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XILIU YANG, University of Stuttgart, Stuttgart, Baden-Wurttemberg, Germany

NELUSA PATHMANATHAN, University of Stuttgart, Stuttgart, Baden-Wurttemberg, Germany

SARAH ZABEL, University of Hohenheim, Stuttgart, Baden-Wurttemberg, Germany

FELIX AMTSBERG, University of Stuttgart, Stuttgart, Baden-Wurttemberg, Germany

SIEGMAR OTTO, University of Hohenheim, Stuttgart, Baden-Wurttemberg, Germany

KUNO KURZHALS, University of Stuttgart, Stuttgart, Baden-Wurttemberg, Germany

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Xiliu Yang
Institute for Computational Design and Construction
University of Stuttgart
Stuttgart, Germany
xiliu.yang@icd.uni-stuttgart.de

Nelusa Pathmanathan
Visualization Research Center
University of Stuttgart
Stuttgart, Germany
nelusa.pathmanathan@visus.uni-stuttgart.de

Sarah Zabel
Department of Sustainable Development and Change
University of Hohenheim
Stuttgart, Germany
sarah_zabel@uni-hohenheim.de

Felix Amtsberg
Institute for Computational Design and Construction
University of Stuttgart
Stuttgart, Germany
felix.amtsberg@icd.uni-stuttgart.de

Siegmar Otto
Department of Sustainable Development and Change
University of Hohenheim
Stuttgart, Germany
siegmar.otto@uni-hohenheim.de

Kuno Kurzhals
Visualization Research Center
University of Stuttgart
Stuttgart, Germany
kuno.kurzhals@visus.uni-stuttgart.de

Michael Sedlmair
Visualization Research Center
University of Stuttgart
Stuttgart, Germany
michael.sedlmair@visus.uni-stuttgart.de

Achim Menges
Institute for Computational Design and Construction
University of Stuttgart
Stuttgart, Germany
achim.menges@icd.uni-stuttgart.de

Figure 1: Photos of the Study. Left: user inserting screws while the robot holds the beam. Centre: two users discussing how to intervene in the robotic task. Right: two users collaboratively assembling a timber beam during human-human collaboration.

Abstract

As robots are introduced into construction environments, situations may arise where construction workers without programming expertise need to interact with robotic operations to ensure smooth and successful task execution. We designed a head-mounted augmented reality (AR) system that allowed control of the robot's tasks and motions during human-robot collaboration (HRC) in timber assembly tasks. To explore workers' feedback and attitudes towards HRC with this system, we conducted a user study with 10 carpenters. The workers collaborated in pairs with a heavy-payload industrial robot to construct a 2 x 3 m timber panel. The study contributes an evaluation of multi-human-robot collaboration along with qualitative feedback from the workers. Exploratory data analysis revealed the influence of asymmetrical user roles in multi-user collaborative construction, providing research directions for future work.

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CCS Concepts

• **Human-centered computing** → **Empirical studies in HCI**; **Mixed / augmented reality**; **User studies**.

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1 Introduction

In manufacturing and construction domains, human-robot collaboration (HRC) can combine the strengths of robots and human workers to enhance production processes. Augmented Reality (AR) provides an intuitive interface to support HRC in these environments, with recent research demonstrating its efficacy in task allocation, instruction conveyance, and robot intent visualisation [8, 21]. In timber construction specifically, the high individuality of the parts and the relative light weight of the components make HRC a highly relevant method for production processes [22].

In this paper, we present an exploratory user study on an HRC system for timber construction using AR head-mounted displays (HMDs). The main objective is to elicit user feedback and contribute insights for future work on the use of AR to support HRC in timber construction practice. Building upon prior work that evaluated multi-user collaboration with a heavy payload industrial robot [23], we (1) extended the collaboration possibilities with AR control of the robot's tasks and motions, and (2) focused on evaluating the system with industry users.

The design of this study aimed to capture three aspects of HRC that are highly relevant in construction settings, but remain under-addressed in existing work. First, we examine how **human-human collaboration (HHC)** relates to multi-user HRC. In real-world construction practices, workers operate as teams rather than individuals, making it critical to understand how HHC impacts HRC in construction tasks. This type of interaction is *non-dyadic*, i.e., involving more than one human and one robot. Research on this topic has grown in recent years but mostly focused on humanoid or zoomorphic robots, instead of robotic arms in industrial or manufacturing settings [17]. On the one hand, HHC constitutes an important dimension in non-dyadic HRC, e.g., Pelikan et al. [14] found that the presence of a robot increased the physical and sensory distances between human team members. On the other hand, examining HHC is valuable from a technology evaluation and adoption perspective, providing a baseline to evaluate the strengths and weaknesses of HRC [12].

The second aspect is understanding the influence of **asymmetrical roles and responsibilities** in multi-user situations. Since robot control always requires prior training to ensure production safety and quality, this implies asymmetry in the worker team (between those who can control the robot and those who cannot). This asymmetry can result in different perspectives and user confidence in interactions with the robot. Existing work has shown that an asymmetrical distribution of robot attention or asymmetrical user roles in a team can impact interpersonal dynamics among humans [6, 20]. To shed light on this issue in the context of timber construction, we enforced an asymmetrical role division in the study and incorporated bio-signal recordings to further understand the differences between user roles.

Lastly, we examine **workers' attitudes** towards collaborating with robots. In real-world industrial settings, many factors can influence the acceptance of HRC [9]. Attitudes are a key predictor of technology adoption and use in general [3] as well as behaviour towards robots [10]. Research on human-robot interaction suggests that attitudes towards robots affect the time spent talking with and touching robots [11], as well as prosocial behaviour towards robots [19], among others. The human operator's attitude can thus be viewed as a driver of optimal HRC, where the human engages the robot for all tasks it is designed to perform. To capture attitudes towards robot collaboration, we rely on the tripartite model of attitude [18], which posits that attitudes consist of cognitive (beliefs about the robot's usefulness), affective (emotional responses to robots), and behavioural components. The aim of integrating these three components into one measurement is to provide a precise prediction of actual collaboration behaviours in applied settings.

Guided by these objectives, we conducted a user study with 10 workers from a timber construction company. The study contributes (1) an evaluation of an AR-based HRC system in timber construction and (2) exploratory findings on the influence of user attitude, construction role, and human team collaboration in multi-human-robot construction.

2 Study Design

To elicit relevant feedback from the workers, we designed a task environment matching a timber construction assembly setup. This included the use of large-scale construction components for the assembly tasks, and a heavy-payload industrial robot for the collaboration.

2.1 Setup and Tasks

The study was set up in the large-scale robotic laboratory over an area of 6 x 5 m (Figure 2, left). The space was vertically divided by a timber wall, where components should be assembled. A KUKA KR210-R3100-2 industrial robot (reach of 3.1 m and a rated payload of 210 kg) was positioned in front of one side of the wall.

The participants were tasked with assembling timber beams on this wall under two collaborative scenarios: the first scenario involves two humans and a heavy-payload industrial robot (HHRC) and the other with only two humans (HHC). Each user was randomly paired with another and participated in both construction scenarios with an assigned role, A and B. User A acted as the *assembler* and user B acted as the *installer*.

HHC Task Scenario: A and B assembled three vertical beams with each other. B placed and held the beam on the wall while A screw-fixed it from the opposite side. The positions for the placement and screws were displayed in AR.

HHRC Task Scenario: A and B assembled six horizontal beams with the robot. B supervised the robot and fed it with timber beams to place. The robot placed and held the beam in position for A to screw-fix.

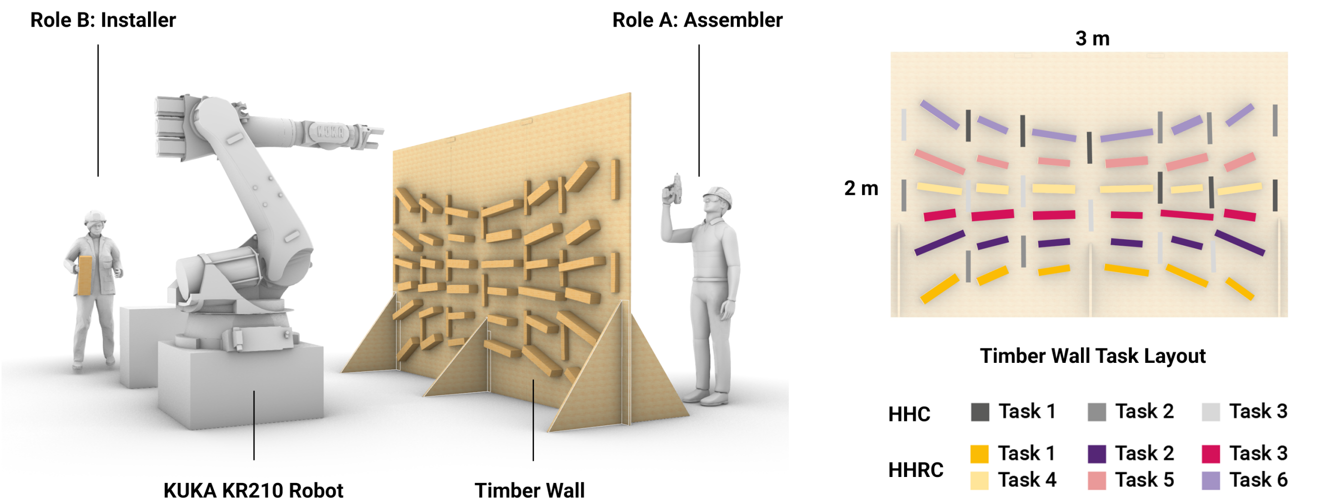

Figure 2: Study Setup. Left: physical layout of the workspace. Right: beam assembly tasks on the wall.

Out of of the six robotically placed beams in HHRC, four beams were programmed with intentional errors (Figure 2 right, magenta and purple), requiring users to correct the issue using the AR interface. Beam 2 and 6 were placed 10 cm lower than intended (**position error**), and beam 3 and 5 included beams that needed to be replaced (**material error**). When an error triggers, the system emits a message to both users *"Something doesn't look right, can you help?"*. We instructed the users to discuss and decide on the action together. The functions to control the robot however was only available for user B.

2.2 System Implementation

The multi-user HRC system coordinated the construction process by distributing tasks to the humans (AR devices) and robots (robot control programmes). In prior work, the AR interface included task instruction, task list, task geometries, robot trajectories, and safety information [23]. We extended the system with a multi-user interface and robot control interface, described below.

2.2.1 Multi-user Interface. Since multiple users are involved in the process, we added alerts to inform each user of the other's task status. We also visualised each user's head as a sphere for other team members to enhance collaborator awareness in case the line of sight is blocked by obstacles. During robotic tasks, we included two modes for the motion visualisation to support users: (1) a **look-ahead** mode showing the position of the robot one step ahead, and (2) a **real-time** mode displaying a digital twin of the physical robot, allowing users who cannot directly see the robot to be aware of its movements.

2.2.2 Task and Motion Control. When robotic tasks encounter an error, the interface enables users without programming experience to intervene in the robotic tasks to ensure smooth execution. For this purpose, we implemented three task and motion controls – **adjust**, **takeover**, or **restart** – summarised in Figure 3 (a).

The **adjust** option (motion control) allows the user to "nudge" the robot into position, guided by the visualised task target. This triggers the gesture detection loop on the headset, and an adjustment menu appears in front of the user, illustrating the gestures they can perform. The *pointing* gesture triggers a planning request for linear motions in the direction of pointing, and the *trigger* gesture actuates the robot.

The **takeover** option (task control) allows the user to replace the robot by executing its task manually. Selecting takeover instructs the robot to return to its home position, steering clear of the workspace for human access. Once homing completes, the system re-distributes the task to the human worker. The **restart** option (task control) allows the user to correct material errors or technical issues by first resetting and then repeating the current task. Selecting restart first prompts the robot to revert back to the starting point. After the user corrects the error, they tap a second *restart* to repeat the task.

2.3 Ethics Statement

The study was approved by the university's ethics commission. We recruited workers from an industry partner who specialised in timber construction. No additional monetary rewards were offered for taking part in the study. Prior to participation, all workers were provided with an information sheet, which described the study's objectives and procedures, as well as the option to withdraw at any time without consequences. Informed consent was obtained from all participants. The bio-signal recordings, questionnaires, and qualitative data are coded prior to processing and analysis to ensure anonymity.

2.4 Procedure

Two users joined the study as a pair. After informed consent and safety briefing, we assigned users with roles A and B and provided a brief introduction of the interface. The pair carried out two rounds of assembly, and the starting task was alternated to control order

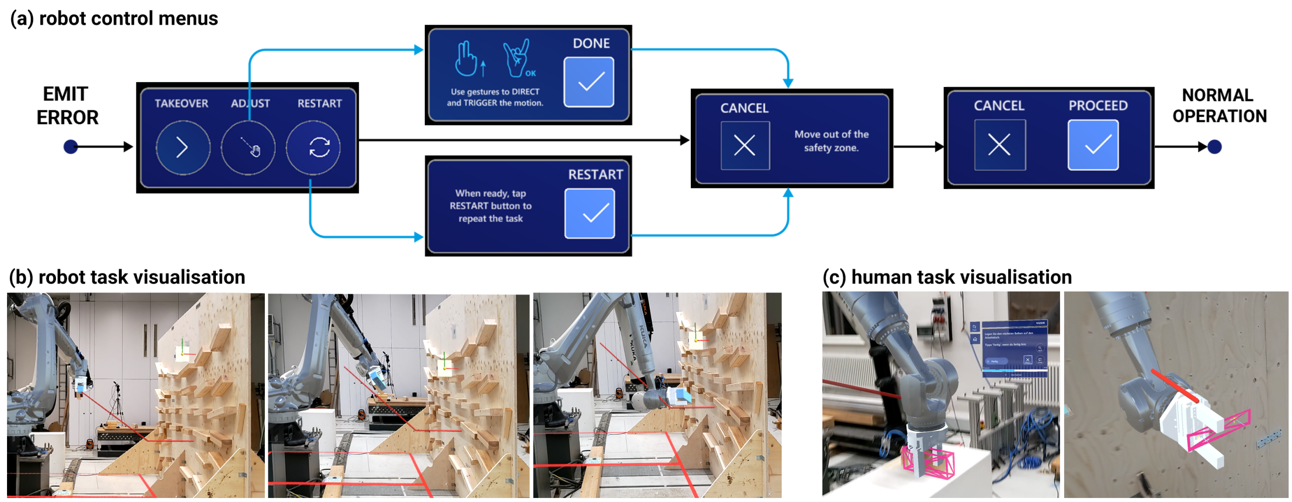

Figure 3: AR Interface. (a) robot control flow diagram (b) robot task visualisation, including the trajectory, robot geometry, and safety zones (c) human task visualisation, refill beam for installer (left) and screw beam location for assembler (right).

effects (pair 1 started with HHRC and pair 2 started with HHC, etc.). The initial task was conducted under the guidance of a research assistant, who explained the possible actions on the interface, and the rest were conducted independently. After the tasks were completed, users filled in the questionnaires, and we concluded the session with a 20-minute interview.

2.5 Measurements

We collected four types of data: questionnaires, collaboration recordings, task performance, and exit interviews during the study. The questionnaires included (1) System Usability Scale (SUS), (2) physical and mental workload (from NASA-TLX), (3) custom questions on the perception of teamwork and safety with the robot, and (4) the Attitude Toward Robot Collaboration (ARC) scale. The ARC scale, which consists of 5 cognitive, 5 affective, and 5 behavioural items, was developed for this study, showing a high reliability of .77 [24]. All questions were provided on a scale of 1 (strongly disagree) to 5 (strongly agree).

Eye-tracking, heart rate and video recordings were collected to complement our understanding of user experience and collaboration behaviours [13]. The duration of each beam assembly step was recorded to measure task performance. At the end of the questionnaires, we collected responses to "*I can imagine using this system for my profession in timber construction.*" using a score from 1 to 5 along with a written response on the reasons for this answer. This is followed by a semi-structured interview with each pair of participants.

3 Results

10 workers from a construction company participated in the study. Due to the limited availability of female workers at the company, we only had male participants in the study. Workers were aged between 21 and 66 years old ($\mu = 34.6, \sigma = 14.7$), and their experience in timber construction ranged from 1 to 48 years ($\mu = 14.7, \sigma = 14.6$).

3.1 Questionnaire Data

The average SUS was 73.8 with a standard deviation of 9.5 (assembler: $\mu_A = 72.5, \sigma_A = 10.6$, installer / controller: $\mu_B = 75.0, \sigma_B = 9.2$). Users agreed with the statement *"I collaborated with the robot on this task"* with an average score of 4.2 out of 5 ($\mu_A = 3.6, \sigma_A = 1.67$, $\mu_B = 4.8, \sigma_B = 0.45$). For the statement *"I collaborated with my partner on this task"*, the agreement averaged 3.9 ($\mu_A = 3.2, \sigma_A = 1.79$, $\mu_B = 4.6, \sigma_B = 0.55$). In both collaboration questions, the assembler rated collaboration lower on average.

The perception of safety around the robot was rated 4.4 out of 5 (assembler: $\mu_A = 4.4, \sigma_A = 0.89$, installer / controller: $\mu_B = 4.4, \sigma_B = 0.89$). Self-rated mental demand of the tasks averaged 2.3 ($\mu_A = 2.0, \sigma_A = 0.71$, $\mu_B = 2.6, \sigma_B = 0.89$). Self-rated physical demand averaged 1.4. All assemblers strongly disagreed that the task was physically demanding ($\mu_A = 1.0, \sigma_A = 0$) while only 2 out of 5 installers disagreed strongly.

3.2 Task Performance

Total task duration for the HHRC tasks averaged 26.9 minutes and HHC averaged 6.4 minutes. Figure 4 summarises task performance time per beam. A learning effect can be observed in the average durations – the first execution of the task (darker shade) took longer than subsequent ones (lighter shade). Comparing normally executed HHRC assembly (beam 1 and 4) with beams in the HHC assembly, HHC was faster on average: $\mu_{HHC} = 2.08, \sigma_{HHC} = 1.19, \mu_{HHRC} = 3.03, \sigma_{HHRC} = 1.10$; Pearson's r showed low correlation between how each pair performed the two ($r = 0.21$).

For the HHRC beams with material errors, three pairs used takeover (once in each pair) and restart was used in all other cases. For the beams with position errors, two pairs used takeover (once in each pair) to resolve the issue and the remainder used adjust. Each pair of workers used takeover exactly once during the fabrication.

On average, beams with position errors (2 and 6) required a longer task duration than beams with material errors. There was

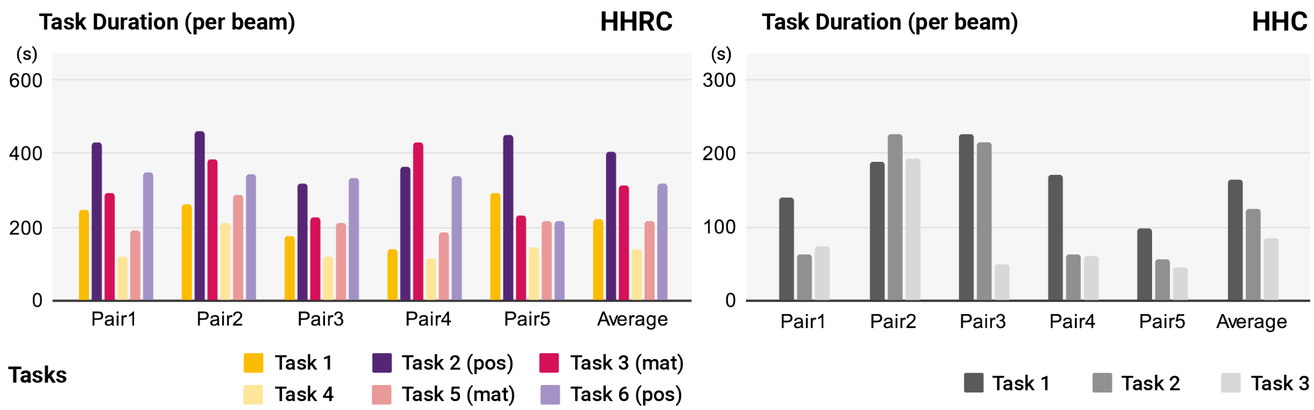

Figure 4: Task performance during HHRC and HHC tasks.

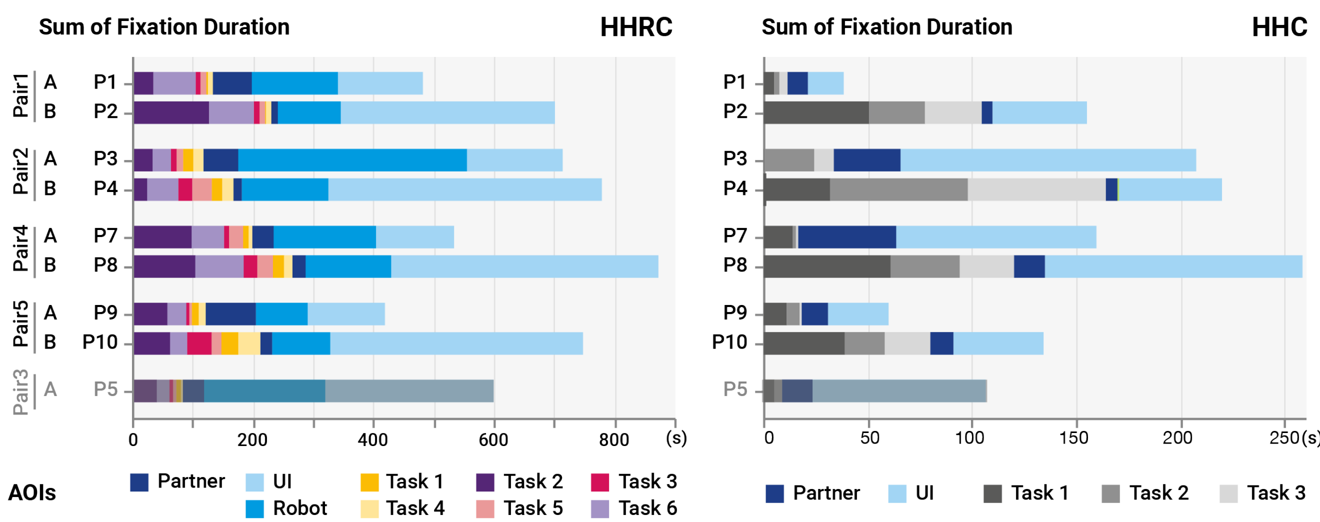

Figure 5: Sum of fixation durations (dwell times) for HHC and HHRC tasks by Areas of Interest (AOI).

a moderate correlation between performance time in HHRC tasks that were normally executed v.s. those with errors ($r = 0.69$).

3.3 Bio-signal Recordings

We conducted an exploratory analysis on the recordings to shed light on potential differences between user roles and HHC/HRC teams.

3.3.1 Gaze Data. We collected 9 complete eye tracking recordings (30Hz) with one incomplete (installer user in pair 3). We analysed these data by examining fixation durations (dwell times) on different Areas of Interest (AOIs). A summary of fixation durations on the AOIs for each pair of participants can be seen in Figure 5. The dwell times on the Partner AOI (dark blue) are high in the HHRC and HHC plots, especially for the assemblers (A). The Mann-Whitney U-Test showed that there is a significant difference between the fixation durations on the partner AOI for the assembler (A) and installer (B) in HHRC ($\mu_A = 459.35ms, \mu_B = 351.48ms, p < 0.05, U = 65414.5$).

We can also observe that in HHC, the installer (B) has longer fixation durations on the tasks than the assembler (A) ($\mu_A = 199.61ms, \mu_B = 425.3ms, U = 125226.0, p < 0.01$). The same holds for the fixation durations in the HHRC tasks ($\mu_A = 417.87ms, \mu_B = 475.22ms, U = 1351117.0, p < 0.01$). However, here we can notice that the assemblers (A) fixation duration on the tasks is much higher in contrast to the HHC tasks. The fixation duration on task 2 and task 6 are also longer in HHRC for both roles, since the tasks involved motion adjustment. Overall, AOI with the highest fixation duration during HHRC is the UI, followed by the robot visualisations.

3.3.2 Heart Rate. We collected 9 complete heart rate recordings (1Hz) with one incomplete (assembler in pair 3). These recordings are then split into $3 + 6 = 9$ segments corresponding with each beam assembly task, resulting in 81 segments for 9 participants.

Table 1: Summary of the Study Participants, A = Fixation Count on the Robot, B = Average Duration of Fixations on the Robot, C = *"I can see myself using this system in my profession in timber construction"* (1 = strongly disagree, 5 = strongly agree).

ID	**Pair**	**Role**	**Experience** (years)	**A** (#)	**B** (ms)	**C** (1-5)	**SUS** (0-100)	**ARC**
P1	Pair 1	Assembler	26	337	426.3	3	77.5	-1.12
P2	Pair 1	Installer	20	257	411.2	5	75	0.83
P3	Pair 2	Assembler	48	787	511.9	5	80	0.41
P4	Pair 2	Installer	14	449	327.3	3	60	-1.39
P5	Pair 3	Assembler	5	506	397.6	4	55	-0.85
P6	Pair 3	Installer	1	/	/	5	85	0.05
P7	Pair 4	Assembler	6	578	294.9	5	80	0.05
P8	Pair 4	Installer	20	359	396.1	5	77.5	0.83
P9	Pair 5	Assembler	2	286	300.6	2	70	-0.85
P10	Pair 5	Installer	5	378	354.5	2	77.5	-1.12

We extracted mean and standard deviation from each segment as indicators of cardiac activity and variability. These results are then compared between different user roles (assembler v.s. installer) and task scenarios (HRC v.s. HHC).

The analysis revealed that the assemblers had a lower average heart rate than installers ($\mu_A = 77.1, \mu_B = 83.5, U = 515.0, p = 0.002$). Average heart rates during HHC were higher compared to HRC ($\mu_{HRC} = 79.0, \mu_{HHC} = 83.7, U = 546.0, p = 0.04$). Standard deviation was higher in HRC than HHC ($\mu_{HRC} = 4.85, \mu_{HHC} = 3.98, U = 1006.0, p = 0.015$). No significant differences in standard deviation were found between the user roles.

3.4 Attitude Toward Robot Collaboration (ARC)

The participants' ARC scores and backgrounds are summarised in Table 1 along with the SUS and gaze fixations on the robot. For the current sample, attitudes toward robot collaboration showed substantial variation - the Rasch analysis [1] showed that participants' attitudes ranged from -1.39 to 0.83. This range indicates that while some individuals are highly collaborative and likely to engage with robots, others are far less inclined to do so. The scores are based on a logarithmic transformation of response probabilities in the Rasch model, meaning that differences in scores are not linearly spaced but reflect a probabilistic measurement of attitude. Theoretically, the values can range from negative to positive infinity, however, in practice, most scores fall within a more limited range. A score of 0 would reflect a neutral stance toward collaboration, demonstrating that some participants exhibit attitudes that deviate from neutrality—either positively or negatively.

ARC showed a positive correlation with behavioural intention to use the robot (column C in Table 1), $r = .85, p = .002$, indicating that individuals with a more positive attitude toward collaboration were also more willing to integrate the robot into their work. Additionally, there was a moderate but insignificant correlation between ARC and usability perception (SUS) ($r = 0.52, p = .12$), suggesting a trend where users with a more positive collaboration attitude also rated the HRC system as more usable.

3.5 Qualitative Feedback

Can you see yourself using this in timber construction? : 7 out of 10 users responded positively but provided additional constraints, e.g., *"in the hall yes, outside no"* (P4), *"for repetitive work"* (P3), *"this is conceivable in high degree of prefabrication, but everything concerning renovation and individual solutions would be difficult"* (P3). 3 out of 10 users believed the system is not ready for use in construction and provided reasons related to accuracy and ergonomic issues – *"at some point, when it works more accurately"* (P1), *"The system is currently too imprecise and the glasses are not suitable for permanent work"* (P10).

Which aspects of the system need improvement? : The most frequently mentioned issue is the accuracy of the overlay (6 out of 10 users) – *"better calibration for virtual / real"*(P9), *"more accuracy"*(P6). This is followed by interaction issues (5 out of 10) – *"confirming (pressing the buttons) could react a little better"*(P8). 2 users mentioned the balance of physical objects and virtual overlays – *"Visualisation should not overlay the real objects so much"*(P10) – and 2 users mentioned the ergonomics of the HoloLens device – *"Blind spot when wearing glasses, the field of vision is restricted"*(P7).

Collaboration Experience : All users responded positively towards the collaboration with robots, finding it *"fascinating"*, *"fun"*, *"innovative"*. 3 out of 5 pairs commented along the lines of – *"it is surprising that this actually works."*(P1). Pairs 1 and 3 proposed including a second robot: *"It is strange if you stand around a lot waiting for the robot ... when this robot is working I can already start with the second one"* (P2); *"could have a second robot to screw ... why does the human have to do this?"* (P6). P5 and P6 also mentioned feeling like *"the 'little man' working"* while the production process has been pre-programmed; instead, they would prefer to programme the robots themselves.

4 Discussion and Conclusions

This paper presented an exploratory study with construction workers on the use of an AR-HMD system for multi-user HRC. Below, we summarise key usability barriers we found in the study and highlight findings related to the three dimensions of multi-user HRC outlined in the introduction.

The usability of the system was found to be good by the workers (73.8 out of 100, given a benchmark average of 68 [15]). The AR interface coordinated the collaboration and allowed users to visualise the robot either in anticipation of its next movement or in real time, depending on their roles. The reported perception of safety with the robot was high for both roles (4.4 out of 5). The most notable issues were the positional accuracy of the overlay (6 out of 10 users) and the balance of virtual and real objects during physical work (2 out of 10 users). Given the nature of construction tasks, we highlight **accuracy and visual balance between virtual/real objects** as two critical usability factors to consider for future designs.

Correlation between the teams' performance in HHC and HHRC was low. Therefore, we are not certain whether the performance of human teams can predict the performance of the same team with a robot. However, we noted that HHC tasks showed lower standard deviations in heart rates than HHRC ($p<0.01$), which can be explained by larger fluctuations in activity levels when users had to *"stand around a lot waiting for the robot"* (P2) and resume work when needed. Additionally, the participants' mean heart rate was higher during HHC ($p<0.05$), indicating consistently higher effort. This aligns with the result that HHC assembly was faster on average than HHRC. Though previous studies have found dyadic HRC to be faster than HHC in wood assembly tasks [7], we highlight that **reduced fluency of collaboration in non-dyadic HRC may challenge the performance gains**.

The asymmetrical study setup meant that only the installer (B) had authority to control the robot through AR. This led to several differences. During HHRC, the assembler fixated significantly more on the visualisation of their partner ($p<0.05$). One interpretation of this effect is that the assembler has a stronger reliance on their partner than vice versa. Other interpretations, such as a lack of engagement or boredom, are also possible, though we have no further support for a decisive interpretation. The assembler also rated both questions *"I collaborated with my partner / robot"* lower on average. When taken in combination with the fixation difference, we believe this indicates a risk that the **user without robot control authority can become ostracised in a non-dyadic setup**. This aligns with prior work on uneven distribution of robot attention, which can compromise relationship quality in human teams [6].

Importantly, robot control authority may have different impacts depending on the team composition. For instance, in a three-human-one-robot setup, Sebo et al. [20] reported that the robot liaisons, i.e., users who took up the robot control role, reported a lower perception of group inclusion than their peers. Additionally, Haripriyan et al. [5] found that a robot manager, i.e., user in charge of instructing the robot to perform tasks, naturally emerged without any intentional assignment of such a role in the study design. As human-robot teams in construction environments may be complex and dynamic, future work needs to carefully consider this aspect. One potential way to address this is to design robot behaviours which positively shape the interactions between multiple people [4] or can better support individual users' experiences [2].

Alternative designs for the AR control interface may also alleviate these issues. We reference the non-dyadic interaction framework proposed by Schneiders et al. [16] to illustrate such alternatives. For instance, strategies of *coaction* can be applied through either "merging" the simultaneous use by multiple users, e.g., first polling inputs from different users and then executing the decision, or using "division" to separate the artefact into sections, e.g., allowing each user to control a different type of robotic action. The user roles can also be rotated during sequential episodes of interaction, where the *customisation* strategy can be applied towards supporting users with different levels of training.

Lastly, our findings showed **substantial variability in workers' attitudes towards robot collaboration**, highlighting the importance of taking these differences and their potential impact on collaboration behaviour into account. This is supported by the correlation between collaboration attitude and intention to use the system in practice. However, given the small sample size, the strength of this relationship should be interpreted with caution. 3 workers in our study believed the system is not yet ready for practical use due to accuracy and ergonomic reasons. These users (P1, P9, P10) also had negative ARC, indicating initial evidence of the efficacy of the scale. Future studies should examine whether the variability observed in attitudes translates into real-world behaviour, such as the frequency or success of collaboration with robots. A larger and more diverse sample could help confirm such a relationship and explore the connection between users' attitudes and the success of training programs aimed at optimizing human-robot collaboration.

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References

[1] Trevor G. Bond and Christine M. Fox. 2013. *Applying the Rasch Model.* Psychology Press. doi:10.4324/9781410614575

[2] Huili Chen, Sharifa Alghowinem, Cynthia Breazeal, and Hae Won Park. 2024. Integrating Flow Theory and Adaptive Robot Roles: A Conceptual Model of Dynamic Robot Role Adaptation for the Enhanced Flow Experience in Long-term Multi-person Human-Robot Interactions. In *Proceedings of the 2024 ACM/IEEE International Conference on Human-Robot Interaction* (Boulder, CO, USA) *(HRI '24)*. Association for Computing Machinery, New York, NY, USA, 116–126. doi:10.1145/3610977.3634945

[3] Sara J Czaja, Neil Charness, Arthur D Fisk, Christopher Hertzog, Sankaran N Nair, Wendy A Rogers, and Joseph Sharit. 2006. Factors predicting the use of technology: findings from the Center for Research and Education on Aging and Technology Enhancement (CREATE). *Psychology and aging* 21, 2 (2006), 333. doi:10.1037/0882-7974.21.2.333

[4] Sarah Gillet, Marynel Vázquez, Sean Andrist, Iolanda Leite, and Sarah Sebo. 2024. Interaction-Shaping Robotics: Robots That Influence Interactions between Other Agents. *J. Hum.-Robot Interact.* 13, 1, Article 12 (March 2024), 23 pages. doi:10.1145/3643803

[5] Arthi Haripriyan, Rabeya Jamshad, Preeti Ramaraj, and Laurel D. Riek. 2024. Human-Robot Action Teams: A Behavioral Analysis of Team Dynamics. In *2024 33rd IEEE International Conference on Robot and Human Interactive Communication (ROMAN)*. 1443–1448. doi:10.1109/RO-MAN60168.2024.10731176

[6] Malte F. Jung, Dominic Difranzo, Solace Shen, Brett Stoll, Houston Claure, and Austin Lawrence. 2020. Robot-Assisted Tower Construction—A Method to Study the Impact of a Robot's Allocation Behavior on Interpersonal Dynamics and Collaboration in Groups. *ACM Transactions on Human-Robot Interaction* 10, 1 (Oct. 2020), 1–23. doi:10.1145/3394287

[7] Xiaoyun Liang, Usman Rasheed, Jiannan Cai, Bastian Wibranek, and Ibukun Awolusi. 2024. 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 (Aug. 2024). doi:10.1061/jcemd4.coeng-14390

[8] Rasmus S. Lunding, Mathias N. Lystbæk, Tiare Feuchtner, and Kaj Grønbæk. 2023. AR-supported Human-Robot Collaboration: Facilitating Workspace Awareness and Parallelized Assembly Tasks. In *2023 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*. 1064–1073. doi:10.1109/ISMAR59233.2023.00123

[9] Antonia Meissner, Angelika Trübswetter, Antonia S. Conti-Kufner, and Jonas Schmidtler. 2020. Friend or Foe? Understanding Assembly Workers' Acceptance of Human-robot Collaboration. *J. Hum.-Robot Interact.* 10, 1, Article 3 (July 2020), 30 pages. doi:10.1145/3399433

[10] Verena Nitsch and Thomas Glassen. 2015. Investigating the effects of robot behavior and attitude towards technology on social human-robot interactions. In *24th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*. IEEE, 535–540. doi:10.1109/ROMAN.2015.7333560

[11] Tatsuya Nomura, Takayuki Kanda, Tomohiro Suzuki, and Kensuke Kato. 2008. Prediction of human behavior in human–robot interaction using psychological scales for anxiety and negative attitudes toward robots. *IEEE Transactions on Robotics* 24, 2 (2008), 442–451. doi:10.1109/TRO.2007.914004

[12] Chinedu Okonkwo, Xiaoyun Liang, Usman Rasheed, Ibukun Awolusi, Jiannan Cai, and Bastian Wibranek. 2023. *Construction Worker Workload Assessment for Human-Human versus Human-Robot Collaboration in Wood Assembly.* 322–330. doi:10.1061/9780784485248.039

[13] Nelusa Pathmanathan, Tobias Rau, Xiliu Yang, Aimée Sousa Calepso, Felix Amtsberg, Achim Menges, Michael Sedlmair, and Kuno Kurzhals. 2024. Eyes on the Task: Gaze Analysis of Situated Visualization for Collaborative Tasks. In *2024 IEEE Conference Virtual Reality and 3D User Interfaces (VR)*. 785–795. doi:10.1109/VR58804.2024.00098

[14] Hannah R. M. Pelikan, Amy Cheatle, Malte F. Jung, and Steven J. Jackson. 2018. Operating at a Distance - How a Teleoperated Surgical Robot Reconfigures Teamwork in the Operating Room. *Proc. ACM Hum.-Comput. Interact.* 2, CSCW, Article 138 (Nov. 2018), 28 pages. doi:10.1145/3274407

[15] Jeff Sauro and James R Lewis. 2012. *Quantifying the user experience: Practical statistics for user research.* Morgan Kaufmann. doi:10.1016/C2010-0-65192-3

[16] Eike Schneiders, EunJeong Cheon, Jesper Kjeldskov, Matthias Rehm, and Mikael B. Skov. 2022. Non-Dyadic Interaction: A Literature Review of 15 Years of Human-Robot Interaction Conference Publications. *J. Hum.-Robot Interact.* 11, 2, Article 13 (feb 2022), 32 pages. doi:10.1145/3488242

[17] Sarah Sebo, Brett Stoll, Brian Scassellati, and Malte F. Jung. 2020. Robots in Groups and Teams: A Literature Review. *Proc. ACM Hum.-Comput. Interact.* 4, CSCW2, Article 176 (oct 2020), 36 pages. doi:10.1145/3415247

[18] Alfred N Smith. 1971. The importance of attitude in foreign language learning. *The Modern Language Journal* 55, 2 (1971), 82–88. doi:10.2307/321854

[19] Nicolas Spatola and Olga A Wudarczyk. 2021. Implicit attitudes towards robots predict explicit attitudes, semantic distance between robots and humans, anthropomorphism, and prosocial behavior: From attitudes to human–robot interaction. *International Journal of Social Robotics* 13, 5 (2021), 1149–1159. doi:10.1007/s12369-020-00701-5

[20] Sarah Strohkorb Sebo, Ling Liang Dong, Nicholas Chang, and Brian Scassellati. 2020. Strategies for the Inclusion of Human Members within Human-Robot Teams. In *Proceedings of the 2020 ACM/IEEE International Conference on Human-Robot Interaction* (Cambridge, United Kingdom) *(HRI '20)*. Association for Computing Machinery, New York, NY, USA, 309–317. doi:10.1145/3319502.3374808

[21] Ryo Suzuki, Adnan Karim, Tian Xia, Hooman Hedayati, and Nicolai Marquardt. 2022. Augmented Reality and Robotics: A Survey and Taxonomy for AR-enhanced Human-Robot Interaction and Robotic Interfaces. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 553, 33 pages. doi:10.1145/3491102.3517719

[22] Xiliu Yang, Felix Amtsberg, Michael Sedlmair, and Achim Menges. 2024. Challenges and potential for human–robot collaboration in timber prefabrication. *Automation in Construction* 160 (2024), 105333. doi:10.1016/j.autcon.2024.105333

[23] Xiliu Yang, Aimée Sousa Calepso, Felix Amtsberg, Achim Menges, and Michael Sedlmair. 2023. Usability Evaluation of an Augmented Reality System for Collaborative Fabrication between Multiple Humans and Industrial Robots. In *Proceedings of the 2023 ACM Symposium on Spatial User Interaction* (Sydney, NSW, Australia) *(SUI '23)*. Association for Computing Machinery, New York, NY, USA, Article 18, 10 pages. doi:10.1145/3607822.3614528

[24] Sarah Zabel, Nicolas Neef, Xiliu Yang, Cheryl Heinze, and Siegmar Otto. 2025. Assessing Attitudes Toward Collaboration with Robots in the Workplace – One Element of Optimizing Robot Engagement (in press). In *Proceedings of the HCI International 2025, Communications in Computer and Information Science (CCIS)*. Springer.