Enhancing Human-Robot Collaboration Through Augmented Reality Guidance: A Phase-Based Evaluation

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Abstract

Wider adoption of robots in construction is becoming increasingly feasible as sensing, control, and artificial intelligence (AI) technologies advance. However, the inherent complexity and variability of construction activities mean that full automation remains challenging, making human-robot collaboration (HRC) a more practical approach for structural assembly. Effective HRC requires workers to access task-relevant information on work locations and robot actions in a timely and intuitive manner, and augmented reality (AR) offers an in-situ solution for delivering such information. However, research comparing AR with traditional paper-based instructions in structural assembly is limited.

This paper evaluates a head-mounted display (HMD)-based AR instruction approach against paper instructions across three phases: search, placement, and movement. AR reduced search time by 52.7% and eliminated search errors, compared with a 3.75% procedural error rate under paper instructions. During placement, AR increased time by 32.4% but improved positional precision from 20.1mm to 7.7mm. Movement times were nearly identical between conditions (r=0.84). Overall, this study provides an experimental evaluation of AR instruction for HRC structural assembly and demonstrates substantial advantages over paper-based methods in effectiveness and precision, along with a modest improvement (10.3%) in efficiency.

Keywords –

Augmented Reality; Human-Robot Collaboration; Task Instruction; Head-Mounted Display (HMD)

1 Introduction

The construction industry is one of the world's most important economic pillars [1], yet its productivity growth over recent decades has lagged behind the economy-wide average [2]. In contrast, manufacturing has achieved substantial productivity gains, largely driven by automation and the widespread adoption of industrial robotics [3,4]. Transferring similar levels of automation to construction is difficult due to dynamic, unstructured, and often cluttered site conditions and highly customised designs [5]. However, advances in sensing, control, and artificial intelligence (AI) are increasing robot capability and making broader adoption more feasible [6].

Many construction activities remain difficult to fully automate, particularly structural assembly, where variability, tolerance requirements, and safety constraints often demand human judgement and dexterous operation [7]. Human-robot collaboration (HRC) is therefore a practical pathway to deploy robotics by combining the versatility and judgement of human workers with the strength, precision, and consistency of robots. However, HRC also places greater demands on workers for information, as they must understand upcoming steps and target locations and maintain awareness of robot state and intent to coordinate safely and efficiently.

Augmented reality (AR) has been explored to deliver task-relevant information in structural assembly [8–10], but the research quantifying its benefits over traditional paper guidance in HRC remains limited. This study addresses this gap by experimentally evaluating a head-mounted display (HMD)-based AR instruction approach across three phases of structural assembly: search (material/tool retrieval and locating work positions) [11], placement (positioning and aligning components), and movement (walking while wearing the HMD) [12].

The remainder of this paper is organised as follows. Section 2 reviews related work, Section 3 describes the methodology, and Section 4 presents results for the three phases. Section 5 discusses implications, limitations, and future work, and Section 6 concludes the paper.

2 Literature Review

2.1 AR Applications in HRC Structural Assembly

AR has been increasingly explored as an assistive interface for workers in HRC scenarios, particularly due to its ability to overlay task information directly onto the physical environment. In structural assembly contexts, prior AR applications can be summarized into three categories: teleoperation support, supervisory control, and sequential collaboration.

In teleoperation studies, AR supports remote robot control by improving depth perception and situational awareness via integrated camera views and virtual overlays. Lee et al. mounted cameras at the robot's worksite and displayed a 3D model of the target component on a wide-angle AR interface, improving operator awareness and control precision [13]. Using an HMD, Sukumar et al. enabled operators to view the robot-perceived environment, specify target placement locations, and teleoperate the robot to complete assembly actions within the AR-guided workspace [8].

More recent work has examined supervisory control, where robots execute the primary task and AR enables humans to monitor semi-autonomous actions and adjust plans. Kyjanek et al. developed an HMD-based AR interface that displays robot motion trajectories and supports task-sequence modification via Robot Operating System (ROS) [14]. Loy et al. developed an HMD-based AR system to support exploratory human-robot collaborative assembly. The system allows users to align a virtual robot with its physical counterpart through a spatial anchor, refine robot waypoints, and preview planned trajectories before execution. It also supports human intervention at key decision points, including motion refinement and temporary release for manual repositioning [9]. Overall, these interfaces make robot intent more legible and support smoother coordination in shared workspaces.

The third category concerns AR in sequential HRC, where human and robot alternate actions, and AR communicates the robot's active workspace and relevant target locations for human operations. In collaborative timber handling, González-Böhme and Valenzuela-Astudillo used an AR HMD to support a workflow in which the worker marked joinery on the workpiece, and the robot detected the markings and executed cutting, with AR providing motion/workspace previews and collision warnings [15]. Rogeau et al. applied AR to timber assembly by guiding material retrieval and installation locations while also visualising robot trajectories [10]. Overall, sequential AR-HRC systems guide human actions while making robot motion information transparent to support safe coordination.

2.2 AR Versus Traditional Instruction Methods

Research quantifying whether AR yields measurable benefits in HRC, and the magnitude of those benefits compared with traditional methods, remains limited. In structural assembly application scenario, Kaiser et al. applied an HMD to deliver AR instructions comprising two core elements: a step-by-step visual task list and robot-generated requests for human assistance when intervention was required [16]. Compared with a desktop interface, the AR interface reduced completion time by approximately 60% and was rated positively by participants. However, the human contributions in that study were relatively simple, such as triggering robot actions or placing small components, and therefore differed substantially from the more complex structural assembly tasks examined in the present work.

Comparative studies have also been conducted in the manufacturing field. Anderson et al. compared an AR approach with desktop- and paper-based methods for a car-door assembly task, evaluating efficiency, effectiveness, and user satisfaction [17]. They observed limited differences in efficiency, but improvements in effectiveness and user satisfaction with AR. Importantly, structural assembly in construction often involves larger workspaces, higher safety risk, and stronger reliance on spatial cognition, making direct transfer of conclusions from manufacturing nontrivial.

To summarize, a clear gap remains in rigorously evaluating AR assistance for complex HRC structural assembly using a comprehensive set of performance dimensions. Building on the three phases identified in the previous section, this study experimentally evaluates an HMD-based AR assistance approach tailored to HRC structural assembly tasks.

3 Methodology

This study used a controlled laboratory experiment to evaluate an AR instruction method across the HRC assembly workflow, focusing on three phases: search, placement, and movement. Each participant completed the structural assembly task twice, once with AR instructions delivered via an HMD and once with conventional text-and-image paper instructions. The order of the two processes was randomized to minimize learning effects.

3.1 Experimental Design

The experiment was designed to simulate a real-world structural assembly workflow in a laboratory setting. Participants were tasked to assemble a timber floor frame (2.045 m × 1.045 m). All components had a 45 mm × 70 mm cross-section, with the 45 mm face in contact with the floor. The workflow comprised two stages: component placement, in which participants carried each timber element from a storage area to its designated location in the assembly zone, and connections, in which participants used a nail gun to fasten pre-positioned components at predefined connection points. To better reflect practical work patterns, participants returned to the storage area after completing each component placement task and each bundled connection task (two connection points per bundle). Task allocation and the execution sequence for both the human participant and the robot were fixed in advance. Each participant completed 10 placement (P) tasks and 6 bundled connection (BC) tasks (highlighted by red dashed boundaries in Figure 1), while the robot performed the remaining tasks in the overall assembly process.

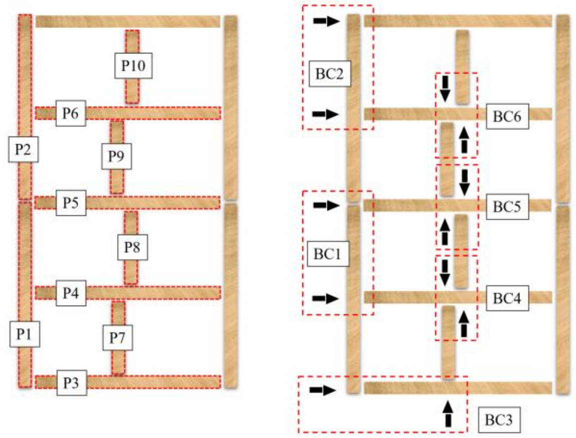

Figure 1. Schematic representation of human tasks in structural assembly

The task sequence was determined based on three principles. First, it respected the workflow dependency of the assembly process, such that component placement tasks had to be completed before the corresponding connection tasks. Second, as illustrated in Figure 1, the robot executed its tasks in a bottom-to-top order. To create opportunities for close human-robot proximity during assembly, the human task sequence was designed to generally follow the same order, thereby enabling the experiment to capture the potential influence of robot intrusion on human task performance. Third, the task step orders under the AR and paper instruction conditions were varied to reduce potential learning effects across conditions.

The experimental workspace was divided into designated zones for human and robot movement (as shown in Figure 2). The human participant and the robot performed tasks primarily within their respective zones. The floor frame was located in the human moving zone, while human materials and tools were organized in a storage zone. During the robot placement operation, the robot arm and the component carried by the robot could intrude into the human moving zone, potentially causing a collision if the human participant was not sufficiently aware of the robot's movement.

The robotic system comprised a UR10e collaborative robotic arm [18] equipped with a two-finger OnRobot RG6 gripper [19], mounted on a MiR100 mobile platform [20]. The six-DoF UR10e was selected for its flexibility and inherent safety for HRC assembly studies. Robot motions, dwell commands, and gripper actions were pre-programmed in PolyScope (UR controller). The MiR100 served as a mobile base to extend the robotic arm's reachable workspace. It supports SLAM-based navigation and uses onboard LiDAR for obstacle detection and avoidance. Navigation routes were planned and executed via the MiR web interface.

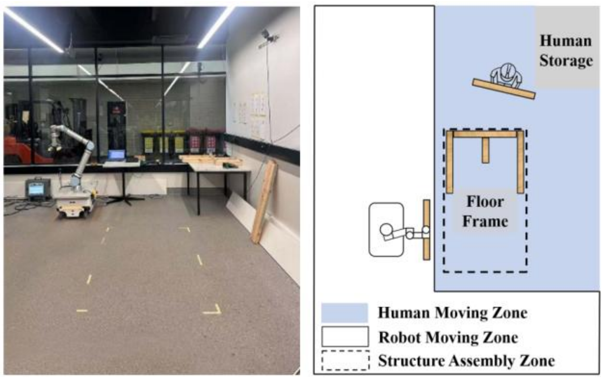

Figure 2. Lab environment and schematic site plan

3.2 Task Instruction Methods

Participants completed the assembly tasks under two instruction methods: AR assistance and paper-based text-and-image instructions.

The AR system was developed in Unity to support HRC task execution by (i) providing step-by-step guidance for human actions, including storage locations and target placement positions, and (ii) presenting an AR-based preview of robot motion to help participants better understand upcoming robot actions. At the start of the assembly, the AR scene displayed all storage zones and target positions for human-assigned components in a neutral greyish-white color. For each placement task, the relevant storage position and corresponding target position were highlighted by flashing in red at 1 Hz; the flashing stopped once the participant completed the placement (Figure 3a).

(a) Instruction of placement task (b) Visualization of robot motion trajectories in AR environment

Figure 3. AR System Functions for HRC Assembly

To support anticipation and safety during close human-robot proximity, a digital twin of the robot arm and mobile base was overlaid in the AR scene. Pre-recorded robot trajectories were used to generate a motion preview that appeared in the AR headset 2s before the robot executed the physical movement (Figure 3b), enabling participants to adjust their posture or position in advance if needed.

The AR hardware was a Microsoft HoloLens 2, and the application was streamed via Holographic Remoting, with Unity running on a laptop (Intel Ultra 9 185H CPU; NVIDIA GeForce RTX 4070 Laptop GPU).

The paper-based instruction method used a step-by-step instruction sheet, where each step corresponded to either a single placement task or a bundled connection task. The sheet was organized into three columns: step number, storage position, and work position. For placement tasks, the required component was highlighted in the storage position column, and the target placement position was shown in the work position column. The current task was displayed in color, while components completed in earlier steps were shown in grey in subsequent steps to indicate work progress (Figure 4).

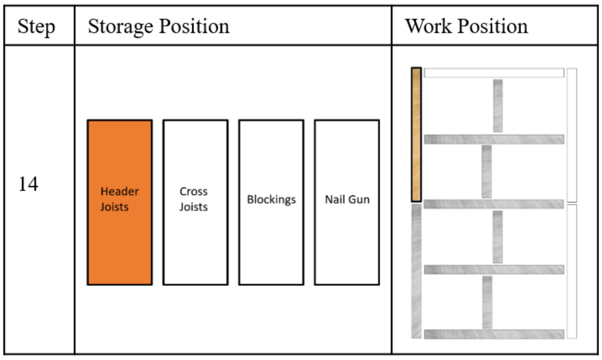

Figure 4. Example of paper-based instructions

3.3 Measurement Methods

Data were collected using (i) video recordings and (ii) an OptiTrack motion-capture system. The primary data source was video, which captured each participant's full experiment process.

In the search phase, participants identified the required component's storage location and its corresponding work position using either AR assistance or the paper instructions. Under AR, this information was provided directly in the immersive scene. Under the paper condition, participants interpreted the paper sheets and mentally mapped the indicated locations onto the physical workspace (search phase in Figure 5). Search time was measured from the moment the participant stopped at the storage area to consult the instruction until the participant started material pickup for the next task.

In the placement phase, participants positioned the component as precisely as possible at the target location (placement phase in Figure 5). With AR assistance, the target placement was visualized precisely in the headset, and participants aligned the physical component to the virtual overlay. In the paper condition, only the periphery of the structural assembly zone was marked by yellow tape, and participants relied on relative spatial relationships between components to achieve correct placement. Placement time was measured after the participant arrived at the work position, starting when the participant began crouching to align the component and ending when the participant stood up after placement.

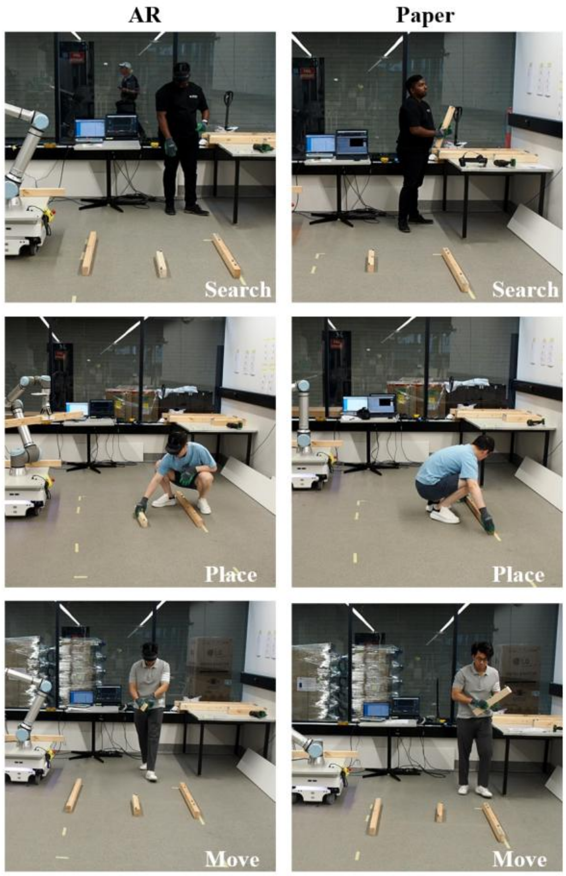

Figure 5. Illustration of the three task phases (search, placement and movement) under AR and paper instruction

The movement phase captured participant locomotion during assembly, including walking from storage to the work position and returning (movement phase in Figure 5). This phase was used to evaluate mobility performance with and without the AR headset. Movement time was measured as the duration of the participant's physical movement between these locations.

The OptiTrack motion-capture system comprised eight infrared cameras installed around the laboratory to maintain tracking coverage under partial occlusions [21]. It recorded the pose (position and orientation) of the placed components. Reflective markers were attached to the diagonal corners of each component; the component center was computed as the midpoint of the two markers, and the in-plane orientation was obtained from the line connecting them. Placement precision was quantified by comparing the measured pose to the corresponding target pose, using position and orientation errors as the primary metrics.

3.4 Participants

Three pilot tests were conducted to verify procedural feasibility and refine the experimental flow. The collected data from these pilots were excluded from the result analysis. After finalizing the protocol, 15 participants (11 male, 4 female) were recruited for the formal study under Monash University human ethics approval. Participants were aged 21-35 and were primarily postgraduate civil engineering students with experience interpreting construction drawings and assembling timber furniture or structural elements. Participants' background information, including prior experience with structural assembly and AR HMDs, was collected via a pre-experiment survey.

Table 1 Participant demographics and prior experience

	Category	Count	Percentage
Gender	Male	11	73.3%
	Female	4	26.7%
Age	21-25	3	20.0%
	26-30	6	40.0%
	31-35	6	40.0%
Experience with timber assembly	Yes	15	100%
	No	0	0%
Experience with AR HMD	Never	6	40.0%
	Under 5 times	4	26.7%
	Over 5 times	5	33.3%

4 Results

The results are presented across three task phases: search, placement, and movement, which are reported in the following three subsections. In addition to the primary efficiency outcome, this section reports the effectiveness results measured by the number of mistakes under the two instruction conditions, and placement precision based on position and orientation errors for the placement tasks.

4.1 Search Phase

4.1.1 Efficiency

Across the 16 tasks, the mean total search time per participant under the AR instruction condition was 36.4s (≈2.3s per task), compared with 76.9s under the paper instruction condition (≈4.8s per task), representing a 52.7% reduction with AR. The variability in total search time was also substantially lower under AR (SD=10.9 s) than under paper instructions (SD=28.9 s), indicating more consistent participant performance using AR assistance.

To examine how the instruction method affected different task types, task-level results are reported in Table 2. For placement tasks, the mean search time per task was 2.1s with AR and 4.7s with paper instructions. For bundled connection tasks, the corresponding times were 2.6s (AR) and 5.0s (paper). These results indicate that AR provided efficiency gains for both task types. The longer search times for bundled connection tasks are expected because each bundled step involves two work positions, requiring additional interpretation and locating effort under both conditions.

Overall, AR search times remained relatively stable across steps (SD=0.7s), whereas paper-based search times showed greater variability (SD=1.8s), highlighting the benefit of directly overlaying task-related visual cues onto the workspace.

Table 2 Task-level search and placement mean time under AR and paper instructions

Task Label	AR Step	Paper Step	AR Search Time (s)	Paper Search Time (s)	AR Place Time (s)	Paper Place Time (s)
P1	1	1	1.4	2.8	5.8	4.6
P2	14	14	1.8	2.6	7.1	6.0
P3	4	4	2.6	6.3	7.4	4.6
P4	5	6	2.3	4.4	7.9	5.2
P5	8	9	2.3	6.0	8.5	5.7
P6	11	11	2.5	4.8	7.0	4.8
P7	3	2	2.7	4.4	4.4	3.7
P8	2	7	2.0	6.4	4.3	3.1
P9	9	3	1.6	4.8	4.5	3.9
P10	12	12	1.8	4.1	2.9	3.5
BC1	16	15	2.2	4.0	N/A	N/A
BC2	15	16	2.1	2.7	N/A	N/A
BC3	7	5	4.5	5.9	N/A	N/A
BC4	6	8	2.6	3.5	N/A	N/A
BC5	10	10	1.6	9.7	N/A	N/A
BC6	13	13	2.3	4.4	N/A	N/A
All tasks (mean ± SD)			2.3 ±0.7	4.8 ±1.8	6.0 ±1.9	4.5 ±1.0

4.1.2 Effectiveness

Assembly effectiveness was assessed by the number of errors during assembly. Under the AR instruction, all 15 participants completed the tasks in the correct order and used the correct storage and work positions throughout. Under the paper instruction, five participants made a total of nine errors. Given 16 steps per participant and 15 participants in total, this corresponds to an overall error rate of 3.75% (9/240).

These nine errors can be grouped into three categories. First, some participants selected an incorrect step, for example, executing Step 13 when Step 10 was required. All such errors occurred after Step 10, suggesting that the greater fatigue and cognitive load in later stages of the session made participants more prone to step-selection errors.

Second, some participants selected the correct component but placed it at an incorrect work position, for instance, placing a member at the location for Task P8 instead of Task P9. This indicates that even when the intended work position is specified on the instruction sheet, participants may still rely on their own assumptions or memory when placing components.

Third, in bundled connection tasks, participants selected the correct tool but completed one connection at the correct position and the other at an incorrect location. This extends the second error category, indicating that multi-position tasks are more prone to partial completion errors and highlighting the value of AR instructions in real-world HRC structural assembly.

4.2 Placement Phase

4.2.1 Efficiency

Only the ten placement tasks were included in the placement phase evaluation. Across participant trials, the mean total placement time was 59.6 s under AR (≈6.0s per task) and 45.0 s under paper instructions (≈4.5s per task), indicating that AR required 32.4% more time. The explicit visual reference offered by AR assistance encouraged participants to pursue higher placement precision and spend more time on fine adjustments. In addition, placement times showed greater variability under AR (SD=30.2s) than under paper instructions (SD=21.4s), suggesting larger inter-participant differences when visual placement cues were available.

A task-level breakdown is provided in Table 2. For joists (P1-P6), the mean placement time was 7.3s with AR and 5.2s with paper instructions, a 41.4% increase. For blocking members (P7–P10), the corresponding times were 4.0s and 3.6s, a 13.4% increase. These results indicate that the overall difference was driven primarily by joists (longer components). In other words, AR instructions elicited additional fine-tuning when component geometry made accurate pose matching more visually demanding.

4.2.2 Precision

Despite requiring longer placement time, AR instructions resulted in substantially higher placement precision. Across all placement tasks, the mean positional (distance) error per component was 7.7 mm under AR instruction, compared with 20.1 mm under paper instruction. AR also produced markedly more consistent performance, with a much lower standard deviation of distance error across components (SD = 1.0mm for AR versus 7.2mm for paper). Improvements in orientation accuracy were smaller than those in position, but remained pronounced, with AR reducing the mean orientation error from 1.03° to 0.70° (32.0% lower) compared with paper instructions.

Task-level results further showed that AR errors remained relatively uniform across components (SD=0.9 mm), whereas paper-based placement errors showed substantially greater divergence (SD=6.8 mm). At the task level, positional precision under paper instructions depended strongly on the availability of physical references. For perimeter components (Tasks P1-P3), the yellow tape provided a positional guide, and the mean distance error under paper instructions was 11.6 mm, which was 49.8% higher than that under AR. For interior components (Tasks P4-P10), where no such reference was available, the mean paper-based distance error increased to 23.7 mm, 207.9% higher than the AR condition. In practical assembly settings, clear physical references are often unavailable, making millimeter-level placement accuracy difficult to achieve.

4.3 Movement Phase and Overall Completion Time

For the movement-phase evaluation, movement time across all 16 tasks was summed for each participant. The results indicate that movement performance was generally unaffected by the instruction condition. The mean total movement time was 127.3s under AR and 127.1s under paper instructions, with comparable variability (SD = 16.4s and 17.6s, respectively). The paired mean difference was 0.15s, and a strong within-subject correlation was observed ($r=0.84$), indicating that individual mobility characteristics primarily drove movement performance. These results suggest that wearing the HoloLens 2 did not noticeably affect participants' walking time within the workspace.

Summing the three phases yields the total completion time for the assembly task. The mean total completion time under AR was 223.3 s, compared with 249.0 s under paper instructions, corresponding to a 10.3% reduction. Although AR required more time in the placement phase, this was offset by a substantial reduction in search time, resulting in an overall time advantage.

5 Discussion

5.1 Effects of AR Instruction

The findings suggest that the contribution of AR instruction in HRC structural assembly is strongly phase-dependent. The clearest efficiency benefit was observed in the search phase, where spatial cues were directly overlaid onto the workspace, reducing the need to interpret abstract instructions and mentally map them to physical locations. This mechanism lowered human participants' cognitive load and helped standardize performance, consistent with the substantially reduced variability across participants compared to paper instructions.

In the placement phase, AR instruction increased completion time, particularly for longer components. One possible interpretation is that participants spent more time making careful placement adjustments rather than simply working less efficiently. The observed improvements in positional and orientation precision are consistent with this explanation, although causality is not directly established in the present study. The precision results also highlight an important practical implication. Paper-based placement relied heavily on physical references on the periphery, and performance degraded substantially for interior components where such references were absent. Given that real structural assembly often lacks clear positional guides, AR location reference overlays have the potential to be particularly valuable in reference-scarce activities, supporting consistent, high-precision placement.

Effectiveness outcomes indicate that AR can improve procedural compliance by reducing sequencing errors and multi-position execution errors that may become more likely as fatigue and cognitive demands accumulate. Finally, movement times were essentially unchanged between the two instruction methods, suggesting that wearing a HoloLens 2 did not meaningfully affect participants' walking in the tested workspace.

5.2 Limitations and Future Research

Several limitations should be considered when interpreting these results. First, the experiment was conducted in a controlled laboratory setting with a timber floor-frame task designed to remain feasible within space constraints. The assembly scale, number of components, and density of connection tasks were therefore limited. Moreover, the HRC setting considered in this study was relatively simplified rather than dynamically responsive. Although partial workspace overlap existed during robot placing operations, the overall interaction did not represent a highly coupled or real-time coordinated HRC scenario. It remains to be tested whether the observed advantages of AR, particularly in search efficiency and placement precision, persist under larger and more complex assemblies.

Second, this study did not evaluate how robot motions affect human performance when the AR motion preview feature is available. In HRC settings, robot motions during close-proximity collaboration may influence perceived safety, attentional demands, and work efficiency. Future work should therefore compare conditions with and without active robot operation, and assess safety-related outcomes such as separation distance and perceived workload across different robot motion profiles and collaboration strategies.

Third, the sample size and participant profile in this study may limit the statistical strength and generalizability of the findings. Since all participants were young postgraduate students, the results may differ from those of actual construction workers or industry practitioners. Future work should therefore involve a larger and more diverse participant group, together with more comprehensive statistical analysis.

Fourth, the results may be influenced by the specific AR hardware used. Since the system was implemented on a HoloLens 2, performance may differ with other devices, such as alternative optical see-through HMDs or projector-based spatial AR systems. Future work should examine how device-related factors, including comfort, field of view, and tracking stability, affect efficiency, effectiveness, and precision.

Finally, multi-agent collaboration was not examined. In real projects, multiple workers and robots may share constrained spaces, increasing interference, safety risks, and coordination complexity. Future work will extend the AR instruction framework to multi-human/multi-robot scenarios and larger assemblies, while evaluating adapted visualization strategies for these settings.

6 Conclusion

This study examined the value of HMD-based AR instructions for HRC structural assembly by benchmarking them against paper-based guidance across search, placement, and movement phases. The results indicate that AR's contribution is not uniform across the workflow. In the search phase, spatially registered cues reduced time by 52.7%, and no search-related errors were observed under AR, whereas paper instructions resulted in a 3.75% procedural error rate. For placement, AR primarily acted as a precision aid rather than a speed aid. Participants spent longer on fine adjustments (mean placement time +32.4% under AR), but achieved higher positional accuracy, 7.7 mm vs. 20.1 mm, with the largest gains for interior components where references were limited. Movement performance was comparable across conditions, suggesting that wearing the HoloLens 2 did not measurably affect walking in the tested setup.

Overall, the time saved during search outweighed the additional placement time, resulting in a reduction of 10.3% in total completion time. These findings support AR as a promising instruction modality for HRC structural assembly, especially in reference-scarce workspaces. Several limitations should be considered. The study was conducted in a controlled laboratory setting with a single timber floor-frame task and a limited number of components, which may constrain generalizability to larger and more complex site conditions. Robot motions were pre-programmed, and safety-related measures such as separation distance, near-miss events, and perceived workload were not systematically assessed. Future work should validate the findings across diverse assemblies and motion strategies.

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