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HUMAN RESPONSES TO FAILURE AND TASK PACE IN CONSTRUCTION HUMAN-ROBOT COLLABORATION

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Abstract

In construction, human-robot collaboration (HRC) has primarily focused on advancing robotics technology, yet considering human factors can be critical, as worker responses have the potential to influence HRC performance. This study examines how robotic factors—specifically task pace and failure—affect cognitive, emotional, and behavioral responses during a controlled lab experiment. Eleven participants supervised a manipulator robot performing a line-drawing task under varying conditions, with cognitive and emotional responses assessed through questionnaires and behavioral responses measured using vision-based pose estimation. The results indicate that failure rate and task pace influenced both cognitive and emotional states, while behavioral responses varied across individuals.

Introduction

The construction industry continues to face labor shortages, safety risks, and persistent inefficiencies resulting from labor-intensive practices. In response, advancements in robotics have led to the development of various construction robots capable of performing repetitive or specialized tasks, including material handling, site inspection, and automated assembly. By integrating these robots into construction sites, industry stakeholders anticipate significant improvements in productivity and safety. Building on these technological developments, Human-Robot Collaboration (HRC) has gained increasing attention for its potential to combine robotic capabilities with human expertise, paving the way for more efficient and sustainable construction practices.

Given the technological potential of HRC, early research concentrated to enhance task performance metrics such as speed, accuracy, and efficiency and optimize these aspects (Liang Ci-Jyun et al., 2021). Meanwhile, studies in social robotics have shown that cognitive and emotional responses, such as perceived control, trust, and frustration, can affect how humans interact with robots, influencing their acceptance and performance (Hancock et al., 2011). However, in construction, such responses have received relatively less attention. Unlike controlled manufacturing environments, construction tasks are often characterized by unpredictability and require continuous human decision-making (Bock, 2015). As robots take on more repetitive physical tasks, human workers are expected to assume more cognitively demanding roles. Therefore, understanding workers' cognitive responses may be essential for managing mental workload and task engagement, while investigating emotional responses can help identify workers' arousal, valence including overall well-being during collaboration.

Although broader HRC research has demonstrated that robotic parameters can significantly influence factors such as cognitive and emotional responses (Hancock et al., 2011; Weidemann & Rußwinkel, 2021), these issues remain relatively unexplored in construction (Baek et al., 2024). Specifically, several studies in non-construction domains have explored how task pace and failure rate could potentially influence workers' cognitive and emotional responses (Koppenborg et al., 2017; Salem et al., 2015). Task pace of HRC may affect levels of cognition and vigilance, while failure rates may impact trust and emotional states of co-worker. Although similar robotic parameters have been studied in other domains, construction work imposes distinct demands on workers. In particular, cognitive and physical loads in construction are closely tied to safety outcomes, both as a consequence of safety hazards and as a contributing factor to potential safety incidents (Ibrahim et al., 2023; Liko et al., 2020). Compared to structured and automated settings such as manufacturing, construction workers often operate in dynamic and uncertain environments, where elevated cognitive load and sustained vigilance are required to ensure safety and task continuity. Given this tight coupling between workload and safety, understanding how workers' load is affected in robot behavior, such as pace and reliability, becomes particularly relevant. This highlights the need to investigate how these robotic factors affect human responses in construction-specific contexts.

While several HRC studies measured internal psychological responses (Baek et al., 2024; Shayesteh et al., 2022), in studies involving physical tasks and full-body movement, behavioral measures can offer complementary insights. Vision-based pose estimation is one approach that enables monitoring of physical responses without the need for intrusive equipment (Park & Brilakis, 2016). Specifically, behavioral responses are particularly relevant in construction, as they can directly influence task performance and worker safety. Meanwhile, cognitive and emotional states are often assessed through subjective measures such as questionnaires, which provide direct insights into participants' perceived cognitive load and emotions. Furthermore, understanding how these psychological responses relate with observable behaviors can provide deeper insights into human-robot interactions.

Building on these backgrounds, this study explores how task pace and failure rate influence workers’ cognitive, emotional and behavioral responses in a construction-inspired HRC scenario. Eleven participants evaluated a robot manipulator’s task performance in a controlled laboratory setting, where questionnaires were used to assess cognitive and emotional states, and a DNN-based 3D pose estimation model was employed to analyze behavioral responses across different conditions. The findings of this study are expected to provide insight into how these parameters affect workers’ psychological and behavioral responses, especially in understanding the relationship between cognitive or emotional states and behavioral cues. Recognizing these behavioral adaptations can help identify worker strain and improve task conditions in HRC environments.

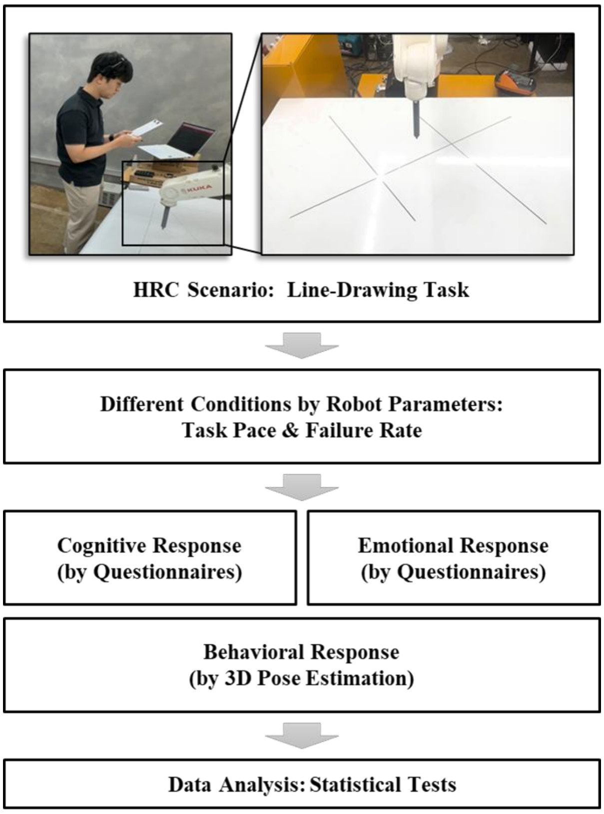

Figure 1: Research Methodology

Methodology

This study conducted a lab experiment where eleven participants monitored a manipulator robot performing a line-drawing task, designed to represent repetitive and precision-oriented construction activities, such as welding or drilling. This type of supervisory interaction reflects current construction robotics practices, where physical collaboration remains limited due to safety concerns and task complexity. The scenario corresponds to the coexistence and synchronized collaboration levels within the broader collaborative levels of HRC (Müller et al., 2017), where the human supervises robot activity without direct physical interaction. These interaction types are often observed in early-stage construction robotics, which typically focus on task automation in relatively structured and repetitive settings (Brosque et al., 2020). Although the line-drawing task does not replicate the full complexity of construction work, it serves as a simplified analogue for structured inspection or welding applications. Participants supervised the robot drawing a straight line between two designated points and verified its accuracy, simulating typical human-robot collaboration scenarios where human workers observe robotic performance and manage errors.

Cognitive responses were assessed using the NASA-TLX scale and vigilance level, while emotional responses, specifically valence and arousal, were measured through the Self-Assessment Manikin (SAM) scale. Behavioral responses were captured through full-body tracking using a vision-based pose estimation model. The experimental conditions were parametrized by two robotic factors: task pace (arm speed at three levels: 15 cm/s, 25 cm/s, 50 cm/s) and failure rate (low <20% and high >30%). This approach provided a comprehensive examination of psychological and physical responses in a construction-like environment.

Robot Parameters for HRC

This study focuses on two robot parameters, task pace and failure rate, to analyze how workers adapt and respond to different HRC conditions in construction environments:

- **Task Pace:** Several studies show that the task pace of HRC influences attentiveness, stress, and perceived workload (Koppenborg et al., 2017; Prewett et al., 2010). Slower robotic movements may be seen as inefficient, leading to disengagement, while excessively fast speeds can increase stress and reduce a worker’s sense of control (van Dijk et al., 2023). When using manipulator robot, arm speed is a particularly relevant parameter affecting both task efficiency and human perception of control (Story et al., 2022; Tan et al., 2009). For this study, the robot’s line-drawing speed was set at three levels—15 cm/s (slow), 25 cm/s (moderate), and 50 cm/s (fast).
- **Failure Rate:** Several studies show that failures in HRC can increase workers’ cognitive load and decrease trust in the robotic system (Salem et al., 2015; Weidemann & Rußwinkel, 2021). Frequent robotic failures may also lead to workers’ frustration and disengagement (Chang et al., 2023; Rovira et al., 2014). Such failures can result in observable behavioral changes that further elevate cognitive demands and increase task complexity (Honig & Oron-Gilad, 2018). For this study, the robot's failure

Table 2: Subjective Measurement of Participants' Vigilance Level

Q1	**How would you describe your predominant state?**								
	Extremely alert							**Extremely sleepy**	
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Q2	**How attentively have you been observing?**								
	Extremely attentively							**Extremely inattentively**	
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Q3	**How did you perceive the robot?**								
	Extremely varied							**Extremely monotonous**	
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Q4	**How did you feel about the Human-Robot Collaboration Task?**								
	Extremely interesting							**Extremely boring**	
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**

rate was set at two levels—low (<20%) and high (>30%).

By systematically exposing participants to each combination of these parameters, the experiment provided a controlled means to observe how different arm speeds and failure rates influenced both subjective evaluations and behavioral reactions. Participants underwent four sessions (Table 1); sessions 1, 2, and 3 focused on comparing different task paces, while sessions 1 and 4 examined the impact of failure rates.

Table 1: Experimental Design

Sessions	Task Pace (Arm Speed)	Failure Rate
1	25 cm/s	10 %
2	15 cm/s	10 %
3	50 cm/s	10 %
4	25 cm/s	40 %

Participants

A total of eleven participants were recruited, consisting of eight men and three women, all students in construction-related disciplines. By recruiting students, the study minimized potential biases linked to occupational concerns commonly found among construction workers (Morikawa, 2017). They were fully briefed on the study's objectives and methods, and formal approval was obtained from the Seoul National University Institutional Review Board (IRB). They were not informed about the robot's specific operating parameters in each session and simply monitored whether the line-drawing output met the given standards.

Data Collection

Cognitive and Emotional Response Measurement: Following each line-drawing session, participants completed a set of three questionnaires aimed at capturing cognitive and emotional responses to the robot's performance. The first, the Self-Assessment Manikin (SAM), measured emotional states by asking participants to indicate valence, arousal and dominance on nine-level scale (Bradley & Lang, 1994). The second, the NASA Task Load Index (NASA-TLX), evaluated cognitive load across dimensions such as mental demand, physical demand, temporal demand, effort, performance and frustration; each dimension was assessed on a twenty-level scale, following the established NASA-TLX methodology (Hart, 2006).

Finally, a questionnaire was designed to assess vigilance, reflecting how alert participants remained while the HRC (Table 2). The questionnaire was built with four items, developed from prior studies that modified established vigilance measures, including the Karolinska Sleepiness Scale (KSS) and the Inattention and Monotony (ATT/MON) scales (Akerstedt & Gillberg, 1990; Ma et al., 2018; Schmidt et al., 2009). To assess the internal consistency of the questionnaire, Cronbach's alpha was computed using 11 participants' responses, resulting in a value of 0.74. This indicates acceptable internal consistency and suggests that the scale was suitably reliable for capturing vigilance during the experiment.

By systematically measuring cognition and emotion, these three questionnaires provided insight into how participants experienced different task pace and failure rate conditions in HRC.

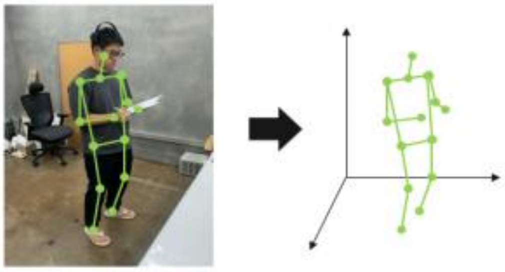

Figure 2: Behavioral Data with 3D Pose Estimation

Behavioral Response Measurement: In this study, behavioral responses are explored as potential indicators of participants' cognitive and emotional states during HRC. To capture these responses, a vision-based approach using 3D pose estimation was adopted, allowing for full-body motion tracking through an RGB camera. As shown in Figure 2, a 3D pose estimation utilizing benchmark DNN model was used to track angles at the shoulders, elbows, hips, knees, and other relevant joints throughout each session (Kim et al., 2023).

Table 3: Results(P-Values) of ANOVA/T-test on Behavioral Metrics

Participants		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Task Pace	**Arm Expansion Angle**	**0.004**	0.215	0.192	0.846	**0.012**	**0.016**	0.284	**0.000**	0.934	0.334	**0.000**
	Total Movement	0.063	0.207	**0.039**	0.867	**0.001**	**0.001**	0.818	0.455	0.524	**0.009**	**0.000**
Failure Rate	**Arm Expansion Angle**	0.998	0.266	**0.003**	0.095	0.482	**0.004**	0.425	0.158	0.936	0.831	0.981
	Total Movement	0.968	0.814	0.383	0.747	0.434	**0.001**	**0.001**	0.967	0.579	**0.048**	0.975

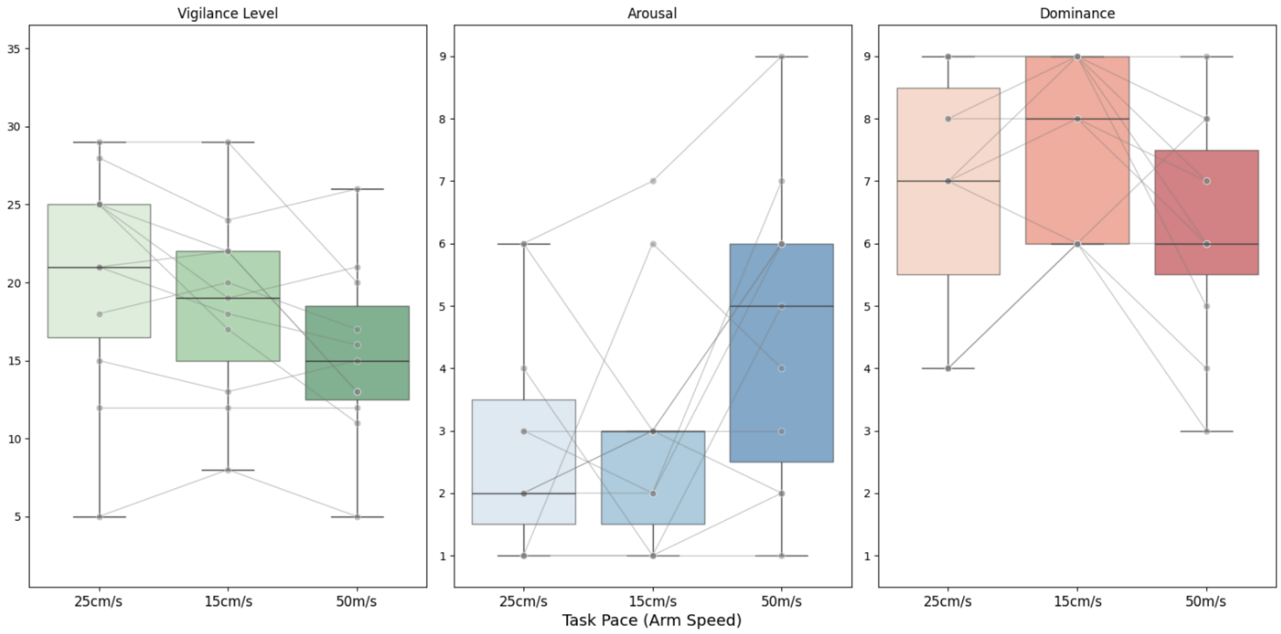

Figure 3: Comparison of Vigilance, Arousal, Dominance by Task Pace

Building on existing study suggesting that bodily configurations can change in response to cognitive or emotional shifts, this study concentrated on two main metrics that may be sensitive to such variations (Försterling et al., 2024). The first, Arm Expansion Angle, reflects tension or relaxation in the arms and can correlate with emotion or vigilance. The second, Total Movement, sums the overall changes in tracked joint angles over time and may indicate discomfort or alertness. Arm Expansion Angle was calculated according to Equation (1):

$$angle = cos^{-1}\frac{vec1 \cdot vec2}{norm(vec1) \cdot norm(vec2)} \qquad (1)$$

In deriving Arm Expansion Angle, angles at the shoulders and elbows were extracted from each frame, and differences from an assumed “relaxed” baseline were integrated to yield a continuous measure of tension. Total Movement was then computed according to Equation (2):

$$\frac{1}{N_\theta}\frac{1}{N_{Frames}}\left(\Sigma_i^{N_{Frames}-1}\Sigma_i^{N_\theta} abs\left(\theta_{i,j}-\theta_{i+1,j}\right)\right) \qquad (2)$$

This metric aggregated the absolute variations in joint angles (e.g., shoulders, elbows, hips, knees) between consecutive frames, capturing an overall sense of motion potentially related to discomfort or increased vigilance. These two measures provide concise yet insightful data of participants’ behavioral states as they supervised and assessed the robot’s line-drawing performance under different conditions.

Results

Cognitive and Emotional Responses to Robot Parameters

To examine how task pace and failure rate influenced participants’ cognitive loads and emotion, these factors were analyzed under varying experimental conditions. Failure rate comparisons were conducted using a paired t-test, while differences among the three task pace levels (15 cm/s, 25 cm/s, and 50 cm/s) were evaluated using Repeated Measures (RM) ANOVA.

A statistical comparison of NASA-TLX scores under low (10%) and high (40%) failure rates is presented in Table 4, indicating that participants in the high-failure condition exhibited a significantly higher overall NASA-TLX score ($p < 0.05$). Further analysis of the subscales suggests elevated Mental Demand, Physical Demand, Temporal Demand, and Frustration, each approaching significance at the $p < 0.10$ level. These findings suggest that a higher failure rate places additional cognitive demands on workers, increasing mental and physical strain while elevating frustration levels. Frequent robotic failures may require workers to allocate more attention to monitoring and correcting failures, potentially reducing efficiency and increasing safety risks. This underscores the importance of minimizing failure rates to support effective HRC.

Table 4: Comparison of NASA-TLX score by Failure Rate

Failure Rate	**NASA-TLX Score**	
	Mean	**Standard Deviation**
10%	**7.24**	**4.49**
40%	**8.74**	**4.49**
t(p)	**-2.604 (0.026)** **	

$p^{*}<0.10$, $p^{**}<0.05$

For task pace, repeated measures (RM) ANOVA showed significant effects on Vigilance, Arousal, and Dominance ($p < 0.05$). Post-hoc Tukey's HSD analysis did not show statistically significant differences among the specific paces. However, Figure 3 shows that vigilance was highest at the moderate speed of 25 cm/s, whereas speeds slower (15 cm/s) or faster (50 cm/s) resulted in lower vigilance levels. Arousal displayed the opposite tendency: it was lowest at 25 cm/s and increased at both 15 cm/s and 50 cm/s. In contrast, Dominance was higher at slower speeds and tended to decrease as speed rose, suggesting that participants felt less in control at higher velocities. These findings suggest that moderate task pace helps maintain vigilance by balancing cognitive engagement without inducing excessive stress or boredom. Faster speeds may demand quicker reactions, leading to increased arousal but reduced control, while slower speeds might lower engagement, making the task feel monotonous. This emphasizes the need to carefully calibrate task pace in HRC settings to optimize worker attentiveness and comfort.

Behavioral Responses to Robot Parameters

To analyze how each participant's behavioral responses varied under different HRC parameter settings, we applied Equation (3), representing a basic relationship between the measured behavioral metrics (y_i) and the two HRC parameters (x_1 for Task Pace, x_2 for Failure Rate):

$$y_i = \beta + c_1 x_1 + c_2 x_2 \,, \qquad \beta = constant \tag{3}$$

$$y_i = \begin{bmatrix} Arm\ Expansion\ Angle \\ Movement \end{bmatrix}, \quad x_i = \begin{bmatrix} Task\ Pace \\ Failure\ Rate \end{bmatrix}$$

A one-way ANOVA was conducted to compare outcomes across the three task pace sessions, and an independent-samples t-test was performed to examine differences between the two failure rate conditions. The statistical results are presented in Table 3. Of the 11 participants, eight exhibited at least one significant change in Arm Expansion Angle or Total Movement ($p < 0.05$). Specifically, seven participants showed significant differences tied to changes in task pace, and four participants demonstrated significant differences associated with failure rate. These findings underscore that both the robot's operational speed and its reliability can substantially affect human behavior during collaborative tasks, highlighting the importance of accounting for individual variability when designing HRC systems.

Discussion

The findings from this study underscore how task pace and failure rate can profoundly influence the cognitive-emotional and behavioral experiences of workers engaged in a construction-inspired HRC setting.

Participants who experienced a high failure rate exhibited notable increases in overall cognitive load, as reflected in elevated mental demand, physical demand, and frustration levels in NASA-TLX scores. As failures became more frequent, participants had to exert additional effort to compensate, leading to higher overall workload and reduced engagement. This heightened demand not only increased frustration but also appeared to negatively affect vigilance levels, as participants either became overwhelmed by frequent corrections or disengaged due to the unpredictability of the robot's performance. Consequently, such elevated cognitive load and frustration may hinder decision-making and increase error risk (Gonzalez, 2005), which can directly impact safety and productivity in construction settings. Furthermore, although this study focused on participants' instant cognitive and emotional reactions, repeated exposure to robotic failures may influence workers' long-term risk perception and trust in HRC. These findings highlight the importance of minimizing robotic failures in HRC scenarios to prevent excessive cognitive strain on human collaborators.

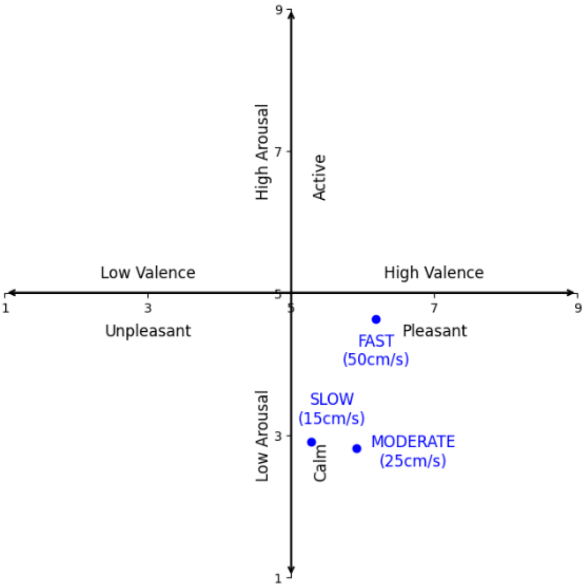

Figure 4: Emotion (Valence-Arousal) by Task Pace

Conversely, task pace influenced vigilance, arousal, and dominance in distinct ways. Moderate speeds maintained stable vigilance levels and controlled movement patterns, whereas both slower and faster speeds led to decreases in vigilance. At the highest speed, participants exhibited heightened arousal but reduced control, suggesting increased stress or discomfort, while the slowest speed condition resulted in lower engagement, indicating potential monotony. As illustrated in Figure 4, fastest task pace showed the highest levels of both arousal and valence, suggesting that participants were more engaged but also more reactive to rapid robotic movements. These findings suggest that while higher task pace can enhance engagement, it may also elevate emotional responses, potentially affecting comfort and task performance. Therefore, robot speed adjustments should consider not only efficiency and vigilance but also their impact on workers' cognitive and emotional states in HRC environments.

The observed behavioral responses, particularly Total Movement, offer some insights into how physical behavior might reflect cognitive-emotional states during HRC. While no consistent trends were found across all participants, a closer analysis of the subset of five participants who exhibited significant differences in Total Movement across varying task paces (Table 3) revealed some potential patterns.

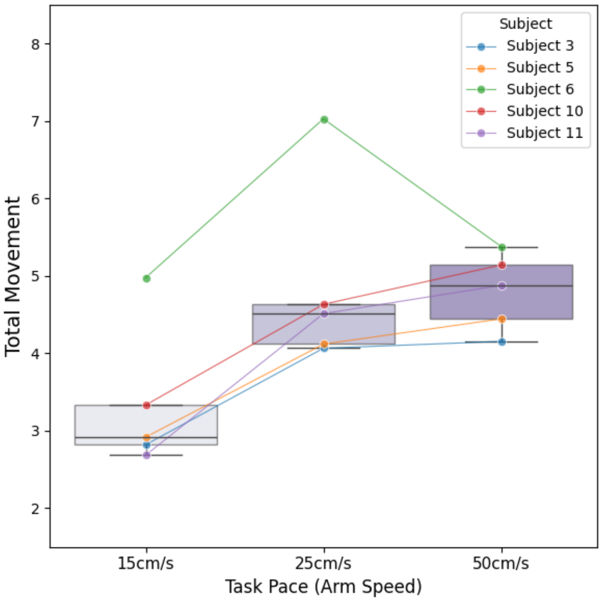

Figure 5: Total Movement by Task Pace

For these participants, as shown in Figure 5, Total Movement tended to decrease during slower task pace conditions, suggesting a possible link between physical activity and reduced valence and arousal, as indicated by subjective measures. This observation aligns with findings from prior studies that associate lower valence levels with reduced movement (Försterling et al., 2024). Similarly, several studies have suggested that user responses to robots can vary depending on individual characteristics and task context, supporting the need for adaptive interaction strategies in HRC systems (Wu et al., 2024). However, in other combinations of robot parameters and behavioral metrics, no consistent patterns were observed.

This variability across individuals suggests that movement patterns may be influenced by various factors but could still provide valuable cues for real-time monitoring in specific cases. In this context, such behavioral variation may support the design of adaptive robotic systems that respond to individual states by adjusting task pace or interaction style. Given the observed individual variability, personalized robot behaviors may help address diverse worker responses and support their attentiveness, even in HRC setups involving indirect supervision. To make such adaptation feasible in practice, our study demonstrates that a camera-based monitoring method offers a practical and non-intrusive approach for capturing behavioral cues. In construction settings, where both cognitive and physical demands on workers vary, recognizing these patterns could help reduce unnecessary workload.

Limitations and Future Work

However, this study has several limitations. Most notably, the experimental setting does not sufficiently capture the complexity and unpredictability that characterize real-world construction scenarios. While it enabled controlled measurement of cognitive, emotional, and behavioral responses in lab-settings, it did not reflect contextual factors such as uncertainty, unpredictability, or dynamic worker activities. As such, the generalizability of the findings may be limited in real construction contexts, where workers are often subject to elevated cognitive and physical demands, especially when interacting with construction robots (Ibrahim et al., 2023; Shayesteh & Jebelli, 2023). These demands can heighten workers' sensitivity to robotic factors such as task pace and failure rate, potentially leading to cognitive and emotional responses that differ from those observed in controlled laboratory settings. This highlights the importance of evaluating such effects specifically in construction environments, where the implications for safety and productivity are critical. Future studies should develop experimental scenarios that better reflect on-site conditions by integrating uncertainty, human activity and realistic construction tasks.

In addition, the study involved only eleven participants, all of whom were students in construction-related disciplines. While they may not fully reflect the characteristics of professional construction workers, their varied perspectives still offer valuable insight into how individuals interpret and respond to robotic behavior. In particular, students in construction-related disciplines can be seen as prospective construction professionals. Their lack of site-specific experience may also reduce task-related biases, allowing clearer observation of general human responses to robot behavior. These individual differences can serve as a useful basis for exploring variability in human responses, which is also a critical consideration in real-world tasks. Moreover, the limited sample size constrains the statistical power of the results and the ability to draw broader inferences. To better distinguish domain-specific human responses in HRC, future research should involve participants from diverse backgrounds, including construction workers and individuals from other industries. This comparative approach may help identify response patterns that are uniquely shaped by the construction context.

Conclusions

This study investigated the effects of task pace and failure rate on worker's cognitive, emotional and behavioral responses in a construction-inspired HRC setting. To achieve this, participants monitored a robot operating under varying conditions. Subjective responses of participants were measured using validated cognitive and emotional assessment tools, while behavioral data were collected through motion tracking.

The results highlight that task pace and failure rate significantly shape both cognitive-emotional and behavioral states. Higher failure rates led to increased cognitive demand and frustration, suggesting that frequent robotic failures impose additional burdens on human collaborators. Meanwhile, task pace influenced workers' cognition where both slower and faster speeds resulted in reduced vigilance. Furthermore, behavioral responses varied across participants, with some showing patterns that aligned with subjective emotional states, suggesting a potential relationship between psychological and behavioral responses.

These findings emphasize the importance of designing adaptive robotic systems that account for human variability in cognitive load, engagement, and stress management. By refining task pace and minimizing failures, robots can better support human collaborators, improving both efficiency and worker well-being in construction settings. Future studies should extend this work by incorporating more realistic and dynamic construction scenarios with experienced workers, including task types that better reflect on-site human-robot collaboration. In particular, further exploration of behavioral signals as indicators of workers' internal states may inform the development of adaptive robotic systems suited for construction environments, where physical activity, cognition, and emotion all contribute to the collaborative task performance.

Declaration of AI-generated text

During the preparation of this work the authors used ChatGPT in order to improve readability. After using this tool, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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