognitive responses of people during HRC [13], the potential impacts of considering cognitive responses of co-workers on the productivity of human-robot teams have not been understood yet. Answering these questions is expected to deepen our understanding for each co-worker's cognitive response during HRC by identifying potential differences in cognitive responses among co-workers, along with their potential impacts on the productivity of human-robot teams.

To fill these knowledge gaps, we aim to examine each co-worker's cognitive response while collaborating with a robot. We analyzed electroencephalogram (EEG) signals from each of 18 participants to identify their cognitive responses while they experienced different collaborating conditions (e.g., robot's different movement speeds) with an arm-type collaborative robot during a simulated construction task in a lab environment. The findings of this study are expected to provide insights into the potential importance of considering cognitive responses, especially individual differences among co-workers, as an effective pathway for fostering productive HRC in construction.

2. METHOD

In this study, we aim to identify the inter-relationship between cognitive responses of each co-worker corresponding to parameters of HRC (e.g., robot's movement speed) during HRC for a construction task. We observed the cognitive responses of 18 people while they were interacting with an arm-type collaborative robot in a lab environment for a simulated bricklaying task (Figure 1a). The participants experienced different collaborating conditions, parametrized by five parameters: 1) robot's movement speed; 2) robot's arm swing speed; 3) proximity; 4) level of autonomy; and 5) leader of collaboration (Figure 1b). Corresponding cognitive responses of people were identified by analyzing EEG signals, measured by a wearable EEG headset (Figure 1c). Notably, this method originates from our prior study [14], which aimed at examining the emotional responses of each co-worker during HRC. In this study, we utilize EEG signals collected from the prior study [14] to identify the cognitive responses of each of the 18 participants.

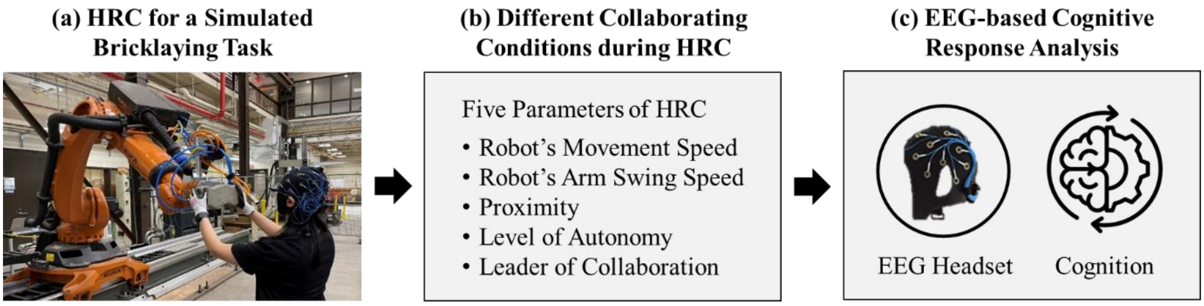

Figure 1. Overview of the proposed method.

2.1. Participants

We recruited 18 participants, consisting of 11 men and 7 women, who were students from various academic backgrounds such as engineering, music, and social science (mean age: 28; standard deviation of age: 3.2; minimum age: 23; and maximum age: 36). These diverse participants were expected to provide a wide range of different cognitive responses during their interactions with a robot, compared to construction workers who may have occupational biases toward robots caused by concern and fear of job loss due to robotic automation [15].

2.2. Bricklaying Task

The bricklaying task can be considered a representative example of distributing tasks between humans and robots in construction [14]. For example, robots take over physically demanding tasks like lifting bricks while workers focus on dexterous tasks like finishing. As such, examining the cognitive responses of people while conducting the bricklaying task with robots is expected to provide a generalizable understanding of the cognitive responses of people to robots in the construction environment. In this context, we conducted some portion of the bricklaying task to simulate the representative task distribution between humans and robots; for a team of one human and one robot, the robot delivered bricks for the human co-worker to lay them in a line.

The bricklaying task was conducted in a lab at the University of Michigan with an arm-type KUKA KR 120 robot. Bricks were attached with steel plates so the robots could lift and deliver them with magnetic end-effector (Figure 2a and 2b). For the safety of participants, our lab environment is equipped with laser sensor to detect and avoid very close proximity between humans and the robot, and the subjects wore the personal protective equipment (PPE) that are generally required by construction workers, such as a safety helmet, gloves, eyewear, and steel toes (Figure 2c).

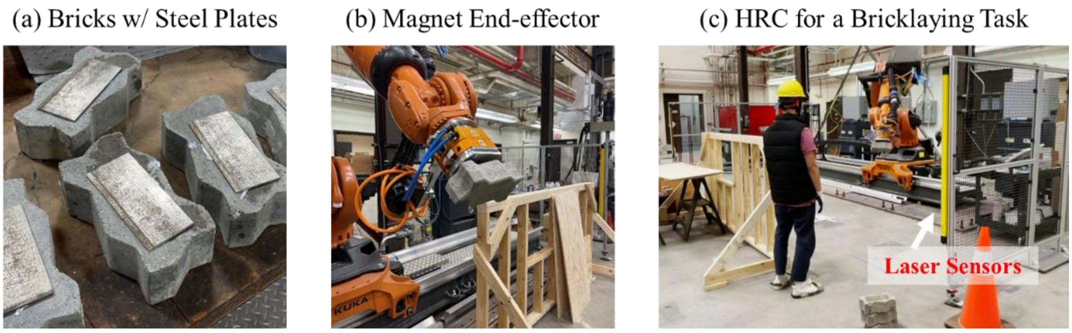

Figure 2. Lab environment for the bricklaying task.

2.3. Five Parameters of HRC

Different collaborating conditions were simulated by changing the conditions of five parameters, determined due to their potential influence on human responses [14]: 1) movement speed; 2) arm swing speed; 3) proximity between humans and robots; 4) level of autonomy; and 5) leader of collaboration. Each participant experienced 8 sessions (Table 1). Each session simulated the different combinations of the conditions of the 5 parameters, which were expected to lead to different human responses based on previous studies [14]. For each session, each participant laid 10 bricks with the robot for 5 minutes (i.e., 2 bricks per team-minute), followed by 3 minutes of break, resulting in 64 minutes duration for the 8 sessions. Cognitive responses from different pairings of the sessions facilitated the analysis of cognitive changes in response to each parameter, with the other four parameters being controlled: sessions 1, 2, and 3 for different robot's movement speed; 1, 4, and 5 for different robot's arm swing speed; 1 and 6 for different proximity; 1 and 7 for different levels of autonomy; and 1 and 8 for different leader of collaboration.

Table 1. Conditions of the Five Parameters of Robots for Each of the 8 Sessions.

Sessions	Movement Speed	Arm Swing Speed	Proximity	Level of Autonomy	Leader of Collaboration	Duration
1	79.8 cm/s	73.2 cm/s	Direct	Auto	Robot	5 mins for session w/ 3 mins break (Total 64 mins)
2	27.8 cm/s	73.2 cm/s	Direct	Auto	Robot	
3	143.8 cm/s	73.2 cm/s	Direct	Auto	Robot	
4	79.8 cm/s	23.8 cm/s	Direct	Auto	Robot	
5	79.8 cm/s	109.1 cm/s	Direct	Auto	Robot	
6	79.8 cm/s	73.2 cm/s	Indirect	Auto	Robot	
7	79.8 cm/s	73.2 cm/s	Direct	Manual	Robot	
8	79.8 cm/s	73.2 cm/s	Direct	Auto	Human	

2.4. EEG-based Cognitive Response Analysis

EEG has been identified as an effective measurement for cognition analysis by capturing brain activities [16]. We used a wearable EEG headset (Emotiv EPOC Flex^{TM}) to collect EEG signals from 14 electrodes over the scalp, which are known to be associated with cognitive activities (Figure 3a and 3b). In this study, we analyzed two distinct cognitive dimensions: task engagement and vigilance, which can affect human performance during task conductance (Figure 3c) [17]. Task engagement can be defined as demands for sensory processing during task conductance, and vigilance can be defined as alertness to external contingencies, which is often interchangeably used with other terms such as arousal and attention [18,19]. The states of task engagement and vigilance can lead to different qualities of human performance by determining the cognitive status, ranging from suboptimal—such as mind wandering, inattentional blindness, and inattentional deafness—to optimal [17]. From EEG signals collected from the electrodes, the task engagement can be measured by calculating the ratio of beta band (12-35 Hz) power over the sum of alpha (8-12 Hz) and theta band (4-8 Hz) power, and the vigilance was calculated by taking ratio of theta band power to beta band power (Eq. 1 and 2) [20].

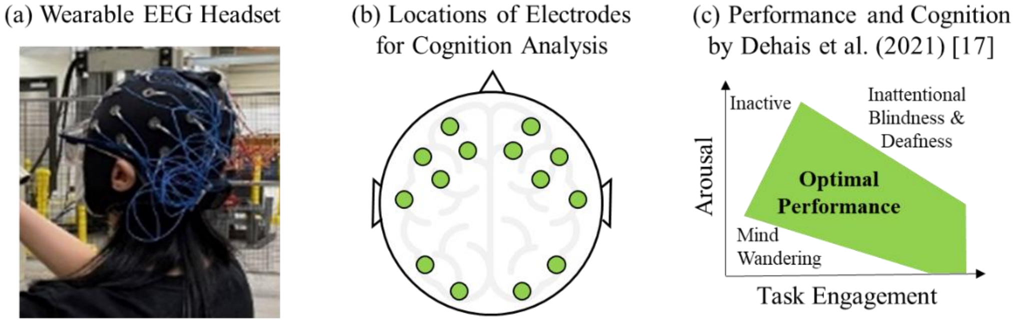

Figure 3. Cognitive response analysis based on EEG signal analysis.

$$Task\ Engagement = \frac{\beta}{\alpha+\theta} \qquad \text{(Eq. 1)}$$

$$Vigilance = \frac{\theta}{\beta} \qquad \text{(Eq. 2)}$$

3. EFFECTS OF CONSIDERING COGNITIVE RESPONSES ON THE PRODUCTIVITY OF HUMAN-ROBOT TEAMS

We examined the cognitive response of each participant according to the five parameters of HRC by following the analyses that were effective in identifying the emotional response of each co-worker during HRC in our prior study [14].

3.1. Effect of HRC Parameters on the Cognitive Responses

We applied a multiple linear regression to characterize each participant's cognitive responses (i.e., task engagement and vigilance) to the five parameters of HRC (Eq. 3). The regression model was empirically determined that was effective in fitting the cognitive responses of 18 participants in general. We obtained two regression models for each participant, one for task conductance and another for vigilance. Notably, the regression model considers time as a control variable to mitigate its effect on the analysis, which could affect human response but is not the focus of this study [21].

$$y_i = c_1 x_1^2 + c_2 x_1 + c_3 x_2^2 + c_4 x_2 + c_5 x_3 + c_6 x_4 + c_7 x_5 + c_8(Time) + \beta \qquad \text{(Eq. 3)}$$

$$where\ y_i = \{Engagement\ Vigilance\ , x_j = \{Move\ Speed\ Arm\ Speed\ Proximity\ Level\ of\ Autonomy\ \ Leader\ of\ Collaboration\ , and\ \beta = constant$$

The F-test of overall significance was conducted to statistically demonstrate the significance of the parameters of HRC to each participant's engagement and vigilance regression models. The results of the F-test revealed that either engagement, vigilance, or both of 17 out of 18 participants (94.5%) were significantly affected by the parameters of HRC, indicated by the significant p values (<0.05).

3.2. Comparison of Cognitive Response of People

We statistically compared cognitive responses of every distinct pair of participants, resulting in 153 pairs from 18 participants. Specifically, we applied a nested linear regression analysis to represent one participant's cognitive responses (i.e., task engagement and vigilance) by using regression coefficients from another participant (c_i) (Eq. 3). Coefficients d_i indicated if c_i was sufficient in representing the participant's response; any non-zero d_i indicated there remained unrepresented cognitive responses by c_i, and thus, two people have statistically different cognitive responses.

$$\begin{aligned} y_i = {} & c_1 x_1^2 + c_2 x_1 + c_3 x_2^2 + c_4 x_2 + c_5 x_3 + c_6 x_4 + c_7 x_5 + c_8(Time) + \beta_1 \\ & + Sbj(d_1 x_1^2 + d_2 x_1 + d_3 x_2^2 + d_4 x_2 + d_5 x_3 + d_6 x_4 + d_7 x_5 + d_8(Time) + \beta_2) \end{aligned} \qquad \text{(Eq. 3)}$$

$$where\ Sbj = \ \{0\ for\ Person\ 1\ 1\ for\ Person\ 2\ , y_i = \{Engagement\ Vigilance\ , x_j = \{Move\ Speed\ Arm\ Speed\ Proximity\ Level\ of\ Autonomy\ \ Leader\ of\ Collaboration\ , \beta_k = constant$$

T-tests were conducted on each of d_i to reveal if any of d_i were statistically equal to zero or not. Results showed that among the 153 comparisons, in 149 (i.e., 97.4%), at least one regression coefficient with respect to either engagement or vigilance or both were significantly different (p<0.05). It presents that almost every participant was likely to show significantly unique cognitive responses during HRC.

3.3. Effect of HRC Parameters on the Cognitive Responses

We examined the relationship between the cognitive response of each co-worker and the estimated productivity of human-robot teams by establishing a parametric connection. Specifically, we estimated productivity in terms of the five parameters of HRC by following the derivation from our prior study [14] (Eq. 3). The identical basis (five parameters of HRC) for estimating both the cognitive responses and the estimated productivity enabled us to examine the intertwined changes according to the five parameters. Estimated productivity, defined as the number of bricks laid for one hour by a human-robot team, was derived by calculating the bricklaying times for one robot and one human based on five HRC parameters were calculated (Eq. 5.1 and 5.2), aggregating these into a human-robot team's bricklaying time (Eq. 5.3), and then converting this into the hourly brick count for the team (Eq. 5.4).

$$\begin{gathered} Time\ (sec)\ for\ a\ robot\ to\ lay\ a\ brick\ (i.e., Robot\text{–}seconds\ per\ brick) \\ = Body\ Traverse\ Time + Arm\ Traverse\ Time + Delay\ by\ Manual\ Control \\ = \frac{Body\ Travel\ Distance}{Movement\ Speed} + \frac{Arm\ Travel\ Distance}{Arm\ Swing\ Speed} + 1(Manual) * \alpha \qquad (Eq. 5.1) \\ where\ Body\ Travel\ Distance\ is\ 6.1m, Arm\ Travel\ Distance\ is\ 2.4m, \\ and\ \alpha\ is\ an\ average\ delay\ of\ 3\ seconds\ caused\ by\ the\ manual\ control\ of\ the\ robot \end{gathered}$$

$$\begin{gathered} Time\ (sec)\ for\ a\ human\ to\ lay\ a\ brick\ (i.e., Human\text{–}seconds\ per\ brick) \\ = Bricklaying\ \ Time + Delays\ by\ Indirect\ Proximity\ and\ Human\ Leader \\ = Bricklaying\ \ Time + 1(Human\ Leader) * \beta + 1(Indirect) * \gamma \qquad (Eq. 5.2) \\ where\ Bricklaying\ Time\ is\ 5\ seconds, \\ \beta\ is\ an\ average\ delay\ of\ 1\ second\ when\ a\ human\ was\ a\ leader, \\ and\ \gamma\ is\ an\ average\ delay\ of\ 2\ seconds\ caused\ by\ the\ indirect\ proximity \end{gathered}$$

$$\begin{gathered} Time\ (sec)\ for\ a\ Human\text{–}Robot\ team\ to\ lay\ a\ brick\ (i.e., Team\text{–}seconds\ per\ brick) \\ = (Eq. 5.1) + (Eq. 5.2) \qquad (Eq. 5.3) \end{gathered}$$

$$\begin{gathered} Estimated\ Team\ Productivity\ (i.e., Bricks\ per\ Team\text{–}hour\ of\ One\ Human\ and\ One\ Robot) \\ = \left\{\frac{1\ Brick}{(Eq. 5.3)\ Team\text{–}second}\right\} \times \left(\frac{3{,}600\ Team\text{–}seconds}{Team\text{–}hour}\right) \\ = \frac{3{,}600}{Eq. 5.3}\ Bricks\ per\ Team\text{–}hour\ of\ One\ Human\ and\ One\ Robot \qquad (Eq. 5.4) \end{gathered}$$

We explored three scenarios of configuring values for the five parameters of HRC, representing different approaches of considering cognitive responses during HRC (Table 2). In the first scenario, the values for the parameters were standardized across all 18 participants by prioritizing productivity without considering cognitive responses. For example, the robot's movement speed was set to its maximum, 143.8 cm/s for all participants. In the second scenario, the parameters were standardized across all the participants, aiming to balance their collective cognitive responses with the maximization of estimated productivity in human-robot teams. Specifically, we selected parameter values expected to evoke moderate levels of task engagement and vigilance in as many participants as possible, which can result in optimal human performance (Figure 3c) [14]. However, since there was no clear numerical boundaries to define moderate levels of task engagement and vigilance, we conducted 3-means clustering to assume the middle cluster as moderate level after collecting cognitive responses according to wide different values of the five parameters within the specific ranges: movement speed from 0 cm/s to 143.8 cm/s; arm swing speed from 0 cm/s to 109.1 cm/s; proximity as either direct or indirect; level of autonomy as either manual or auto; and leader of collaboration as either human leader or robot leader. This approach was inspired by previous studies [22], which analyzed the intensity of human responses (e.g., mental workload) based on unsupervised machine learning techniques like clustering. In the third scenario, we aimed to find individualized values for the five parameters, which could evoke moderate task engagement and vigilance for each participant, while achieving the highest possible estimated productivity during HRC.

Table 2. Three Scenarios of Configuring the Five Parameters of HRC.

Three Scenarios		Consistency	Objectives
1	Productivity-prioritized	Standardized	Only Productivity
2	Collective Response-based	Standardized	Only Moderate Cognitions
3	Individual Response-based	Individualized	Moderate Cognitions and Productivity

For each of the three scenarios, we identified the corresponding estimated cognitive responses of participants and estimated productivity of human-robot teams (Table 3). Results present that individualized configuration of the parameter values for each co-worker can be the most effective strategy to balance the desired moderate cognitive status of people, while achieving high productivity of human-robot teams. As a result of the third scenario, all 18 participants were expected to have moderate cognitive status, while achieving average of 298 bricks for one team-hour, the second highest productivity among the three scenarios. The comparison of this scenario with the first scenario is particularly noteworthy, which was estimated to achieve the highest productivity (i.e., 314 bricks for one team-hour). However, except for 8 out of 18 participants (44.5%), cognitive status of most of the participants were not expected to be moderate during HRC. Prolonged HRC with low or high cognitive activations can restrict human performance by causing mind wandering and inattention, thereby ultimately affecting the overall productivity and cohesiveness in human-robot teams [17]. It is noteworthy that the cognitive changes were observed even though participants noticed they were technically safe during the simulated HRC. This presents that cognitive responses can become another important dimension for HRC to take into account, in addition to the technical capabilities of robots, which have been a major focus of studies for productive HRC in construction. In addition, considering the collective cognitive responses could evoke moderate cognitive status for 12 out of 18 participants, while achieving 207 bricks for one team-hour, which was the lowest. Due to the disparity between cognitive responses among people, it was very challenging to lead to the desired cognitive status for different people with the standardized approach. It was also not very effective in achieving high productivity in human-robot teams. As a result, the most effective strategy was to concentrate on each co-worker's cognitive response, which could achieve a balanced integration of co-workers' cognitive well-being while pursuing the high productivity in human-robot teams.

Table 3. Estimated Cognitive Responses and Team Productivity Across Three Scenarios.

Three Scenarios		# of People of Moderate Cognitions	Estimated Productivity of Human-Robot Teams
1	Productivity-prioritized	8 out of 18	314 bricks per one team-hour
2	Collective Response-based	12 out of 18	207 bricks per one team-hour
3	Individual Response-based	18 out of 18	298 bricks per one team-hour

4. CONCLUSION

HRC is anticipated to improve the productivity of the construction industry by combining the strength of humans and robots. Cognitive responses can be crucial to achieve productive HRC due to their critical impacts on human performance and cohesiveness in human-robot relationships, however, cognitive response of each co-worker during HRC has not been identified. In this study, we examined the cognitive responses for each of 18 participants in response to the different collaborating conditions during HRC for a bricklaying task in a lab environment. The results identified that the cognitive response of almost every participant was significantly and differently affected during HRC, which also could affect the estimated productivity of human-robot teams. The results present the importance of considering each co-worker's cognitive response as an effective pathway for achieving cognitive well-being of different co-workers while pursuing high productivity in human-robot teams, which can ultimately contribute to a more productive HRC. Follow-up studies are expected, which involve the cognitive responses of construction workers during HRC. Going forward, the findings of the study can serve as a solid foundation for future research, aiming to better accommodate human responses with the technical capabilities of construction robots for the successful deployment of HRC in construction.

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