# Understanding Cognitive Impacts of Robots in Worker-Robot Collaboration in Modular Construction

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**Abstract –**

**Human-robot collaboration (HRC) holds significant potential to enhance productivity and efficiency in modular construction (MC). While existing studies in construction HRC have predominantly focused on technical advancements, limited attention has been paid to human factors and the cognitive impacts of robots on workers during collaboration. This study addresses this gap through an experimental investigation. A controlled experiment was conducted to compare conditions with and without a collaborative robot (cobot). Work performance metrics (e.g., time efficiency, angular accuracy, and screwing quality) and human factors (e.g., fatigue levels, individual effort, and stress states) were assessed using statistical analysis and self-report questionnaires. Results of work performance indicate that cobot integration significantly increased task completion time (TCT) (Est. = 0.314, t = 5.18, p < 0.001), with variations observed across tasks (p = 0.00452). Results of human factors revealed increased fatigue (mean scores rising from 18.9 to 22.0), mental effort (mean scores rising from 40.2 to 50.1), and distress (mean scores rising from 12.2 to 15.9) under the cobot condition, suggesting additional cognitive demands during collaboration. These findings underscore the importance of addressing task complexity and cognitive challenges when implementing cobots in MC workflows. This research contributes to advancing robotics integration and safeguarding worker well-being in modular construction.**

**Keywords –**

**Human-robot Collaboration; Work Performance; Human Factors; Collaborative Robots; Modular Construction**

## 1 Introduction

To address the lack of labors and improve productivity, modular constriction (MC) has gained significant attention and development in the construction industry recently [1]. MC refers to an innovative construction approach that transfers on-site works to highly controlled and standardized environments in MC factories. Robotics have been increasingly applied in MC to enhance both efficiency and safety in prefabrication and assembly processes [2-4]. For instance, this promising technique has been successfully integrated into prefabricated component assembly [5], robotics welding [6] and robotics platforms [7]. Among these advancements, collaborative robots (cobots) have emerged as a transformative tool, offering the benefits of flexible manufacturing and cost-effectiveness. As a result, human-robot collaboration (HRC) is poised to play a significant role in the future development of MC.

Human involvement remains essential in HRC due to unique cognitive and reasoning abilities, while robots excel at performing repetitive, precision-demanding and hazardous tasks [8]. Despite this, existing studies in MC primarily focus on technological advancements, such as robotic programming and automated assembly systems, while giving less attention to the effects of HRC as a novel working paradigm on human workers. Previous research [9, 10] indicated that working with robots may increase workers' cognitive load and mental stress. However, there remains a need for a systematic evaluation of how robots influence workers' performance and well-being in MC workflows.

This study aims to address this gap through an experimental investigation of the effects of robots on construction workers. A controlled experiment was conducted to isolate variables and compare conditions with and without the cobot. Statistical analysis and questionnaire surveys were employed to assess work performance and workers' cognitive and physical responses. The outcomes of this research will provide insights into the impacts of cobots on both work performance and human factors. Furthermore, this study offers practical recommendations for optimizing human-robot collaboration by managing task complexity and reducing cognitive load, supporting the effective integration of cobots in MC workflows.

## 2 Literature Review

This section begins with an overview of the applications of cobots in modular construction and then provides a detailed analysis of their impact on human workers.

### 2.1 Cobots' Application in MC

The integration of cobots in MC has gained increasing attention for their ability to enhance efficiency, safety, and precision in prefabrication and assembly processes. By shifting construction activities from unstructured on-site environments to highly controlled factory settings, MC provides an ideal platform for HRC [8]. Cobots are designed to complement human workers by performing repetitive, precision-demanding, and hazardous tasks, thereby enabling greater flexibility and productivity in production workflows.

In MC factories, cobots have been successfully applied in various tasks, including component assembly [5], 3D printing [11], and automated welding [6]. For example, Kyjanek et al. (2019) investigated HRC in timber prefabrication, where cobots achieved precise positioning of timber components while humans performed tasks requiring dexterity, such as screwing [12]. The use of augmented reality facilitated real-time communication and task sequencing, ensuring seamless collaboration between workers and robots. Similarly, Zhu et al. (2021) proposed a smart component-oriented method for multi-robot coordination in prefabricated housing [13]. By utilizing smart construction objects within a Building Information Modeling (BIM) environment, tasks such as transporting and assembling components were efficiently allocated, improving coordination and streamlining collaborative workflows.

While these applications demonstrate the potential of cobots to streamline MC processes, the integration of cobots also introduces new challenges. Existing research has primarily focused on the technical advancements of cobot systems, such as programming optimization, sensor-based control, and hardware innovations [5, 6, 14]. However, limited attention has been given to understanding how cobots affect human workers, particularly regarding their performance and well-being. This highlights the need for a systematic evaluation of cobot integration from a human-centered perspective.

### 2.2 Impact Evaluation of HRC

Despite the importance of understanding cobots' impact on construction workers, research in this area remains limited. Existing studies primarily rely on methods such as self-report questionnaires, interviews, and simulations [15]. For example, Bademosi and Issa (2021) used interviews and surveys with industry experts to explore the challenges of implementing automation and robotic technologies in construction [16]. Similarly, Wu et al. (2022) developed a simulation-based framework to assess the impact of HRC on construction productivity [17]. However, controlled experimental methods are relatively scarce, even though experiments offer stronger empirical evidence and better reflect real-world conditions, making them more persuasive for evaluating cobots' practical impacts.

Work performance is one of the key metrics for evaluating human-robot interaction in HRC. Human factors are equally critical in assessing HRC, as the introduction of cobots should remain human-centered. Baltrush et al. (2022) identified four key job quality factors relevant to HRC: cognitive workload, collaboration fluency, trust, and acceptance and satisfaction [19]. However, construction tasks often involve significant physical labor, highlighting the need to assess physical fatigue and exertion. For example, experimental research conducted by Fang et al. (2015) highlighted the importance of fatigue on construction workers performance [20]. Therefore, this study focuses on fatigue levels, individual effort, and stress levels to comprehensively evaluate the human factors associated with cobot integration in construction.

## 3 Methodology

Experimental analysis method was used in this study to evaluate the impact of cobots on human workers in terms of work performance and human factors. Figure 1 illustrates the overall methodology and process of this study. A typical manufacturing task for a wooden wall panel was designed and decomposed into 9 subtasks. Next, a total of 6 subjects were recruited and a controlled experiment was designed to eliminate the impact of extraneous variables. After setting up an experiment workspace, hardware devices, software system, and tools, each subject was asked to individually conduct experiments in both with/without a cobot for comparison. While the work performance was evaluated from time efficiency, angular accuracy, and screwing quality, human factors were investigated through self-report scales in terms of fatigue levels, individual effort, and stress states.

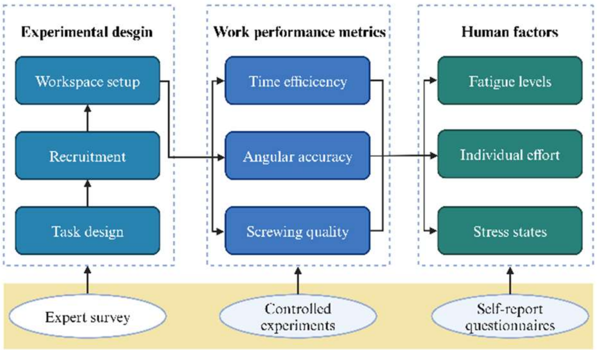



Figure 1. The overall methodology of this study

### 3.1 Task Design

A typical wooden wall panel manufacturing task in MC was designed for this study. Wood framing is a primary building method in MC for residential, commercial, and industrial structures [21]. Among these, wooden wall panels play a critical role as both structural and functional components. To enhance production efficiency and quality, cobots are increasingly integrated into manufacturing tasks. However, their integration requires close collaboration with human workers, raising concerns about potential impacts on human performance and well-being. Therefore, it is crucial to investigate these impacts in the context of wooden wall panel manufacturing.

The manufacturing task was decomposed into nine subtasks: assembling the framework (T1), screwing to connect the framework (T2), covering with an OSB board (T3), screwing to attach the board to the framework (T4), flipping the panel (T5), adding insulation (T6), covering with another board (T7), screwing again to attach the board (T8), and finally moving the completed product (T9). These tasks were designed to replicate a realistic production process, requiring both physical and cognitive effort from human workers.

To compare the effects of conditions with and without a cobot on human workers, a controlled experiment was designed with two groups. In the baseline group, workers completed the entire task in the same workspace with the cobot powered off. In the cobot group, the cobot was activated and assigned to perform subtask 1, which involved picking and placing wooden strips to assemble the framework. The cobot continuously repeated this task throughout the experiment, while human workers completed the entire sequence of subtasks 1 through 9. Each participant was required to complete both the baseline and cobot conditions on different days to minimize the impact of task repetition.

### 3.2 Recruitment

A total of six participants, all aged 18 or older, were recruited for the study. The group consisted of three male and three female undergraduate students from the Department of Civil, Environmental, and Geospatial Engineering at Michigan Technological University (MTU). None of the participants had a history of back disorders. This group was selected because of their experience with construction-related activities, making them well-suited to simulate real-world workers while ensuring safety during the experiment.

The recruitment process complied with guidelines with approval from the MTU Institutional Review Board (IRB), under IRB #: IRB-2024-90. All participants signed informed consent forms, voluntarily agreeing to participate with the option to withdraw at any time.

### 3.3 Workspace Setup

The experimental setup included a UR10e robot equipped with a Robotiq 2F-85 gripper, programmed and controlled using RoboDK software, as shown in Figure 2. The UR10e robot is a versatile and flexible collaborative robot widely used for industrial tasks [6, 22], offering high precision and adaptability for various assembly operations. RoboDK software provides a user-friendly interface for programming and simulating robot tasks [23], making it ideal for ensuring accurate control and program efficiency during experiments.

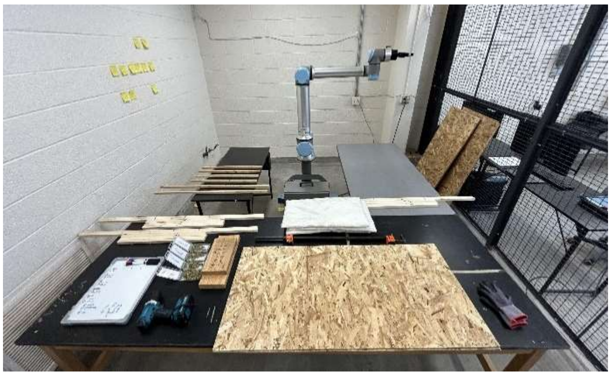


Figure 2. Experimental workspace setup

A dedicated workspace was enclosed with safety barriers to ensure controlled and interference-free experimental conditions. Wooden wall panel components were scaled down to half their actual size (1:2 ratio) to fit the workspace, with all wooden strips and boards pre-cut and pre-drilled to facilitate assembly. Safety equipment, including helmets, safety glasses, and woodworking gloves, is required within the workspace. Prior to the experiment, safety training and an operation test on the use of an electric screwdriver were conducted. The entire experiment was overseen and safeguarded by an experienced safety assistant.

### 3.4 Measurement on Work Performance

The impact of cobots on work performance was evaluated in terms of time efficiency, angular accuracy, and screwing quality. Time efficiency was quantified by recording and comparing the task completion time (TCT) for each subtask between the baseline and cobot groups. To stabilize variance and make the data more suitable for linear modeling, a log transformation was applied to the time variable. For further analysis, two linear mixed-effects models (LMMs) were developed using RStudio. LMMs are appropriate for data that include both fixed effects (predictors of interest) and random effects (sources of variability that must be accounted for but are not the primary focus). The first model examined the effects of experimental conditions (baseline and cobot groups), subtasks (T1 to T9), subjects (individual participants), and trial progression (repeats per participant) on time performance. To better understand the interactive effects among these factors, the second model analyzed how the impact of the cobot condition varied across different subtasks.

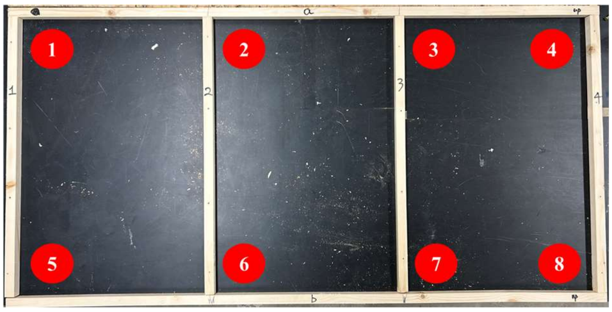



Figure 3. Distribution angles for the framework

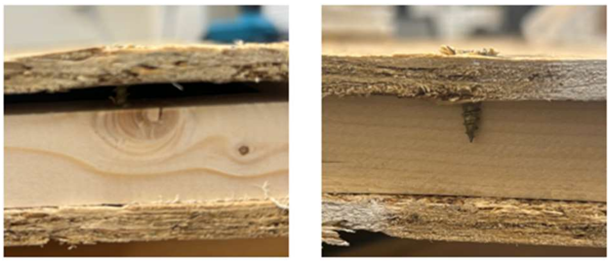
Angular accuracy was assessed by evaluating the total accuracy of the assembled wooden framework and comparing it to the design specifications. Figure 3 shows the distribution of the eight defined angles at each lumber connection within the framework. Raw angle data were collected using a digital angle finder. The accuracy of each joint was calculated using Equations (1) and (2), with the total accuracy of the structure determined using Equation (3) [15]:

$$err = \frac{M_e - M_t}{M_t} \times 100\% \quad (1)$$

$$acc = 1 - err \quad (2)$$

$$acc_{total} = \prod_{k=joint\ 1}^{joint\ 8} acc_k \quad (3)$$

where $err$ = percentage error; $M_e$ = experimental values measured during assembly; $M_t = 90°$, which is the theoretical design value; $acc$ = percentage accuracy, $acc_{total}$ = the total accuracy of an assembled wooden framework (from joint 1 to joint 8); and $acc_k$ = percentage accuracy of each individual joint.



(a) (b)

Figure 4. Two types of failed screws

Screwing quality was evaluated as the percentage of failed screws relative to the total number used in the product. Failed screws included two types: those that did not fully penetrate the structure (Figure 4(a)) and those that fully penetrated but failed to connect to the substructure (Figure 4(b)).

### 3.5 Measurement on Human Factors

The impact of cobots on human factors was evaluated based on fatigue levels, individual effort, and stress states. Data for these dimensions were collected through self-report questionnaires administered after each complete round of nine subtasks. The process was facilitated by the Psychology Experiment Building Language (PEBL) [24], an open-source platform that enables the design and execution of psychological experiments, streamlining the collection and analysis of scale-based data.

Fatigue levels were assessed using the Fatigue Assessment Scale for Construction Workers (FASCW) [25], a 10-item scale where each question is scored on a 5-point scale. The total score is obtained by summing all 10 items. The FASCW comprises two factors: lethargy and bodily ailment. Lethargy, primarily associated with mental fatigue, is calculated as the sum of questions 1, 3, 5, 7, and 9, while bodily ailment, reflecting physical fatigue, is derived from the sum of questions 2, 4, 6, 8, and 10.

Individual effort was measured using Borg's Rating of Perceived Exertion (RPE) [26] for physical effort and Zijlstra's Rating Scale for Mental Effort (RSME) [27] for mental effort. The Borg RPE is a numerical scale ranging from 6 to 20, where participants rate their overall exertion, considering physical stress and fatigue during the task. The Zijlstra RSME, a unidimensional scale, measures subjective mental workload. It consists of a 0–150 scale marked with nine descriptive anchor points representing increasing levels of mental effort.

Stress states were assessed using the Short Stress State Questionnaire (SSSQ) [28], a 24-item scale where each question is rated on a 5-point scale. The SSSQ comprises three factors—distress, engagement, and worry—each represented by eight questions. Distress reflects negative states such as unpleasant mood, tension, lack of confidence, and perceived loss of control. Engagement captures positive states, including task interest, motivation, energetic arousal, and concentration. Worry focuses on cognitive interference, self-focused attention, and self-esteem.

# 4 Results and Discussion

A total of 12 experimental groups were conducted, involving six participants under two experimental conditions: baseline and cobot. Each group completed two repetitions of the entire process consisting of nine subtasks. However, four groups were excluded because participants #3 and #4 did not complete the entire process. As a result, 16 data groups (4 participants × 2 conditions × 2 repetitions) were included in the analysis.

## 4.1 Results of Work Performance

This section examines the impacts of cobots on human work performance from three perspectives: time efficiency, angular accuracy, and screwing quality. Figure 5 illustrates the TCT results under baseline and cobot conditions. Figure 5(a) shows the distribution of TCT in seconds, while Figure 5(b) presents the log transformed TCT distribution for improved clarity and visual comparison. Figure 5(c) displays the mean log transformed TCT across the nine subtasks. In most subtasks, the cobot group exhibited longer completion time compared to the baseline group. However, for subtasks 5 (flipping the panel) and 6 (adding insulation), the differences were minimal or reversed.

To further analyze the effects of experimental conditions, subtasks, subjects, and trial progression on time performance, two LMMs were developed using RStudio. In the first LMM, experimental conditions, subtasks, and trials were included as fixed effects, while subjects were treated as a random effect. The response variable was defined as $LogTCT = \log(time)$ to stabilize variance and improve model fit.

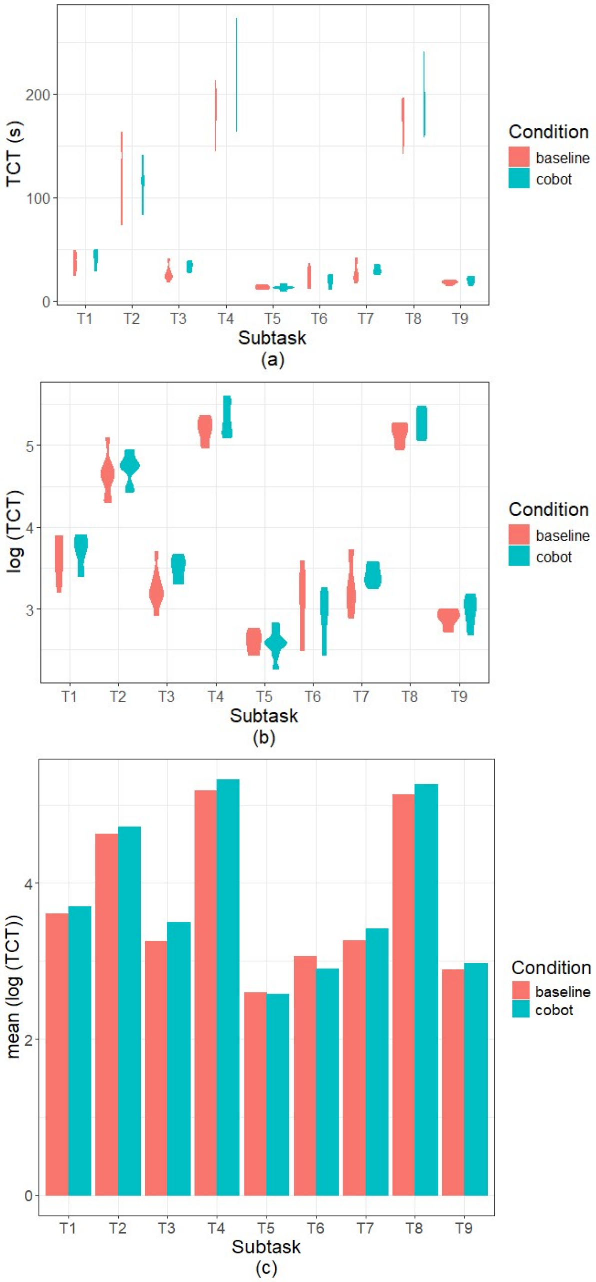



Figure 5. Performances of time efficiency

Table 1. Summary of the LMM coefficients

| Groups | Est. | SE | t-value | p-value |
|---|---|---|---|---|
| Intercept | 3.761 | 0.088 | 42.94 | < 2.2e-16 |
| Condition | 0.314 | 0.061 | 5.18 | < 2.26e-07 |
| Trials | -0.058 | 0.014 | -4.15 | < 3.29e-05 |
| Subtasks | df = 8, Significant, p < 2.2e-16 | | | |
| Subjects | Var = 0.0199, SD = 0.141 | | | |
| Residual | Var = 0.0213, SD = 0.146 | | | |

Table 1 summarizes the LMM results. The “cobot” condition significantly increased $logTCT$ compared to the baseline data ($Est. = 0.314, t = 5.18, p < 0.001$), suggesting that cobot involvement slowed task completion, potentially due to worker distraction or mistrust of the robot. Trail progression also had a significant effect on time performance ($Est. = -0.058, t = -4.15,\ p < 0.001$), indicating that task completion times decreased with repetition, likely reflecting learning and adaptation. Subtasks significantly influenced time performance ($p < 0.001$), with varying effects observed across different tasks. Additionally, the inclusion of a random effect for subjects ($Var = 0.0199, SD = 0.141$) accounted for individual differences in time efficiency, such as variations in skill or experience. Residual variance of the model was 0.0213 ($SD = 0.146$), reflecting some unexplained variability in the data.

Given the significant influence of both condition and subtasks, the interaction between them was further examined using a second LMM. Results revealed a significant "condition * subtasks" interaction ($p = 0.00452$), indicating that the cobot condition's impact on TCT varied across subtasks. Specifically, the main differences observed in subtasks 5 and 6 may be attributed to the nature of these tasks, which require less direct interaction with the cobot. These findings suggest that the cobot's influence on time efficiency is task-dependent, highlighting the need for further investigation into the underlying mechanisms.

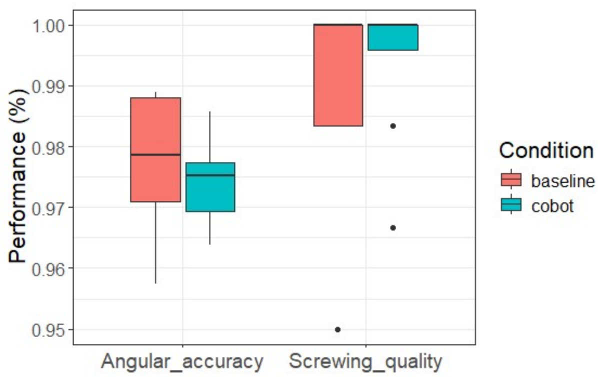



Figure 6. Performances of angular accuracy and screwing quality

Figure 6 presents the results for angular accuracy and screwing quality under the two experimental conditions. Angular accuracy was evaluated by comparing the total structural accuracy of the assembled wooden framework with the design specifications. The results indicate a slight reduction in angular accuracy in the cobot condition. This minimal effect can be attributed to the framework's structural properties, where the extrusion between wooden strips naturally constrains angular deviations, reducing observed variability.

Screwing quality, measured as the percentage of failed screws, showed negligible differences between the two conditions. The simplicity of the screwing task likely contributed to the lack of observable differences. These results suggest that for straightforward tasks, such as screwing, collaborative robots have a limited impact on the performance of screwing quality. Future studies should consider increasing task complexity to better assess the influence of cobots on such outcomes.

## 4.2 Results of Human Factors

This section examines the impact of cobots on human workers from three human factor perspectives: fatigue levels, individual effort, and stress states. Figure 7 presents the results of fatigue levels measured by the FASCW. The total average FASCW score shows an increase from 18.9 to 22, suggesting that participants experienced greater fatigue under the cobot condition. Specifically, both FASCW factors—lethargy (associated with mental fatigue) and bodily ailment (associated with physical fatigue)—demonstrated upward trends, with lethargy showing a more pronounced increase.

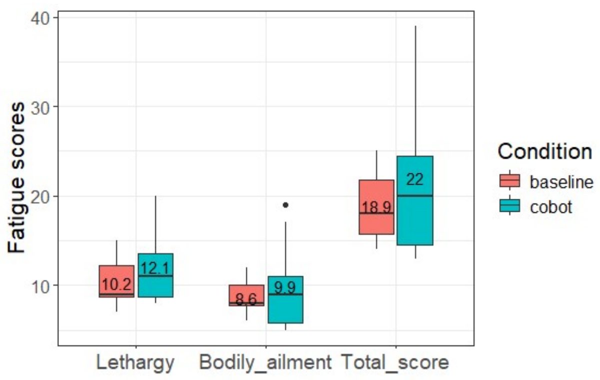



Figure 7. Results of fatigue levels

Figure 8 illustrates the results of physical and mental effort, measured using Borg's RPE scale and Zijlstra's RSME, respectively. The results reveal a slight increase in RPE scores (mean rising from 11.1 to 11.9) and a more substantial increase in RSME scores (mean rising from 40.2 to 50.1) under the cobot condition. This indicates that collaboration with robots resulted in a greater increase in mental effort compared to physical exertion.

These findings on individual effort align with the fatigue results, as both measures highlight increases in cognitive or mental dimensions (i.e., lethargy and mental effort). The observed effects may be attributed to the increased cognitive load and potential distractions introduced by the cobot.

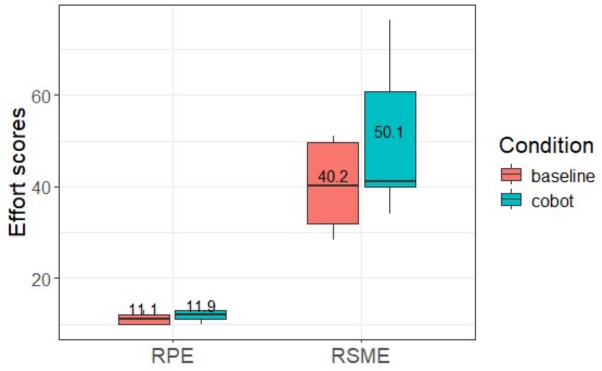



Figure 8. Results of individual effort

Figure 9 presents the results of the SSSQ for assessing the stress levels. The findings reveal a significant increase in distress scores (mean rising from 12.2 to 15.9) under the cobot condition, while engagement and worry exhibited only slight changes. This suggests that collaboration with cobots increases emotional strain and discomfort, distinguishing it from the psychological interference associated with worry and the motivational focus represented by task engagement.

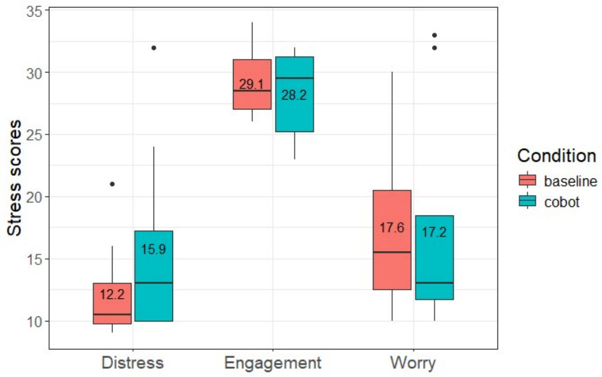



Figure 9. Results of stress states

### 4.3 Limitations and Future Works

This study has certain limitations. The sample size was relatively small (N=6), and the participants were undergraduate students rather than experienced construction workers. While these participants had relevant construction-related knowledge, their responses and performance may not fully represent those of seasoned professionals. Future research should involve a larger and more diverse participant pool, including experienced construction workers, to enhance the generalizability of the findings.

While cobots offer significant potential for enhancing productivity, their cognitive impact on human performance and well-being must be carefully managed. Future research should explore more complex tasks and diverse working scenarios to gain deeper insights into the dynamics of human-robot collaboration. By incorporating tasks that more closely mimic real-world MC workflows, future research can provide more practical and actionable insights for optimizing cobot integration in industrial settings.

## 5 Conclusion

The study assessed the impacts of collaborative robots on construction workers' work performance and human factors. Work performance was assessed in terms of time efficiency, angular accuracy, and screwing quality, while human factors were examined through fatigue levels, individual effort, and stress states. The results showed that cobot involvement significantly increased task completion time (Est. = 0.314, $t = 5.18$, $p < 0.001$), with variability observed across different task types ($p = 0.00452$). Angular accuracy showed a slight decline, though structural constraints reduced deviations, while screwing quality remained largely unaffected due to the task's simplicity. Human factor results revealed increased fatigue levels, with mean scores rising from 18.9 to 22.0, mental effort scores increasing from 40.2 to 50.1, and distress scores rising from 12.2 to 15.9 under the cobot condition. These findings suggest that collaborating with robots increases cognitive load and emotional strain among workers, highlighting the need for careful consideration of task complexity and worker cognitive demands when integrating cobots into MC workflows.

## References

[1] C.-H. Yang, T.-H. Wu, B. Xiao, and S.-C. Kang. Design of a Robotic Software Package for Modular Home Builder. In *Proceedings of the 36th international symposium on automation and robotics in construction, ISARC*, pages 1217-1222, Banff, Canada, 2019.

[2] B. Xiao, C. Chen, and X. Yin. Recent advancements of robotics in construction. *Automation in Construction*, 144:104591, 2022.

[3] C.-J. Liang, X. Wang, V. R. Kamat, and C. C. Menassa. Human–robot collaboration in construction: classification and research trends. *Journal of Construction Engineering and Management*, 147(10):03121006, 2021.

[4] B. Xiao, Y. Wang, Y. Zhang, C. Chen, and A. Darko. Automated daily report generation from construction videos using ChatGPT and computer vision. *Automation in Construction*, 168:105874, 2024.

[5] C. Liu, J. Wu, X. Jiang, Y. Gu, L. Xie, and Z. Huang. Automatic assembly of prefabricated components

based on vision-guided robot. *Automation in Construction*, 162:105385, 2024.

[6] D. Lee and K. Han. Vision-based construction robot for real-time automated welding with human-robot interaction. *Automation in Construction*, 168:105782, 2024.

[7] H. J. Wagner, M. Alvarez, O. Kyjanek, Z. Bhiri, M. Buck, and A. Menges. Flexible and transportable robotic timber construction platform – TIM. *Automation in Construction*, 120:103400, 2020.

[8] Y. Fu, J. Chen, and W. Lu. Human-robot collaboration for modular construction manufacturing: Review of academic research. *Automation in Construction*, 158:105196, 2024.

[9] S. Shayesteh and H. Jebelli. Investigating the impact of construction robots autonomy level on workers' cognitive load. In *Proceedings of the Canadian society of civil engineering annual conference 2021*, pages 255-267, Singapore, 2022.

[10] F. Baek, D. Kim, G. Lee, B. Choi, and S. H. Lee. Effect of human emotional responses on human-robot team pty in construction. *Automation in Construction*, 166:105608, 2024.

[11] M. Alabbasi, A. Agkathidis, and H. Chen. Robotic 3D printing of concrete building components for residential buildings in Saudi Arabia. *Automation in Construction*, 148:104751, 2023.

[12] O. Kyjanek, B. Al Bahar, L. Vasey, B. Wannemacher, and A. Menges. Implementation of an Augmented Reality AR Workflow for Human Robot Collaboration in Timber Prefabrication. In *Proceedings of the 36th international symposium on automation and robotics in construction, ISARC*, pages 1223-1230, Banff, Canada, 2019.

[13] A. Zhu, P. Pauwels, and B. De Vries. Smart component-oriented method of construction robot coordination for prefabricated housing. *Automation in Construction*, 129:103778, 2021.

[14] B. Belousov et al. Robotic architectural assembly with tactile skills: Simulation and optimization. *Automation in Construction*, 133:104006, 2022.

[15] X. Liang, U. Rasheed, J. Cai, B. Wibranek, and I. Awolusi. Impacts of collaborative robots on construction work performance and worker perception: Experimental analysis of human–robot collaborative wood assembly. *Journal of Construction Engineering and Management*, 150(8):04024087, 2024.

[16] F. Bademosi and R. R. A. Issa. Factors influencing adoption and integration of construction robotics and automation technology in the US. *Journal of Construction Engineering and Management*, 147(8):04021075, 2021.

[17] M. Wu, J. R. Lin, and X. H. Zhang. How human-robot collaboration impacts construction productivity: An agent-based multi-fidelity modeling approach. *Advanced Engineering Informatics*, 52:101589, 2022.

[18] D. Mitterberger, L. Atanasova, K. Dörfler, F. Gramazio, and M. Kohler. Tie a knot: Human–robot cooperative workflow for assembling wooden structures using rope joints. *Construction Robotics* 6(3):277–292, 2022.

[19] S. J. Baltrusch, F. Krause, A. W. de Vries, W. van Dijk, and M. P. de Looze. What about the human in human robot collaboration? *Ergonomics*, 65(5):719–740, 2022.

[20] D. Fang, Z. Jiang, M. Zhang, and H. Wang. An experimental method to study the effect of fatigue on construction workers' safety performance. *Safety Science*, 73:80–91, 2015.

[21] N. Gutiérrez, J. Negrão, A. Dias, and P. Guindos. Bibliometric review of prefabricated and modular timber construction from 1990 to 2023: Evolution, trends, and current challenges. *Sustainability*, 16(5):2134, 2024.

[22] S. Espinosa, M. Slepicka, and A. Borrmann. Integration of laser profiler feedback into FIM for additive manufacturing in construction. In *Proceedings of the 41st international symposium on automation and robotics in construction, ISARC*, pages 89-96, Lille, France, 2024.

[23] I. M. Sarivan, O. Madsen, and B. V. Wæhrens. Automatic welding-robot programming based on product-process-resource models. *International Journal of Advanced Manufacturing Technology*, 132(3):1931–1950, 2024.

[24] S. T. Mueller and B. J. Piper. The psychology experiment building language (PEBL) and PEBL test battery. *Journal of Neuroscience Methods*, 222:250–259, 2014.

[25] M. Zhang et al. Development and validation of a fatigue assessment scale for U.S. construction workers. *American Journal of Industrial Medicine*, 58(2):220–228, 2015.

[26] G. A. V. Borg. Psychophysical bases of perceived exertion. *Medicine and Science in Sports and Exercise*, 14(5):377–381, 1982.

[27] F. R. H. Zijlstra. Efficiency in work behaviour: A design approach for modern tools. PhD diss., Delft University of Technology, Delft: Delft University Press, 1993.

[28] W. S. Helton. Validation of a short stress state questionnaire. In *Proceedings of the human factors and ergonomics society 48th annual meeting*, pages 1238-1242, New Orleans, USA, 2004.